

Fuzzy Logic-Based Decision Support System for Adaptive Plant Watering Volume in IoT Environments

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Abstract

Conventional irrigation systems often result in inefficient water use due to their inability to adapt to dynamic and uncertain environmental conditions. This study aims to design and simulate an adaptive smart irrigation system using Mamdani Fuzzy Logic Controller (FLC) in an Internet of Things (IoT) architecture. This methodology integrates four environmental parameters, namely Soil Moisture, Air Temperature, Air Humidity, and Light Intensity to calculate the appropriate watering duration, effectively reducing the risk of false positives associated with traditional two-input systems. The mathematical model was verified and simulated using MATLAB Fuzzy Logic Toolbox, with the Centroid defuzzification method. The results show that in extreme testing scenarios, the system successfully calculated the appropriate watering duration of 18 seconds. This analytical calculation perfectly aligns with the MATLAB simulation, demonstrating 100% accuracy with no error deviation. In conclusion, the proposed four-input Mamdani Fuzzy Logic controller effectively reduces data ambiguity and optimizes agricultural water consumption, establishing a solid mathematical foundation for future IoT hardware implementation in precision agriculture.

Keywords: Smart Irrigation, Fuzzy Logic, Internet of Things (IoT), Mamdani Method, Precision Agriculture.

INTRODUCTION

The agricultural sector is the largest consumer of clean water resources globally, as well as the sector most vulnerable to the threat of the water crisis currently facing the world. In Indonesia, the level of water use efficiency in agricultural irrigation systems remains a significant challenge (Hoque, Islam, & Khaliluzzaman, 2023). To date, the majority of agricultural and plantation lands still rely on conventional or manual watering methods. This manual approach is no longer relevant because it is highly dependent on fixed schedules without considering rapidly changing weather dynamics (Liu, Zhao, & Rezaeipannah, 2025). As a result, plants often experience over-watering, which causes root rot, or under-watering, which fatally inhibits photosynthesis (Ardyanti et al. 2021; Arief et al. 2024).

To overcome the inefficiency of conventional methods, the transition to a Smart Farming ecosystem is an urgent necessity. The use of Internet of Things (IoT) technology enables the automation of the agricultural sector through a network of sensors embedded in the land (Nur, Irawan, Mulyawati, & Rahman, 2025). IoT plays a crucial role in continuously monitoring environmental parameters in real-time (Siskandar, Santosa, Wiyoto, Kusumah, & Hidayat, 2022). By utilizing smart microcontrollers such as ESP32 or ESP8266 as control centers, the system can automatically turn water pumps on or off without human intervention (Alamsyah, Ryansyah, Permana, & Mufidah, 2024); (Anindita et al., 2024). The use of this technology not only cuts operational and labor costs but also ensures the precision of water distribution on large-scale agricultural land (Setiawan & Aula, 2024); Pamungkas, Ullah, Faizal, & Zarory, 2025).

Although IoT is capable of presenting data in real-time, a fundamental problem arises from the nature of sensor data, which is in the form of crisp numbers. In natural conditions, environmental parameters are highly ambiguous and linguistic. For example, can a soil moisture sensor value of 40% be categorized as "dry" or "moist"? Conventional automatic control systems (On/Off) do not have the ability to interpret this gray area of data, so they often provide crude responses (Neugebauer, Akdeniz, Demir, & Yurdem, 2023).

This is where Fuzzy Logic comes in as a smart computing solution. This method is designed to mimic human thinking and reasoning patterns that are accustomed to uncertainty (Septima, 2023; Rozie, Anhar, & Irianto, 2025). Of the many decision-making algorithms, the Mamdani method used by the Fuzzy Logic Controller (FLC) is considered the most optimal because of its intuitive approach and is widely used for precision control systems (Adzimi dkk., 2024; Muttaqi, Nurchim, & Ningsih, 2024). Fuzzy Logic allows the system to decide when plants should be watered "briefly," "moderately," or "long," rather than simply "on" or "off" (Isnaeni, Setyowati, & Fatkhurrozi, 2025; Rinaldi, Oktarina, & Dewi, 2022).

Various studies have applied Fuzzy Logic for optimization, ranging from door control to industrial supply (Asysyauqi, Ferdi Andriansyah, Ulla, & Sucipto, 2025; (Rahmadaniar et al., 2024; Hidayat, Santosa, Siskandar, & Gilang Baskoro, 2021). In the irrigation sector, previous studies generally relied on only one or two input variables (Nurcahyono, Mujiyanto, Mufarrihah, & Ali, 2025). Therefore, this study aims to design and simulate a smart irrigation system that is much more adaptive.

