Journal of Applied Science, Technology & Humanities
Volume 3, Issue 3, June, 2026, Pages 1066-1084

ISSN 3032-5765
DOI: https://doi.org/10.62535/zxfzgx38

Journal of Applied Science Technology & Humanities

Fuzzy Logic-Based Paddy Field Irrigation Control Using pH, Moisture, and Water Level

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Efficient irrigation management is a crucial factor in increasing rice agricultural productivity and maintaining water resource sustainability. Conventional irrigation systems, which are still manually controlled, often lead to water waste, unstable soil moisture, and inappropriate water pH levels for plant growth. This research aims to design and implement a fuzzy logic-based rice field irrigation control system by considering three primary parameters: soil moisture, water level, and irrigation water pH. The system utilizes an Arduino Uno microcontroller integrated with a soil moisture sensor, an HC-SR04 ultrasonic sensor, and a pH sensor. The Mamdani Fuzzy Method is employed as the inference system to determine the opening angle of the water gate controlled by a servo motor. The rule base consists of 27 rules derived from the combination of three linguistic sets for each input variable. The defuzzification process uses the Centroid method to generate a crisp value in the form of the servo angle. The test results demonstrate that the system is capable of adaptively regulating water flow based on soil conditions and water quality, thereby reducing the risk of over-irrigation or under-irrigation. The proposed system exhibits more flexible performance compared to conventional threshold-based systems.

Keywords: *Arduino Uno, Fuzzy Logic, pH, Rice field irrigation, Soil Moisture.*

INTRODUCTION

In order to support national food security, agriculture plays a crucial role, particularly in rice cultivation in paddy fields (Galitan et al., 2024). The availability and management of water are the main determinants of production success in paddy farming systems. To sustain physiological functions and nutrient absorption, rice plants need certain water levels, steady soil wetness, and suitable water quality. Conventional irrigation systems are still widely used and are typically operated manually based on farmers' estimates rather than real-time field conditions (Cahyani et al., 2023). According to studies, intelligent control systems that can modify water discharge in real time using data from soil moisture sensors and field condition monitoring outperform manual irrigation techniques in terms of speed and accuracy (Zhang & Zhao, 2022). This condition often results in water waste, uneven distribution, and imbalanced soil conditions. Without precise parameter data, farmers must physically visit the field to open or close the water gates. This practice leads to inefficient water use. It also increases the risk of crop failure due to excessively dry or saturated soil conditions and non-ideal water pH levels. (Sari & Rasyid, 2022).

By integrating sensors and actuators that can function autonomously, the advancement of Internet of Things (IoT) technology provides ways to increase irrigation system efficiency (Simulingga et al., 2025). When compared to manual techniques, automatic irrigation systems based on microcontrollers and soil moisture sensors have been shown to increase water use efficiency (Alamsyah et al., 2024; Saragih & Kurniawan, 2025). IoT integration can further offer more precise and adaptable irrigation control with fuzzy logic. Without lowering agricultural output, this increases water use efficiency (Adiwilaga et al., 2024; Dhumale et al., 2023; Jadhav, 2024). In addition, the implementation of fuzzy logic in irrigation systems enables more adaptive decision-making in response to changing environmental conditions (Ibrahim, 2018).

The Fuzzy Logic method is widely used in intelligent control systems due to its ability to handle uncertain and linguistic data (Sihombing, 2024). Fuzzy logic implementation is not only applied in irrigation systems but also in various microcontroller-based applications. One study applied a fuzzy-based Arduino approach to develop a freshwater fish disease severity prediction system using the Fuzzy Logic method, implemented through the Arduino IDE and simulated using Proteus ISIS (Siskandar et al., 2023). The study showed that the fuzzy approach can be successfully applied in embedded systems based on microcontrollers and can generate accurate and adaptive judgments based on a variety of dynamic input factors. This demonstrates the great adaptability of fuzzy logic in decision-making systems that rely on sensors and Arduino (Habibie et al., 2025; Siskandar et al., 2023). Fuzzy logic, which is used in a variety of intelligent control systems, is often founded on the idea of degrees of membership and flexible IF-THEN rules within fuzzy sets. According to (Kastina & Silalahi, 2016) and (Setia & Ramadan, 2019), this allows it to incorporate complicated and unpredictable sensor input data into more fluid control decisions that closely mimic human thinking.

Soil fertility and plant nutrient availability are significantly influenced by pH in addition to soil moisture factors. Plant growth and productivity might be hindered by soil that has a pH level outside of the ideal range (Rizal & Jamaludin, 2019). In order to maintain ideal soil conditions, prior research has created an Internet of Things-based system for monitoring and controlling soil pH and moisture using the Fuzzy Mamdani technique (Wijayanti et al., 2025). This suggests that control systems with multiple parameters are more efficient than those with just one parameter (Sari & Rasyid, 2022).

The water level in paddy fields is an important factor that has a direct impact on the stages at which rice plants grow. To increase irrigation efficiency, automatic water gate control and ultrasonic sensor-based water surface height measurement have been developed (Sahibu & Ahmad, 2025). Furthermore, when combined with actuators such as servo motors to automatically control water discharge, ultrasonic sensors for water level monitoring have been shown to be more effective (Kusumadiarti & Qodawi, 2021). However, the majority of existing studies still focus on only one or two parameters, such as temperature and soil moisture (Alamsyah et al., 2024). There is still limited research integrating pH, soil moisture, and water level simultaneously in a single paddy irrigation control system. This limitation indicates a significant research gap in developing a comprehensive and adaptive multi-parameter irrigation control system. (Putera et al., 2023; Sari & Rasyid, 2022).

This project intends to use the Fuzzy Logic approach to build and implement a paddy irrigation control system based on three primary parameters: water level, pH, and soil moisture. A servo motor serves as the actuator for the water gate, and an Arduino Uno microcontroller with integrated pH, soil moisture, and ultrasonic sensors is used in the system's development. It is anticipated that this approach will result in an adaptive irrigation system that uses water efficiently and maintains optimal field conditions. This study contributes by integrating pH, soil moisture, and water level into a unified fuzzy logic-based control system for more accurate irrigation decision-making.