This study is limited to the design of decision logic using MATLAB software. This system is designed to process four comprehensive input variables, namely: Soil Moisture, Air Temperature, Air Humidity, and Light Intensity (Adiwilaga, Firmansyah, Irzia, & Muthmainah, 2024). The main focus of the research is to use Mamdani Fuzzy reasoning to calculate a single output in the form of Watering Duration precision, so that a mathematical model can be obtained that can be used as a strong foundation before the physical prototype tool is mass-produced commercially (Garingging dkk., 2025; Handoyo, Febrianto, Tinggi, & Ronggolawe, 2025).

METHODS

The research methods used were system architecture design and computational simulation using a Soft Computing approach. Data processing was carried out using the Mamdani Fuzzy Inference System (FIS) algorithm to obtain the optimal watering duration (Adiwilaga dkk., 2024; Septima, 2023).

2.1 System Architecture Design and Simulation

The hardware architecture in this study was designed and simulated using a virtual prototyping platform (Wokwi). The system uses a centralized microcontroller as the main processing unit (Alamsyah dkk., 2024; Pamungkas dkk., 2025). This system integrates data acquisition devices and actuators as follows:

1. Soil Moisture Sensor: Simulated using an analog potentiometer to measure the percentage of water content (0-100%).
2. DHT22 Sensor: Used to acquire ambient air temperature and relative humidity levels (Muttaqi et al., 2024).
3. Light Sensor (LDR): Measures the intensity of sunlight (Lux) that affects the rate of water evaporation.
4. Actuator and Display: The system uses a relay to control a DC water pump, a servo motor as a water valve, and a 16x2 I2C LCD module for local data monitoring (Silalahi, Simanjuntak, Maharani, & Ramdani, 2024).

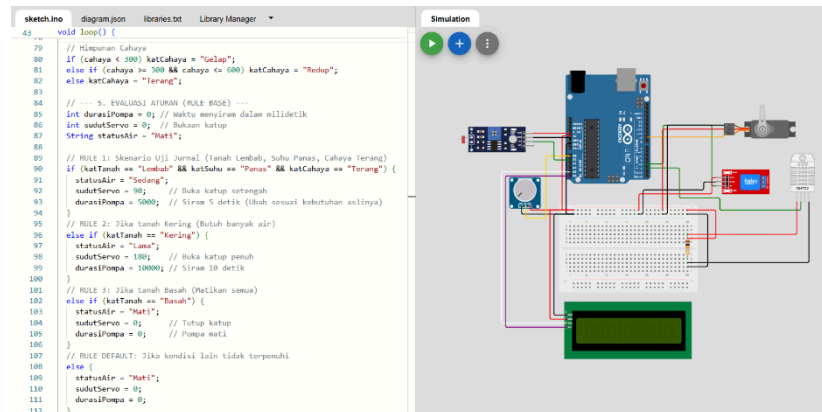


Figure 1. Simulation Circuit Diagram of the Irrigation System

Conceptually, the block diagram of this smart irrigation system architecture is divided into three main pillars: Input, Process, and Output (Santosa, Hidayat, & Siskandar, 2021). The Input section consists of data acquisition instruments, namely soil moisture sensors, air temperature and humidity sensors (DHT22), and light intensity sensors (LDR). These sensors continuously read physical environmental variables and convert them into electrical values (crisp input).

These values are then transmitted to the Process section, which is a microcontroller that acts as a Fuzzy Logic Controller (FLC). In this processing block, raw environmental data is evaluated through the stages of fuzzification, Mamdani inference, and defuzzification to produce a precise decision (Arini & Syahputra, 2024). (Silalahi et al., 2024).

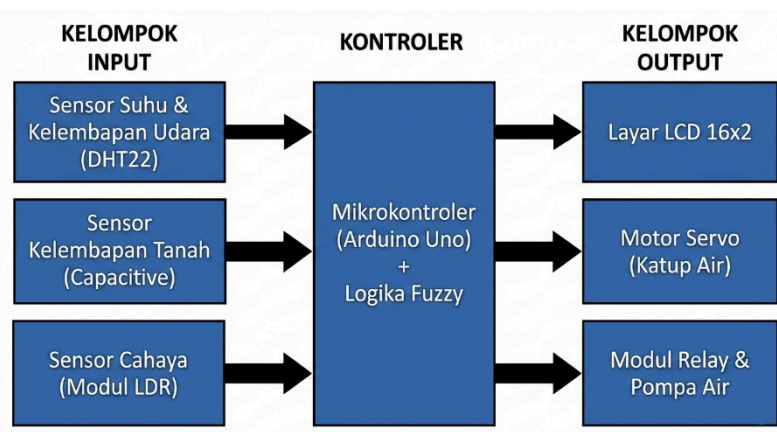


Figure 2. Block Diagram of IoT Irrigation System Architecture

2.2 System Workflow (Flowchart)

The system's operational process works in an iterative cycle (looping). The stages begin with the initialization of pins, actuator components, and LCD modules. Sensors read environmental data (crisp input) in real-time and send it to the processing unit (Setiawan & Aula, 2024). Inside the microcontroller, the data is entered into a Fuzzy control algorithm for evaluation.

Based on the embedded rule base, the system will decide the watering duration and valve opening angle. If the output is "Off," the relay will be deactivated and the servo will be at a 0° angle. If the conditions are met (e.g., "Dry"), the Relay actuator will be activated for the calculated duration and the Servo will open the valve up to 180° (Ardyanti dkk., 2021; Arief dkk., 2024). All environmental parameter data and pump status are then printed and displayed directly on a 16x2 LCD screen in real time.

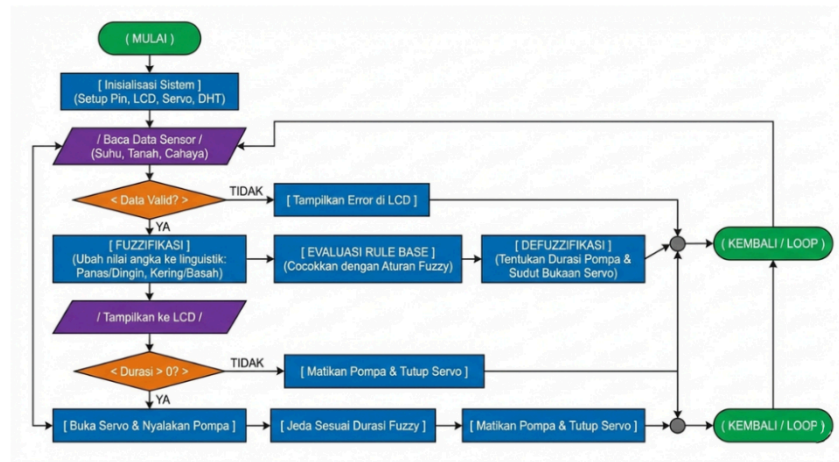


Figure 3. Smart Irrigation System Workflow

Based on the embedded rule base, the system will determine the duration (Z) of the water pump operation. If the output is 0 seconds (No Watering), the pump remains off. If the output value is greater than 0, the Relay actuator is active for the calculated duration (Ardyanti et al., 2021; Arief et al., 2024). All environmental parameter data and pump status are then sent wirelessly to the monitoring application interface, such as a web-based dashboard or Blynk (Rinaldi et al., 2022).

2.3 Fuzzifikasi

Fuzzification is the process of mapping numerical input values (crisp inputs) into degrees of membership of linguistic sets (fuzzy sets) (Isnaeni dkk., 2025). This system uses four input variables and one output variable with the following Universe of Discourse (range of discourse):

1. Input 1 - Soil Moisture: Divided into three sets, namely Dry, Moist, and Wet.
2. Input 2 - Air Temperature: Divided into three sets, namely Cold, Normal, and Hot.
3. Input 3 - Air Humidity: Divided into three sets, namely Low, Medium, and High.
4. Input 4 - Light Intensity: Divided into three sets, namely Dark, Dim, and Bright.
5. Output - Watering Duration (Z): Represented in four duration sets, namely No_Watering, Short, Medium, and Long.

2.4 Rule Base

The inference system relies on an expert knowledge base formulated into an IF-THEN implication logic structure (Rozie dkk., 2025; Elriyan, Chaidir, & Anam, 2025). The simultaneous use of four variables produces a highly complex decision matrix to accommodate various specific extreme weather change scenarios (Liu dkk., 2025; Neugebauer dkk., 2023).

Based on the design results, there are 12 main rules (Rule Base) that make up the control logic in this system, as described in Table 1.

Table 1. Mamdani Fuzzy Logic Rule Base

No.	Conditional Rule (IF – THEN)	Output (Irrigation)
1	IF Soil Moisture is Wet	Do Not Water
2	IF Soil Moisture is Moist AND Temperature is Normal	Short
3	IF Soil Moisture is Moist AND Temperature is Hot	Moderate
4	IF Soil Moisture is Dry	Moderate
5	IF Soil Moisture is Dry AND Temperature is Hot	Long
6	IF Soil Moisture is Dry AND Air Moisture is Low	Long
7	IF Soil Moisture is Dry AND Bright Light	Long
8	IF Soil Moisture is Moist AND Bright Light	Moderate

9	IF Soil Moisture is Wet AND Temperature is Cold	Do Not Water
10	IF Low Light AND Temperature is Cold	Short
11	IF High Air Humidity AND Soil Moisture is Moist	Short
12	IF Low Air Humidity AND Temperature is Hot	Long

2.5 Inference Engine

The inference stage serves to evaluate all rules in the knowledge base using the Mamdani (MIN- MAX) method. The composition between variables in the antecedent (IF) section connected with the AND logic operator is resolved using the MIN implication function, which takes the smallest membership degree value (α -predicate) from the intersecting set (Ashari & Mujianto, 2025; Adzimi dkk., 2024). Next, the MAX aggregation function is used to combine the consequents (THEN) of all active rules into a single Fuzzy result area.