METHODS

The development of intelligent irrigation systems has become increasingly important to improve water efficiency and agricultural productivity, particularly through the integration of fuzzy logic and IoT technologies (Nasir & Jalil, 2025). Moreover, the integration of fuzzy logic within irrigation architectures has been empirically demonstrated to significantly optimize water consumption efficiency relative to traditional manual intervention strategies (Saragih & Kurniawan, 2025). IoT-based autonomous irrigation systems have effectively implemented similar microcontroller, soil moisture sensor, and ultrasonic water level monitoring combinations to enhance water use efficiency and responsive sluice gate management (Haj et al., 2025).

2.1 System Architectural Framework

The proposed system architecture employs the Arduino Uno as its primary computational controller, tasked with sensory data acquisition, the execution of fuzzy inferential logic, and the subsequent regulation of the servo motor actuator. The amalgamation of multifaceted parameters within a fuzzy-based control framework has been empirically validated to enhance decision-making granularity relative to univariate configurations (Ibrahim et al., 2018). Fuzzy logic is appropriate for managing uncertainty in soil fertility parameters like pH and moisture, as evidenced by the use of multi-parameter fuzzy inference to integrate soil moisture, water level, and water quality indicators for irrigation and fertilization recommendations (Simanjorang et al., 2026).

A variety of sensor types make up the system input parameters, which are utilized to track and regulate field environmental conditions. Real-time data from these sensors is necessary for precise analysis and effective system operation:

1. pH Sensor: To measure the acidity level of water/soil.
2. Soil Moisture Sensor: To detect water content in the soil (Hafni & Jaya, 2024).
3. Ultrasonic Sensor (HC-SR04): To measure the water level in rice fields (Cahyani et al., 2023).

The terminal output of this architecture is a servo-based actuator responsible for modulating the irrigation gate's mechanical position. Acquired sensory metrics are subsequently transmitted to a cloud-based repository via Wi-Fi protocols, facilitating seamless telemetric observation and remote oversight for the end-user. (Simulingga et al., 2025). Data-driven smart farming and future autonomous control are made possible by similar IoT-based systems that have shown success in remote supervision and real-time monitoring of irrigation parameters (Pogasang, 2024; Pramana et al., 2025).

The system's operational sequence is executed within a real-time temporal domain, commencing with the simultaneous acquisition of analog and digital data streams from the sensor array. Metrics regarding chemical acidity and edaphic moisture are ingested via the Arduino's analog-to-digital input channels. In contrast, the ultrasonic transducer utilizes a pulse-timing mechanism through digital trigger and echo pins to derive spatial displacement based on wave reflection latency. These crisp input values are subsequently mapped onto linguistic descriptors during the fuzzification phase, facilitating high-level reasoning within the Mamdani-based fuzzy rule architecture.

The system hardware circuit configuration is shown in Figure 1.

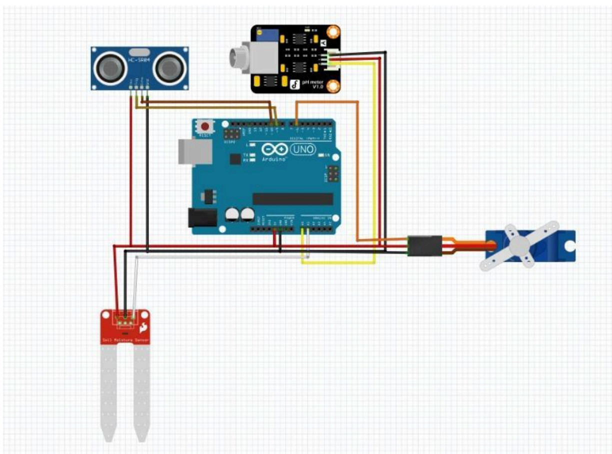

Figure 1 System Architecture

Figure 1 shows the relationship between the Arduino Uno and the pH sensor, soil moisture sensor, HC-SR04 ultrasonic sensor, and servo motor as an irrigation door actuator.

ID	Component	Pin Component	Connected
1 HC-SR04		VCC	5V
		GND	GND
		TRIG	D9
		ECHO	D10
2 Sensor pH Module		VCC	5V
		GND	GND
		AO (Analog Out)	A0
3 Soil Moisture		VCC	5V
		GND	GND
		SIG/AO	A1
4 Servo Motor		VCC	5V
		GND	GND
		Signal	D6

Table 1 System Pin Configuration

Table 1 shows that the pH and soil moisture sensors use analog pins (A0 and A1), while the ultrasonic sensor uses digital pins D9 and D10. The servo motor is controlled via PWM pin D6 to adjust the opening angle of the irrigation gate.

2.2 Fuzzy Logic Design

The Mamdani-type Fuzzy Inference System (FIS) is the control strategy used (Sihombing, 2024). Fuzzification, rule base, aggregation, and defuzzification are the four primary phases of data processing.

A. Fuzzification

During this computational stage, quantitative sensor metrics are transmuted into linguistic variables through the application of membership functions (Cahyani et al., 2023). Based on the structural design, the input array encompasses Edaphic Moisture, Aquatic Elevation, and pH levels, while the output is defined as the ‘Gate’, representing the angular orientation of the servo-actuated mechanism

B. Rule Base

The actuator's actions are automatically determined by the system based on key rules that integrate the circumstances of the three sensors (Tama et al., 2020). In order to increase decision-making precision and enable adaptive water control responses, a multi-parameter rule basis has also been implemented in a variety of IoT-based irrigation systems utilizing various fuzzy techniques (Santa et al., 2024; Suryatini & Fauzandi, 2019).

C. Aggregation

At this computational juncture, the inferential derivatives from each triggered rule are consolidated into a unified output fuzzy manifold. Subsequent to quantifying the firing strength of each heuristic through the AND (Minimum) t-norm operator, the system executes an amalgamation procedure utilizing the Maximum (MAX) method. This aggregation phase is strategically executed to synthesize a comprehensive fuzzy region that encapsulates the holistic decision-making of the framework relative to the multifaceted input configurations (Tama et al., 2020). Consequently, the synthesized aggregate is transitioned to the defuzzification stage for final numeric conversion.

D. Defuzzification

The terminal stage of the procedure involves the transmutation of fuzzy inferential derivatives back into a discrete numerical format, specifically the crisp output. This is executed via the Centroid (Center of Area) methodology, in which the framework computes the geometric center of the aggregated fuzzy distribution to determine the precise rotational displacement of the servo motor (Tama et al., 2020).

RESULTS AND DISCUSSION

A series of preliminary evaluations were executed to verify the measurement precision of each sensory unit prior to its integration into the fuzzy logic algorithm. This validation phase was essential to guarantee that the parameters utilized within the inference system remained scientifically accurate and stable.

The performance of the soil moisture sensor was rigorously assessed across various environmental gradients, encompassing arid, damp, and saturated soil conditions. Empirical findings indicated that the analog output values exhibited a proportional correlation with the rise in soil water content, thereby validating the sensor's capacity to characterize moisture levels consistently. Furthermore, the HC-SR04 ultrasonic sensor was evaluated within a detection range of 5–20 cm, yielding a marginal mean error rate of less than 2%, which underscores its efficacy for precise water level monitoring. Finally, to ensure the integrity of the acidity data, the pH sensor underwent a systematic calibration procedure utilizing standardized buffer solutions of pH 4.0 and 7.0 prior to data acquisition

1. Humidity Variable

   Within the proposed control framework, the soil moisture variable is defined across a numerical spectrum of 0 to 100 and is categorized into three distinct linguistic labels: Dry, Normal, and Wet. The ‘Dry’ state is characterized by a trapezoidal membership function (trapmf) with the parameters [0 0 10 22], where a full degree of membership is maintained between 0% and 10%, followed by a linear attenuation to zero at the 20% threshold. The ‘Normal’ classification is delineated using a triangular membership function (trimf) with coordinated [10 20 30], reaching its maximum intensity at 20% while tapering to zero at both the 10% and 30 boundaries, Conversely, the ‘Wet’ condition is modeled via a trapezoidal function (trapmf) with parameters [18 28 100 100], exhibiting a linear ascent from 20% to achieve a stable peak at 30%, which then remains constant through the 100% limit. This configuration is strategically engineered to facilitate seamless transitions between environmental states, thereby enabling the irrigation system to modulate water delivery with high adaptability and operational stability.

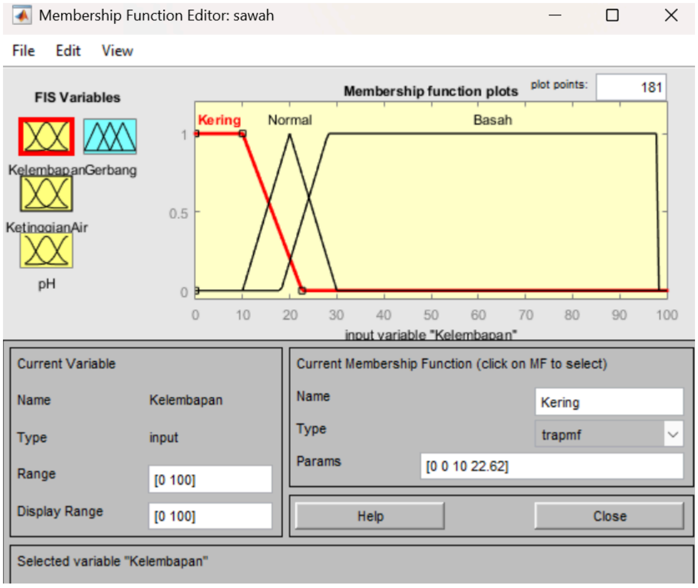

Figure 2 Humidity Input

2. Water level variables

The aquatic elevation variable within this framework is quantified across an operational range of 0 to 20 cm, discretized into three primary linguistic sets: Low, Moderate, and High. The ‘Low’ state is characterized by a trapezoidal membership function (trapmf) with the parameters [0 0 5 10], indicating that a complete membership degree is maintained for elevations between 0 and 5 cm, followed by a linear attenuation toward the zero point at the 10 cm boundary. The ‘Moderate’ classification is delineated via a triangular membership function (trimf) defined by coordinates [5 10 15], achieving peak intensity at 10 cm and tapering to zero at both 5 cm and 15 cm. Conversely, the ‘High’ category is represented through a trapezoidal function (trapmf) with parameters [9 14 19 19], where the degree of membership exhibits a linear ascent starting from 10 cm to reach a stable maximum at 15 cm, which persists until the 20 cm threshold, This structural design permits the system to discern gradual transitions between low, standard, and elevated water stage conditions, ensuring higher precision in regulation of the irrigation gate aperture