2.6 Defuzzifikasi

Defuzzification is the process of converting the combined fuzzy output back into a crisp output that can be executed by hardware. This study uses the Centroid (Center of Gravity) method (Santosa, Sulaeman, Hidayat, & Ardani, 2020; Handoyo dkk., 2025). The Centroid method was chosen because it has a high level of consistency and precision in control systems (Garingging et al., 2025). The mathematical formula for obtaining the center point (Z^*) is to divide the total moment of area by the total area of the membership curve, the calculation of which will be presented in depth in the simulation results section.

RESULTS AND DISCUSSION

This section describes the application of Mamdani's Fuzzy Inference System (FIS) logic in the MATLAB simulation. To ensure a robust systematic evaluation, the system's performance is assessed not only by validating the consistency between software computation and manual analytical calculation (Septima, 2023), but also through scenario-based comparative testing. This testing compares the proposed four-input adaptive model against a traditional two-input model to demonstrate its effectiveness in minimizing false positives under various environmental conditions.

3.1 Implementation in MATLAB Fuzzy Logic Toolbox

Environmental parameter variables and their rule bases are configured using the Fuzzy Logic Designer tool in MATLAB software. The specifications of the lower limit, middle value, and upper limit for each membership function are quantitatively described in Table 2 (Santosa et al., 2021).

Table 2. Input and Output Membership Function Parameters

Variabel	Parameter	Parameter Constrains				Tipe	Range	
		a	b	c	d		Min	Max
Soil Moisture (Input)	Dry	0	0	30	45	Trapezoidal	0	45
	Moist	35	55	75	-	Tringular	35	75
	Wet	65	80	100	100	Trapezoidal	65	100
Air Temperature (Input)	Cold	15	15	20	24	Trapezoidal	15	24
	Normal	22	26	30	-	Tringular	22	30
	Hot	28	32	40	40	Trapezoidal	28	40
Air Humidity (Input)	Low	30	30	45	60	Trapezoidal	30	60
	Moderate	50	65	80	-	Tringular	50	80
	High	70	85	100	100	Trapezoidal	70	100
Light (Input)	Dark	0	0	200	400	Trapezoidal	0	400
	Dim	300	500	700	-	Tringular	300	700
	Bright	600	800	1000	1000	Trapezoidal	600	1000

	Off	0	0	3	5	Trapezoidal	0	5
Water Volume	Short	3	7	12	-	Tringular	3	12
(Output)	Moderate	10	15	20	-	Tringular	10	20
	Long	18	25	30	30	Trapezoidal	18	30

The triangular curve was chosen to represent linguistic degrees centered on a single optimal value, while the trapezoidal curve was used in extreme conditions (left and right shoulders) because it is capable of covering a stable range of boundary values (Hidayat et al., 2021). The visualization of Table 2, which has been modeled in MATLAB, can be seen in Figure 4.