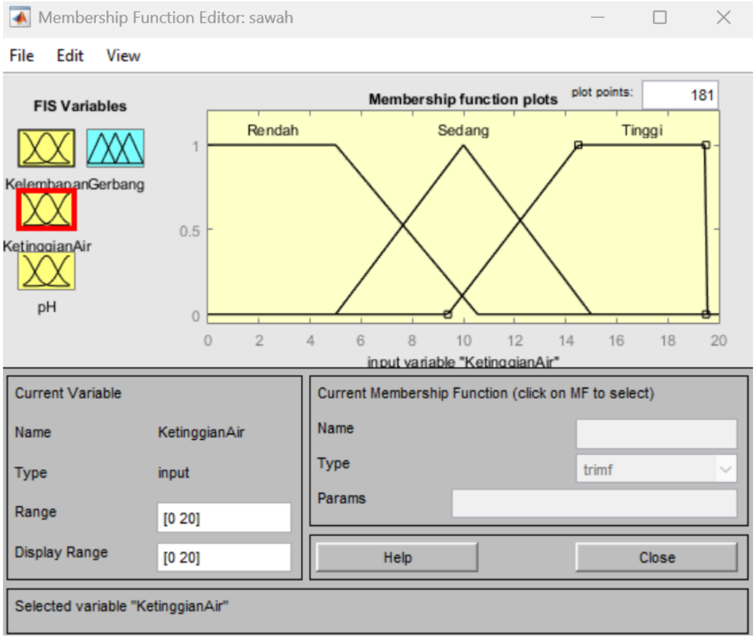

Figure 3 Water Level Input

3. pH variables

The chemical acidity variable, operationalized as the potential of Hydrogen (pH) within a numerical span of 0 to 14, is delineated through three distinct linguistic sets: Acidic, Neutral, and Alkaline. The 'Acidic' classification is mathematically characterized using a trapezoidal membership function (trapmf) with the coordinates [0 0 5.5 6.5]; this configuration maintains a unity membership degree for pH values up to 5.5, subsequently undergoing a linear attenuation toward nullity at the 6.5 threshold. For the 'Neutral' descriptor, a triangular membership function (trimf) with parameters [6 7 8] is employed, reaching its peak intensity at a pH of 7 and tapering to zero at both the pH 6 and pH 8 boundaries. Conversely, the 'Alkaline' state is modeled via a trapezoidal descriptor (trapmf) with coordinates [7.5 8.5 14 14], where the membership degree follows a linear ascent from 7.5 to reach full saturation at 8.5, remaining constant until the upper limit of 14. This structural arrangement empowers the intelligent system to integrate water quality gradients dynamically, ensuring that the irrigation gate modulation accounts for both volumetric requirements and the chemical equilibrium requisite for optimal crop development

Figure 4 pH Input

4. Gate Variable

The system's output component is operationalized as the 'Gate' variable, which regulates the servo motor's angular orientation across a 0–90° spectrum. This variable is decomposed into three primary linguistic sets: Closed, partially Open, and Fully Open. The 'Closed' state is mathematically characterized by a trapezoidal membership function (trapmf) with parameters [0 0 0 15], establishing a maximum membership degree at the 0° point followed by a subsequent linear attenuation to zero at 15°. The 'Partially Open' classification is delineated using a triangular membership function (trimf) with coordinates [15 30 50], reaching its maximum intensity at 30° to detonate an intermediate gate aperture. Furthermore, the 'Fully Open' condition is modeled via a trapezoidal function (trapmf) with parameters [50 70 90 90], in which the degree of membership ascends linearly from 50° to reach total saturation at 70°, remaining constant at unity through the 90° upper bound

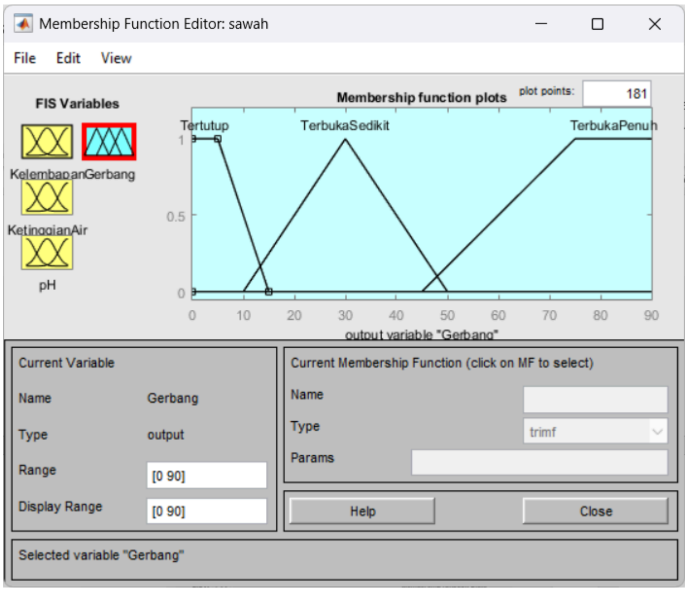

Figure 5 Gate Output

A. Membership Association

The membership mapping phase is initiated to quantify the membership degree of discrete input data relative to the fuzzy partitions predefined within the Fuzzy Inference System. The architectural framework incorporates three primary input dimensions: Soil Moisture (0-100), Aquatic Elevation (0-20 cm), and chemical pH levels (0-14), with the servo-regulated Gate (0–90°) designated as the operational output. To validate the system's inferential logic, an exemplary computational scenario is employed, featuring a moisture level of 25%, a water depth of 12 cm, and a pH index of 7.6.

1) Membership Functions
   a) Humidity Variable

$$\mu(x, a, b, c) =$$

$$\mu Kering(x) = \{1,\ \frac{20-x}{20-10},\ 0, \qquad 0 \leq x \leq 10\ 10 \leq x \leq 20\ x \geq 20$$

$$\mu Normal(x)\{0,\ \frac{x-10}{20-10}\ \frac{30-x}{30-20},\ ,\ x \leq 10\ atau\ x \geq 30\ \ 10 < x \leq 20\ 20 < x < 30$$

$$\mu Basah(x) = \{0,\ \frac{x-20}{30-20},\ 1, \qquad x \leq 20\ 20 < x < 30\ 30 \leq x \leq 100$$

   b) Water Level Variables

$$\mu Rendah(x) = \{1,\ \frac{10-x}{10-5}\ 0,\ , \qquad 0 \leq x \leq 5\ 5 < x < 10\ x \geq 10$$

$$\mu Sedang(x) = \{0,\ \frac{x-5}{10-5},\ \frac{15-x}{15-10}, \qquad x \leq 5\ atau\ x \geq 15\ 5 < x \leq 10\ 10 < x < 15$$

$$\mu Tinggi(x) = \{0,\ \frac{x-10}{15-10},\ 1, \qquad x \leq 10\ 10 < x < 15\ 15 \leq x \leq 20$$

   c) pH variables

$$\mu Asam(x) = \{1,\ \frac{6.5-x}{6.5-5.5},\ 0, \qquad 0 \leq x \leq 5.5\ 5.5 < x < 6.5\ x \geq 6.5$$

$$\mu Netral(x) = \{0,\ \frac{x-6}{7-6},\ \frac{8-x}{8-7}, \qquad x \leq 6\ atau\ x \geq 8\ 6 < x \leq 7\ 7 < x < 8$$

$$\mu Netral(x) = \{0,\ \frac{x-7{,}5}{8.5-7.5},\ 1, \qquad x \leq 7.5\ 7.5 < x < 8.5\ 8.5 \leq x \leq 14$$

2) Calculation of Membership Degrees

In accordance with the previously established membership parameters, a computational analysis was executed to determine the irrigation gate's operational status using specific input metrics: 25% edaphic moisture, 12 cm aquatic elevation, and a 7.6 pH level. These values intersect within the overlapping regions of the fuzzy sub-sets, consequently generating multiple membership coefficients across each variable. Analytical results demonstrate that a 25% moisture level yields a value of 0.5 for the 'Normal' category and 0.5 for the 'Saturated' classification. Simultaneously, a water height of 12 cm corresponds to membership degrees of 0.6 for 'Moderate' and 0.4 for the 'High' sets. Furthermore, a pH index of 7.6 exhibits membership values of 0.4 and 0.1 for the 'Neutral' and 'Alkaline' domains, respectively. This data underscores that the system is not restricted to a singular state but rather operates within a transitional equilibrium, triggering the concurrent activation of several fuzzy rules

   1) Moisture

$$\mu Normal(25) = \frac{30-25}{30-20} = \frac{5}{10} = 0,5$$

$$\mu Basah(25) = \frac{25-20}{30-20} = \frac{5}{10} = 0,5$$

   2) Water levels

$$\mu Sedang(12) = \frac{15-12}{15-10} = \frac{3}{5} = 0,6$$
$$\mu Tinggi(12) = \frac{12-10}{15-10} = \frac{2}{5} = 0,4$$

3) pH

$$\mu Netral(7,6) = \frac{8-7,6}{8-7} = 0,4$$
$$\mu Basa(7,6) = \frac{7,6-7,5}{8,5-7,5} = 0,1$$

B. Rule Inference

The inferential mechanism employed in this study is synthesized through the linguistic integration of three primary input parameters: Edaphic Moisture (categorized as Arid, Normal, and Saturated), Aquatic Elevation (Low, Moderate, and High), and the pH index (Acidic, Neutral, and Alkaline). Consequently, the framework encompasses a robust aggregate of 27 heuristic If-Then rules, derived from 3 x 3 x 3 combinatorial matrix of environmental input states. This architecture facilitates a multidimensional decision-making process that surpasses the capabilities of singular or dual parameter models, as it simultaneously evaluates both the volumetric availability and the chemical equilibrium of the irrigation water. Each conditional rule is activation intensity (firing strength) is dictated by the lowest membership coefficient among the input vectors. Such an approach fosters an adaptive control response to the stochastic environmental fluctuations within the rice fields, significantly refining the precision of irrigation gate regulation to sustain an optimal hydric balance.

1) IF Kelembapan **Kering** AND Ketinggian Air **Rendah** AND pH **Asam** THEN Gerbang **Terbuka Sedikit**
2) IF Kelembapan **Kering** AND Ketinggian Air **Rendah** AND pH **Netral** THEN Gerbang **Terbuka Penuh**
3) IF Kelembapan **Kering** AND Ketinggian Air **Rendah** AND pH **Basa** THEN Gerbang **Terbuka Sedikit**
4) IF Kelembapan **Kering** AND Ketinggian Air **Sedang** AND pH **Asam** THEN Gerbang **Terbuka Sedikit**
5) IF Kelembapan **Kering** AND Ketinggian Air **Sedang** AND pH **Netral** THEN Gerbang **Terbuka Penuh**
6) IF Kelembapan **Kering** AND Ketinggian Air **Sedang** AND pH **Basa** THEN Gerbang **Terbuka Sedikit**
7) IF Kelembapan **Kering** AND Ketinggian Air **Tinggi** AND pH **Asam** THEN Gerbang **Tertutup**
8) IF Kelembapan **Kering** AND Ketinggian Air **Tinggi** AND pH **Netral** THEN Gerbang **Tertutup**
9) IF Kelembapan **Kering** AND Ketinggian Air **Tinggi** AND pH **Basa** THEN Gerbang **Tertutup**
10) IF Kelembapan **Normal** AND Ketinggian Air **Rendah** AND pH **Asam** THEN Gerbang **Terbuka Sedikit**
11) IF Kelembapan **Normal** AND Ketinggian Air **Rendah** AND pH **Netral** THEN Gerbang **Terbuka Penuh**
12) IF Kelembapan **Normal** AND Ketinggian Air **Rendah** AND pH **Basa** THEN Gerbang **Terbuka Sedikit**

13) IF Kelembapan **Normal** AND Ketinggian Air **Sedang** AND pH **Asam** THEN Gerbang **Terbuka Sedikit**
14) IF Kelembapan **Normal** AND Ketinggian Air **Sedang** AND pH **Netral** THEN Gerbang **Terbuka Sedikit**
15) IF Kelembapan **Normal** AND Ketinggian Air **Sedang** AND pH **Basa** THEN Gerbang **Terbuka Sedikit**
16) IF Kelembapan **Normal** AND Ketinggian Air **Tinggi** AND pH **Asam** THEN Gerbang **Tertutup**
17) IF Kelembapan **Normal** AND Ketinggian Air **Tinggi** AND pH **Netral** THEN Gerbang **Tertutup**
18) IF Kelembapan **Normal** AND Ketinggian Air **Tinggi** AND pH **Basa** THEN Gerbang **Tertutup**
19) IF Kelembapan **Basah** AND Ketinggian Air **Rendah** AND pH **Asam** THEN Gerbang **Tertutup**
20) IF Kelembapan **Basah** AND Ketinggian Air **Rendah** AND pH **Netral** THEN Gerbang **Terbuka Sedikit**
21) IF Kelembapan **Basah** AND Ketinggian Air **Rendah** AND pH **Basa** THEN Gerbang **Tertutup**
22) IF Kelembapan **Basah** AND Ketinggian Air **Sedang** AND pH **Asam** THEN Gerbang **Tertutup**
23) IF Kelembapan **Basah** AND Ketinggian Air **Sedang** AND pH **Netral** THEN Gerbang **Tertutup**
24) IF Kelembapan **Basah** AND Ketinggian Air **Sedang** AND pH **Basa** THEN Gerbang **Tertutup**
25) IF Kelembapan **Basah** AND Ketinggian Air **Tinggi** AND pH **Asam** THEN Gerbang **Tertutup**
26) IF Kelembapan **Basah** AND Ketinggian Air **Tinggi** AND pH **Netral** THEN Gerbang **Tertutup**
27) IF Kelembapan **Basah** AND Ketinggian Air **Tinggi** AND pH **Basa** THEN Gerbang **Tertutup**