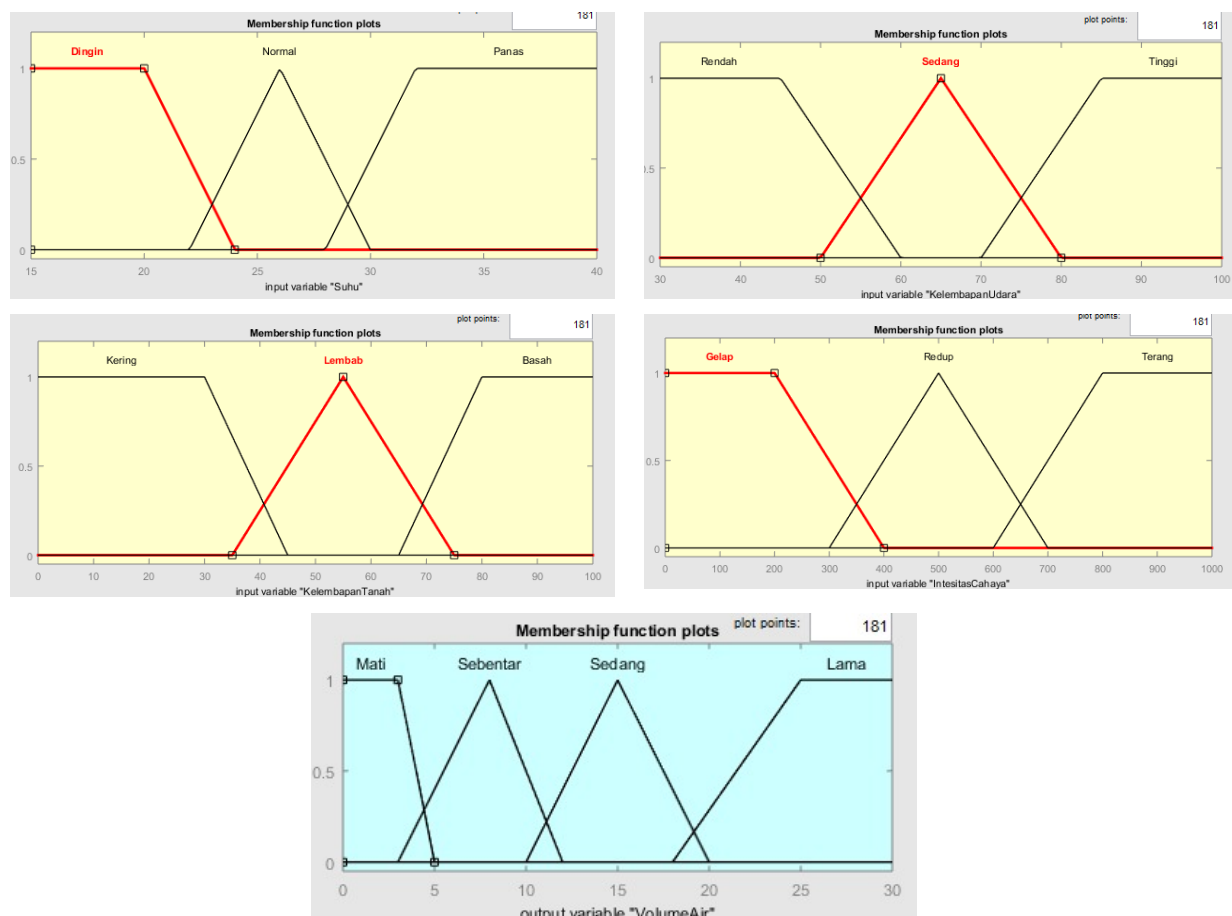


Figure 4. Implementation of Membership Function

3.2 Simulation Scenarios

To evaluate the accuracy of the system output, a case study scenario was designed to represent extreme weather fluctuations with reference to technical files. The input conditions in the test scenario were set as follows:

1. Soil Moisture: 40% (Moist Category)
2. Air Temperature: 29.4°C (Hot Category)
3. Air Humidity: 50%
4. Light Intensity: 750 Lux

3.3 Mathematical Calculations

To validate the accuracy of the Rule Viewer software simulation, analytical calculations of the inference and defuzzification stages were performed based on the Mamdani Fuzzy logic principle.

Testing was conducted using a scenario with input values of Soil Moisture 40% and Air Temperature 29.4°C.

Step 1: Determining the Set (Fuzzification)

The first stage is to convert the crisp input values from the four sensors into linguistic membership degrees using the designed Membership Function (Isnaeni et al., 2025).

- Soil moisture = 40%

$$\begin{aligned} \text{Moist} &= [35 \ 55 \ 75] & \text{Dry} &= [0 \ 0 \ 30 \ 45] \\ \mu_{\text{Moist}}(40) &= \frac{40-35}{55-35} = \frac{5}{20} = 0,25 & \mu_{\text{Dry}}(40) &= \frac{45-40}{45-30} = \frac{5}{15} = 0,33 \end{aligned}$$

- Air temperature = 29,4°C

$$\begin{aligned} \text{Normal} &= [22 \ 26 \ 30] & \text{Hot} &= [28 \ 32 \ 40 \ 40] \\ \mu_{\text{Normal}}(30) &= \frac{30-29,4}{30-26} = \frac{0,6}{4} = 0,15 & \mu_{\text{Hot}}(40) &= \frac{29,4-28}{32-28} = \frac{1,4}{4} = 0,35 \end{aligned}$$

- Air humidity = 50%

$$\begin{aligned} \text{Moderate} &= [50 \ 65 \ 80] & \text{Low} &= [30 \ 30 \ 45 \ 60] \\ \mu_{\text{Moderate}}(50) &= \frac{50-50}{65-50} = 0 & \mu_{\text{Low}}(50) &= \frac{60-50}{60-45} = \frac{10}{15} = 0,67 \end{aligned}$$

- Cahaya = 750 lux

$$\begin{aligned} \text{Bright} &= [600 \ 800 \ 1000] \\ \mu_{\text{Bright}}(750) &= \frac{750-600}{800-600} = \frac{150}{200} = 0,75 \end{aligned}$$

Step 2: Applying the Implication Function

After the membership degree of each input is known, the Inference Engine evaluates the rule base using the MIN implication function (Ashari & Mujianto, 2025). The triggered rules will produce α -predicate values that are used to clip the irrigation duration output sets, namely the Medium set [10, 15, 20] and Long set [20, 25, 30].