C. Implication Mamdani

Once the comprehensive IF-AND-THEN rule base has been established and the antecedent firing strength (α) is computed via the Minimum (MIN) intersection, the framework proceeds to the implication stage. Within the Mamdani inferential architecture, implication is executed by correlating the α value with the consequent membership functions for each specific rule. This technique is formally categorized as the 'clipping' method, characterized by the truncation of the output fuzzy set at an intensity level congruent with the rule's firing strength. Mathematically, the implication function is defined as:

$$\mu'_{output}(z) = min\left(\alpha i, \mu_{output}(z)\right)$$

For example, the active rule is used in the case study with Humidity = 25%, Water Height = 12 cm, and pH = 7.6, based on the fuzzification results as follows.:

Rule 14:

$$\alpha_{14} = min\left(\mu_{KelembapanNormal}[0,5], \mu_{KetinggianSedang}[0,6], \mu_{pHNetral}[0,4]\right)$$

$$\alpha_{14} = min(0,5,\ 0,6,\ 0,4) = 0,4$$

Rule 15:

$$\alpha_{15} = min\left(\mu_{KelembapanNormal}[0,5], \mu_{KetinggianSedang}[0,6], \mu_{pHBasa}[0,1]\right)$$
$$\alpha_{15} = min(0,5,\ 0,6,\ 0,1) = 0,1$$

Rule 17:
$$\alpha_{17} = min\left(\mu_{KelembapanNormal}[0,5], \mu_{KetinggianTinggi}[0,4], \mu_{pHNetral}[0,4]\right)$$
$$\alpha_{17} = min(0,5,\ 0,4,\ 0,4) = 0,4$$

Rule 18:
$$\alpha_{18} = min\left(\mu_{KelembapanNormal}[0,5], \mu_{KetinggianTinggi}[0,4], \mu_{pHBasa}[0,1]\right)$$
$$\alpha_{18} = min(0,5,\ 0,4,\ 0,1) = 0,1$$

Rule 23:
$$\alpha_{23} = min\left(\mu_{KelembapanBasah}[0,5], \mu_{KetinggianSedang}[0,6], \mu_{pHNetral}[0,4]\right)$$
$$\alpha_{14} = min(0,5,\ 0,6,\ 0,4) = 0,4$$

Rule 24:
$$\alpha_{24} = min\left(\mu_{KelembapanBasah}[0,5], \mu_{KetinggianSedang}[0,6], \mu_{pHBasa}[0,1]\right)$$
$$\alpha_{14} = min(0,5,\ 0,6,\ 0,1) = 0,1$$

Rule 26:
$$\alpha_{26} = min\left(\mu_{KelembapanBasah}[0,5], \mu_{KetinggianTinggi}[0,4], \mu_{pHNetral}[0,4]\right)$$
$$\alpha_{14} = min(0,5,\ 0,4,\ 0,4) = 0,4$$

Rule 27:
$$\alpha_{27} = min\left(\mu_{KelembapanBasah}[0,5], \mu_{KetinggianTinggi}[0,4], \mu_{pHBasa}[0,1]\right)$$
$$\alpha_{14} = min(0,5,\ 0,4,\ 0,1) = 0,1$$

The α14=0,4 firing strength of 0.4 is utilized to perform the clipping operation on the 'Partially Open' output membership set. As a result, the membership intensity of the curve is truncated at 0.4, preventing it from reaching its unity maximum (1). This ensures that only the distribution segment within the threshold is maintained, while the upper region is horizontally flattened at the 0.4 level. The resulting profiles from all concurrent active rules are then synthesized during the aggregation stage through the MAX operator to establish a unified output manifold before undergoing defuzzification

D. Aggregation

In the case study where Humidity = 25%, Water Level = 12 cm, and pH = 7.6, the active fuzzy sets are Normal/Wet, Medium/High, and Neutral/Alkaline. As a result, eight rules are triggered. From these eight rules, based on the previously defined rule base, the consequents (THEN parts) fall into only two output categories: Gate Slightly Open (Rules 14 and 15) and Gate Closed (Rules 17, 18, 23, 24, 26, and 27). Since the aggregation process uses the MAX operator, the final membership value for each output category is determined by selecting the highest firing strength among all rules that produce the same output category.

1) Determining the output degree for each category
   - Gate Slightly Open:
$$\alpha_{Sedikit} = \left(\alpha_{14}, \alpha_{15}\right) = (0,4,\ 0,1) = 0,4$$
   - Gate Closed:
$$\alpha_{Tertutup} = \left(\alpha_{17}, \alpha_{18}, \alpha_{23}, \alpha_{24}, \alpha_{26}, \alpha_{27}\right) = max(0,4,\ 0,1,\ 0,4,\ 0,1,\ 0,4,\ 0,1) = 0,4$$

The implication results to be combined (through aggregation) are a Closed output curve clipped at a height of 0.4, along with a Slightly Open output curve that is also clipped at a height of 0.4

2) Constructing the clipped membership functions
   - Closed Output uses a trapezoidal membership function (trapmf). [0 0 5 15]

$$\mu Tertutup(z) = \frac{15-z}{15-5},\ 0 < z < 15$$

Because the membership function is clipped at 0.4, the corresponding boundary is determined by finding the value of z where μ(z)=0,4

$$0,4 = \frac{15-z}{10}$$

$$4 = 15 - z$$

$$z = 11$$

The clipped **Closed** membership function is therefore expressed as follows:

$\mu'_{Tertutup}(z) = 0,4$ for $0 \le z \le 9$

$\mu'_{Tertutup}(z) = \frac{15-z}{10}$ for $9 < z < 15$

$\mu'_{Tertutup}(z) = 0$ for $z \ge 15$

   - Slightly Open Output is represented using a triangular membership function (trimf) with parameters [10, 30, 50].

Rising edge:

$$\mu(z) = \frac{z-10}{20} = 0,4$$

$$z = 18$$

Falling edge:

$$\mu(z) = \frac{50-z}{20} = 0,4$$

$$z = 42$$

The resulting Slightly Open membership function after clipping can be written as:

$\mu'_{Sedikit}(z) = \frac{z-10}{20}$ for $10 \le z \le 18$

$\mu'_{Sedikit}(z) = 0,4$ for $18 \le z \le 42$

$\mu'_{Sedikit}(z) = \frac{50-z}{20}$ for $42 \le x \le 50$

3) Aggregation (MAX) into a single combined output curve

Mamdani aggregation applies the following formula:

$$\mu_{agg}(z) = max(\mu'_{Tertutup}(z), \mu'_{Sedikit}(z))$$

Since $\mu'_{Tertutup} = (z)$ is active only within the range $0 \le z < 15$ and $\mu'_{Sedikit}(z)$ is active within $15 \le z \le 50$, the aggregated function $\mu_{agg}(z)$ for this case is defined piecewise according to those intervals as follows:

$0 \le z \le 11$: $\mu_{agg}(z) = 0,4$

$11 < z < 13,33$: $\mu_{agg}(z) = \frac{15-z}{10}$

$13,33 \le z < 18$: $\mu_{agg}(z) = \frac{z-10}{20}$

$18 \le z \le 42$: $\mu_{agg}(z) = 0,4$

$42 < z \le 50$: $\mu_{agg}(z) = \frac{50-z}{20}$

During the defuzzification stage, the aggregated function $\mu_{agg}(z)$ is used to compute the crisp value of the servo angle.

E. Defuzzification

Subsequent to the synthesis of a composite fuzzy output manifold during the aggregation phase, the Mamdani inference framework culminates in the defuzzification process. This computational phase is designed to transmute fuzzy sets into a discrete numerical format, known as the crisp output, which is readily interpretable by the actuator—specifically the servo motor responsible for modulating the irrigation gate. The resulting crisp metric quantifies the angular displacement of the aperture within a calibrated operational spectrum of 0° to 90°.

The present study implements the Centroid methodology, also recognized as the Center of Area (COA) technique. This approach ascertains the terminal output value by calculating the geometric center of mass of the area beneath the aggregated fuzzy distribution. The fundamental principle of the Centroid method lies in identifying the equilibrium point within the fuzzy spatial distribution; consequently, the final derivative is not skewed by a single dominant heuristic but instead integrates the holistic contributions of all concurrently active rules.

Mathematically, the defuzzified value is expressed as::

$$Z^* = \frac{\int z \cdot \mu_{agg}(z) dz}{\int \mu_{agg}(z) dz} = \frac{M_{total}}{A_{total}}$$

1) Calculating the Area of Each Section (A)

Area 1:

$$A_1 = (11 - 0) \times 0,4 = 4,4$$

Area 2:

$$A_2 = \frac{1}{2} \times (13,33 - 11) \times 0,4) = \frac{1}{2} \times 2,33 \times 0,4 = 0,466$$

Area 3:

$$A_3 = \frac{1}{2} \times (18 - 13,33) \times 0,4 = \frac{1}{2} \times 4,67 \times 0,4 = 0,934$$

Area 4:

$$A_4 = (42 - 18) \times 0,4 = 24 \times 0,4 = 8,4$$

Area 5:

$$A_5 = \frac{1}{2} \times (50 - 42) \times 0,4 = \frac{1}{2} \times 8 \times 0,4 = 1,6$$

Total Area

$$A_{total} = A_1 + A_2 + A_3 + A_4 + A_5 = 4,4 + 0,466 + 0,934 + 9,6 + 1,6 = 17$$

2) Calculating the Centroid of Each Area ($\bar{z}$)

Area 1:

$$\bar{z}_1 = \frac{0+11}{2} = 4,5$$

Area 2:

$$\bar{z}_2 = 11 + \frac{1}{3}(13,33 - 11) = 11 + 0,78 = 11$$

Area 3:

$$\bar{z}_3 = 13,33 + \frac{2}{3}(18 - 13,33) = 13,33 + 3,11 = 16,44$$

Area 4:

$$\bar{z}_4 = \frac{18+42}{2} = 30$$

Area 5:

$$\bar{z}_5 = 42 + \frac{1}{3}(50 - 32) = 42 + \frac{8}{3} = 44,67$$

3) Calculating the Moment of Each Area

$$M_i = A_i \times \bar{z}_i$$

$M_1 = 4,4 \times 5,5 = 24,2$

$M_2 = 0,466 \times 11,78 = 5,49$

$M_3 = 0,934 \times 16,44 = 15,35$

$M_4 = 9,6 \times 30 = 288$

$M_5 = 1,6 \times 44,67 = 71,47$

Total Moment

$$M_{total} = 24,2 + 5,49 + 15,35 + 288 + 71,47 = 404,51$$

4) Centroid Value (Z*)

$$Z^* = \frac{M_{total}}{A_{total}} = \frac{404,51}{17} = 23,79°$$

In this case study, the defuzzification result was $Z^* \approx 23.79^{\circ}$. Meanwhile, the value obtained from MATLAB Fuzzy Logic was 23.2°. The discrepancy of less than 1 degree is attributed to differences in the calculation approaches.

F. Final Result

The final outcome of the rule base analysis indicates that the system applies a total of 27 rules derived from the combination of three input variables: Humidity, Water Level, and pH. The rule structure suggests that water level plays the most significant role in determining the gate position. A High water level generally leads to a Closed decision, while Dry conditions combined with a Low water level tend to result in a Fully Open gate. Meanwhile, the pH variable functions as an adjustment factor, moderating the gate opening to a more conservative level when the water condition is either Acidic or Alkaline.