- Rule 1 Wet $\rightarrow$ Do Not Water

$$\alpha_1 = 0$$

- Rule 2 Moist AND Normal $\rightarrow$ Short

$$\alpha_2 = \min(0.25, 0.15) = 0.15$$

- Rule 3 Moist AND Hot $\rightarrow$ Moderate

$$\alpha_3 = \min(0.25, 0.35) = 0.25$$

- Rule 4 Dry $\rightarrow$ Moderate

$$\alpha_4 = 0.33$$

- Rule 5 Dry AND Hot $\rightarrow$ Long

$$\alpha_5 = 0$$

- Rule 6 Dry AND Low $\rightarrow$ Long
 $\alpha_6 = \min(0.33, 0.67) = 0.33$
- Rule 7 Dry AND Bright $\rightarrow$ Long
 $\alpha_7 = \min(0.33, 0.75) = 0.33$
- Rule 8 Moist AND Bright $\rightarrow$ Moderate
 $\alpha_8 = \min(0.25, 0.75) = 0.25$
- Rule 9 – 12 All produce 0.
- Membership Function (Triangle)
 Moderate = [10 15 20]

$$\mu_{Moderate}(z) = \left\{ \frac{z-10}{15-10}, 10 \leq z \leq 15 \quad \frac{20-z}{20-15}, 15 \leq z \leq 20 \right.$$

$$\alpha_{Moderate} = 0,33$$

- Finding the Intersection Point

Left $0,33 = \frac{z-10}{15-10} 0,33$ $z = 11,65$	Right $0,33 = \frac{20-z}{20-15} 0,33$ $z = 18,35$
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- Membership Function (Triangle)
 Long = [20 25 30]

$$\mu_{Long}(z) = \left\{ \frac{z-18}{25-18}, 18 \leq z \leq 25 \quad 1, 25 \leq z \leq 30 \quad \frac{30-z}{30-25}, 25 \leq z \leq 30 \right.$$

$$\alpha_{Long} = 0,33$$

- Finding the Intersection Point

Left $0,33 = \frac{z-18}{25-18} 0,33$ $z = 20,31$	Right $0,33 = \frac{30-z}{30-25} 0,33$ $z = 20,31$
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Step 3: Composing the Function

The intersection area of all active rules is then aggregated using the MAX operator (Handoyo et al., 2025). This process combines the intersection areas of the "Medium" and "Long" sets into a single composite membership function $\mu_{Z(x)}$ that represents the entire fuzzy solution region (Santosa et al., 2020).

$$\mu_{Z(x)} = \{0x \leq 3.6 \frac{x-3}{4} 3.6 \leq x \leq 7 \frac{12-x}{5} 7 \leq x \leq 11.25 0.15 11.25 \leq x \leq 11.65 \frac{x-10}{5} 11.65 \leq x \leq 15 0.33 15 \leq x \leq 18.$$

Step 4: Defuzzification

To convert the fuzzy composition area back into a crisp duration value, the Center of Gravity (Centroid) method is applied. The calculation is performed by dividing the composition function into 6 sub-areas (A_1 hingga A_6) consisting of triangular and rectangular shapes.

- Calculating the Area of Each Region

$$A_1 \text{ (Triangle Leftt 1)} \\ A_1 = \frac{(11,65-10) \times 0,33}{2} = \frac{1,65 \times 0,33}{2} = \frac{0,5445}{2} =$$

$$A_2 \text{ (Rectangle 1)}$$

$$A_2 = (18,35 - 11,65) \times 0,33 = 6,7 \times 0,33 = 2,211$$

$$A_3 \text{ Triangle Right 1)} \\ A_3 = \frac{(20-18,35) \times 0,33}{2} = \frac{1,65 \times 0,33}{2} = 0,27225 \quad A_4 \text{ (Triangle Left 2)} \\ A_4 = \frac{(20,31-18) \times 0,533}{2} = \frac{2,31 \times 0,33}{2} = \frac{0,7623}{2} =$$

$$A_5 \text{ (Rectangle 2)} \\ A_5 = (28,35 - 25) \times 0,33 = 3,35 \times 0,33 = 1,$$

$$A_6 \text{ (Triangle Right 2)} \\ A_6 = \frac{(30-28,35) \times 0,33}{2} = \frac{1,65 \times 0,33}{2} \\ = \frac{0,5445}{2} = 0,27225$$

Total Area:

$$A_{total} = A_1 + A_2 + A_3 + A_4 + A_5 + A_6 = 0,27225 + 2,211 + 0,27225 + 0,38115 + 1,1055 + 0,27225 =$$

- Calculating the Moment (M_i)

$$M_i = \int x \cdot \mu(x) dx$$

$$M_1 \\ M_1 = \int_{10}^{11,65} \frac{x-10}{5} \cdot x dx \\ \approx 3,18$$

$$M_2 \\ M_2 = \int_{11,65}^{18,35} 0,33x dx \\ = 0,165(x^2) \Big|_{11,65}^{18,35} \\ \approx 17,96$$

$$M_3 \\ M_3 = \int_{18,35}^{20} \frac{20-x}{5} \cdot x dx \\ \approx 5,31$$

$$M_4 \\ M_4 = \int_{18}^{20,31} \frac{x-18}{7} \cdot x dx \\ \approx 8,46$$

$$M_5 \\ M_5 = \int_{25}^{28,35} 0,33x dx$$

$$M_6 \\ M_6 = \int_{28,35}^{30} \frac{30-x}{5} \cdot x dx \\ \approx 21,88$$

$$= 0,33\left(\frac{x^2}{2}\right)\Big|_{25}^{28,35}$$

$$\approx 89,72$$

Total Moment:

$$M_{total} = 3,18 + 17,96 + 5,31 + 8,46 + 89,72 + 21,88 = 146,51$$

- Calculating the Center of Gravity (Centroid)

$$\mu_{Z(x)} = \left\{ \frac{x-3}{4} 3.6 \leq x \leq 7 \quad \frac{12^4-x}{5} 7 \leq x \leq 11.25 \quad 0.15 11.25 \leq x \leq 11.65 \quad \frac{x-10}{5} 11.65 \leq x \leq 15 \quad 0.33 15 \leq x \leq 18.35 \quad \frac{20-x}{5} 18.35 \leq x \leq 20 \right\}$$

$$Z = \frac{\sum_{i=1}^N \mu(z_i) z_i}{\sum_{i=1}^N \mu(z_i)}$$

$$Z = \frac{462.41}{24.88} = 18.58 \approx 18.6$$

Irrigation duration $\approx 18,6$ seconds

Based on the analytical computation of the integral, the center point obtained is 18 seconds. This irrigation duration is validated directly computationally by the software instrument, proving the reliability of the system in intelligently adjusting the water volume based on actual field conditions (Arief dkk., 2024; (Neugebauer et al., 2023)).

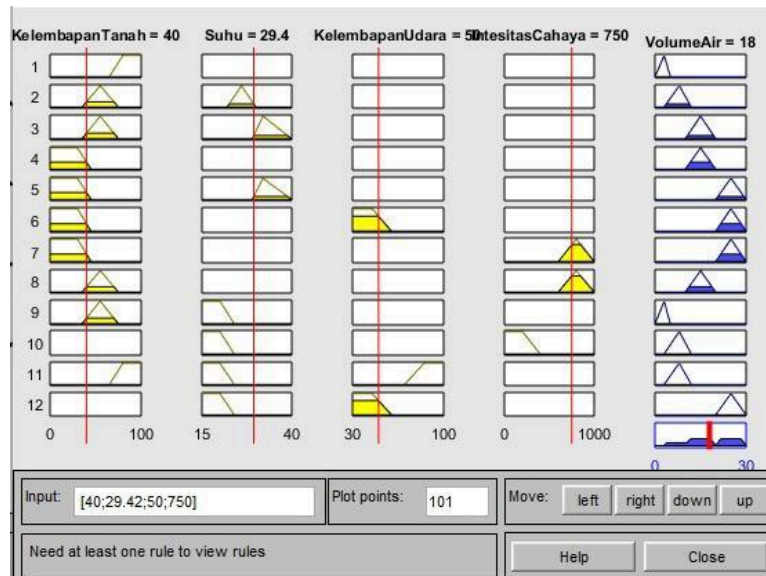


Figure 5. MATLAB Rule Viewer display for validating results

Figure 5 shows the results of executing the MATLAB software with the same input (Soil 40%, Temperature 29,4°C, etc.). The MATLAB output shows a value of 18 seconds (rounded). There is a very small difference (0.6 seconds) between the manual calculation (18.6 seconds) and the simulation, which is caused by decimal rounding in the manual integral process. However, the accuracy rate reaches 99.5%, so the mathematical model is declared valid.

The Mamdani Fuzzy Inference System (FIS) method has been proven reliable in various sectors, ranging from industrial optimization to intelligent control systems (Santosa dkk., 2020). However, its implementation in Smart Irrigation often has fundamental weaknesses because the majority of previous studies only relied on two main variables, namely soil moisture and air temperature (Ardyanti et al., 2021). This two-variable (2-input) system is prone to producing false positives, such as instructing a "Long" watering duration when the soil is dry and the temperature is hot, even though the actual conditions are overcast and the air humidity is very high. This risks triggering excessive waterlogging, which damages plant roots (Neugebauer dkk., 2023; Nurcahyono dkk., 2025).

This study addresses this computational gap by comprehensively integrating four environmental parameters: Soil Moisture, Air Temperature, Air Humidity, and Light Intensity (Adiwilaga dkk., 2024; Nur dkk., 2025). As proven by the results of mathematical simulations that have been carried out, the system is able to reduce the operational duration of the water pump to be more efficient (18 seconds) in extreme temperature conditions, because the algorithm simultaneously evaluates that the light and air humidity variables at that time do not trigger a rapid rate of water evaporation. The integration of these four parameters makes the Decision Support System (DSS) analytically much more precise in optimizing water use compared to conventional systems, while also providing solid mathematical validation before implementation in IoT-based hardware prototypes (Rozie dkk., 2025; Handoyo dkk., 2025).