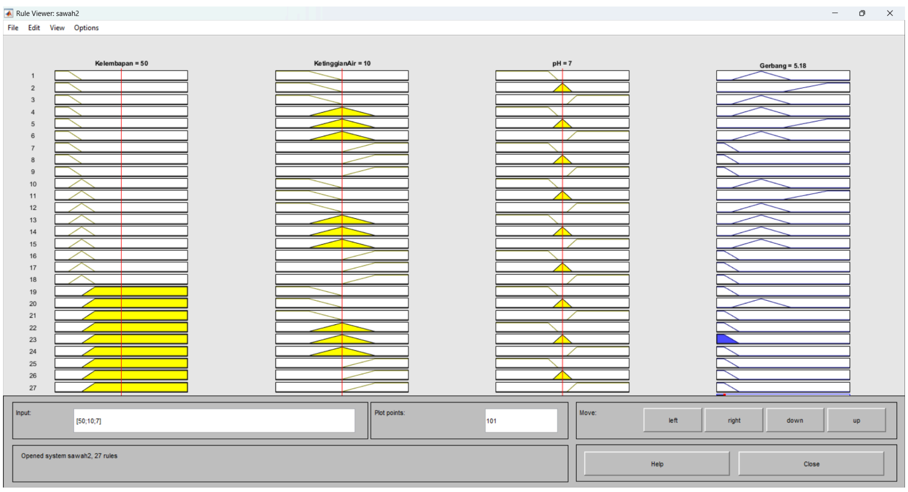

Figure 6 Rule Viewer

The final surface visualization demonstrates that the relationship between the input variables and the gate angle is nonlinear and gradual. The three-dimensional surface shows smooth transitions in the output angle across the boundaries of the fuzzy sets, preventing abrupt changes in the gate opening. This confirms that the Mamdani fuzzy approach is capable of producing a control system that remains stable and responsive under varying environmental conditions.

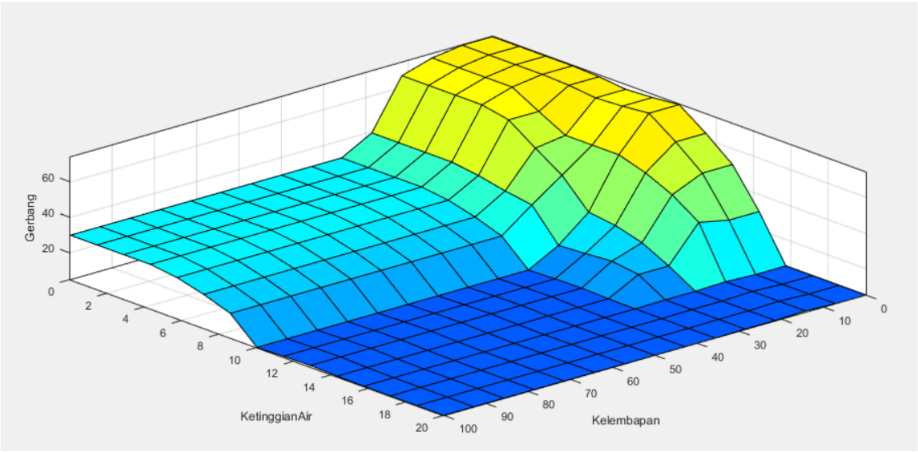

Figure 7 Surface Viewer

The surface plot illustrates that the interaction between the input parameters and the gate angle follows a nonlinear and continuous pattern. The 3D representation reveals smooth variations in the output angle, particularly within the transition zones between fuzzy sets, ensuring that the gate position does not shift abruptly. This outcome indicates that the Mamdani fuzzy method provides a control mechanism that is both stable and capable of adapting to changing environmental conditions.

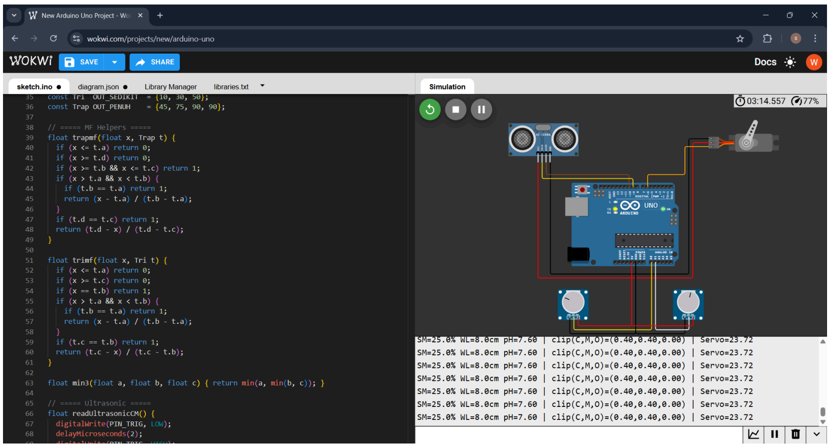

Figure 8 System Simulation

CONCLUSION

This study has successfully designed and implemented a fuzzy logic–based irrigation control system for paddy fields by integrating three essential parameters: soil moisture, water level, and water pH. The Mamdani Fuzzy Inference System, supported by 27 rule combinations, enables the system to determine the optimal gate opening angle through a structured process consisting of fuzzification, rule evaluation, aggregation, and centroid defuzzification.

The results demonstrate that the system operates adaptively, producing smooth and gradual output transitions without abrupt changes in the servo angle. The water level parameter shows a dominant influence in decision-making, while soil moisture and pH function as balancing factors to ensure both adequate irrigation volume and proper water quality.

This study contributes to the development of intelligent irrigation systems by integrating multiple environmental parameters into a unified fuzzy logic framework, enabling more accurate and adaptive decision-making compared to conventional approaches. The small deviation between manual centroid calculation and MATLAB simulation confirms the computational accuracy of the proposed method.

Overall, the developed system provides a stable, flexible, and efficient irrigation control mechanism, with practical implications for improving water use efficiency and supporting sustainable rice cultivation.

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