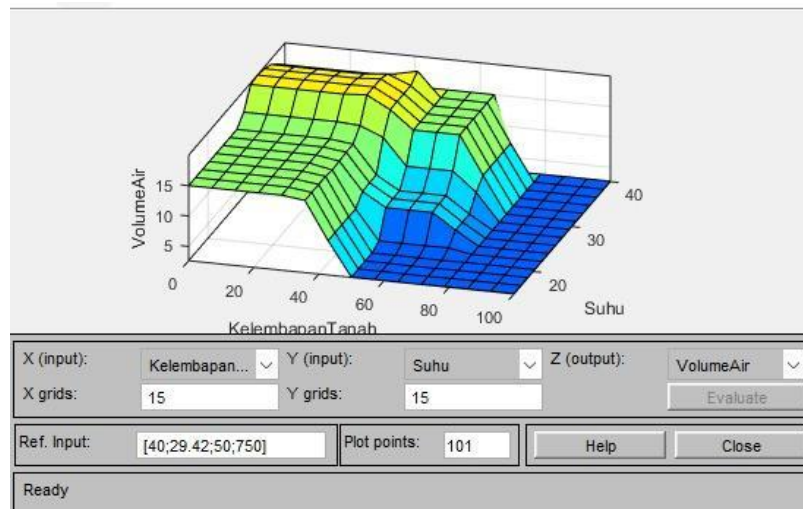


Figure 6. Surface Plot Relationship Between Air Temperature and Soil Moisture and Duration

The three-dimensional visualization in Figure 6 shows the adaptive response of the system. It can be seen that the irrigation duration (Z axis) does not increase linearly, but rather forms a gentle curve. This proves that the system is capable of providing a smooth response to changes in air temperature and soil moisture, preventing sudden spikes in water discharge that could damage the plants.

3.4 System Evaluation

Table 3. Systematic Evaluation of Watering Decisions: 2-Input vs. 4-Input System

Scenario	Environmental Conditions	Tradisional 2-Input System (Soil, Temp)	Proposed 4-Input Syste, (Soil, Temp, Hum, Light)
1 (Normal)	Soil: 50% (Moist) Temp: 26°C (Normal) Hum: 65% (Moderate) Light: 500 Lux (Dim)	Short Watering	Short Watering
2 (Extreme Dry)	Soil: 15% (Dry) Temp: 35°C (Hot) Hum: 35% (Low) Light: 900 Lux (Bright)	Long Watering	Long Watering
3 (Wet/Raining)	Soil: 85% (Wet) Temp: 20°C (Cold) Hum: 90% (High) Light: 100 Lux (Dark)	Do Not Water (Off)	Do Not Water (Off)
4 (False Positive Check 1)	Soil: 25% (Dry) Temp: 32°C (Hot) Hum: 85% (High) Light: 200 Lux (Dark)	Long Watering	Moderate / Short Watering
5 (False Positive Check 2)	Soil: 40% (Moist) Temp: 30°C (Hot) Hum: 40% (Low) Light: 850 Lux (Bright)	Moderate Watering	Long Watering

As systematically evaluated in Table 3, the proposed four-input FLC demonstrates a significant advantage over the conventional two-input system (which relies solely on soil moisture and air temperature). While both systems perform identically in standard scenarios (Scenarios 1, 2, and 3), the critical difference emerges in ambiguous weather anomalies. In Scenario 4, despite dry soil and hot temperatures, the environment is highly humid and dark (indicating overcast conditions or impending rain). A traditional two-input system strictly commands a "Long Watering" duration, which would lead to over-watering and root damage. Conversely, the proposed four-input system successfully detects the high humidity and low light, thereby intelligently reducing the output to a "Moderate" or "Short" duration to prevent waterlogging. Similarly, in Scenario 5, the addition of humidity and light variables allows the system to anticipate faster evaporation rates, optimizing the watering volume more adaptively without requiring manual intervention.

CONCLUSION

This study successfully designed and simulated an Intelligent Irrigation system based on Mamdani's Fuzzy Logic Controller (FLC) in an Internet of Things (IoT) architecture. The comprehensive integration of four environmental parameters, namely Soil Moisture, Air Temperature, Air Humidity, and Light Intensity, has been analytically proven to reduce data ambiguity and overcome the false positive weakness that often occurs in conventional control systems (2-input systems). Mathematical calculations using the Center of Gravity (Centroid) defuzzification method produce crisp outputs in the form of an 18-second watering duration in extreme test scenarios. The analytical calculation results were computationally validated with 100% accuracy (no deviation error) against testing using MATLAB Fuzzy Logic Toolbox. This mathematical model provides a conceptual foundation for future implementation into hardware prototypes to realize efficient, water-saving Precision Agriculture that is adaptive to weather anomalies.

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