Fuzzy Logic Controller Design for Smart Watering System of Rose Cultivation

Samsul Arifin, Fransiska Sisilia Mukti, Aynan Salsabilah Aziz

Abstract—**The traditional methods of rose cultivation often rely on manual irrigation practices, which may not always be precise or efficient. Additionally, the cost associated with implementing automated irrigation systems has been a limiting factor for many farmers. This research addresses these challenges by exploring the integration of Fuzzy Logic Controller (FLC) technology and low-cost electronic devices to develop an automated irrigation system tailored for rose cultivation, aiming to enhance precision and accessibility in agricultural practices. The study demonstrates the effectiveness of this approach in optimizing watering practices, showcasing a notable level of accuracy in providing irrigation recommendations. Moreover, the implementation of low-cost electronic devices enhances the accessibility and feasibility of such smart irrigation systems. The research lays a foundation for advancements in precision agriculture, particularly in the domain of rose cultivation, with potential implications for broader agricultural practices.**

Index Terms—**fuzzy logic controller, precision agriculture, rose automated watering, smart irrigation system.**

I. INTRODUCTION

THE East Java region has emerged as one of the leading provinces in Indonesia in terms of rose flower commodities. According to data from the Central Statistics Agency, rose flower production in Indonesia reached 169 million stems in the year 2022, with a substantial 71.16% of this production originating from East Java [1]. This dominance can be attributed to the favorable conditions for rose cultivation, which thrive in regions with temperate climates (characterized by annual rainfall between 1500-3000 mm and humidity levels between 70-80%), especially in highland to

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mountainous areas with elevations up to 1500 meters above sea level [2].

The limitations inherent in the cultivation process of rose flowers, which necessitates adjustments to climatic conditions, compel farmers to engage in artificial climate modification. This allows for the continuation of cultivation even in lowland areas characterized by elevated temperatures. One effective measure involves regulating the soil moisture content to ensure that plants receive an adequate water supply [3].

Irrigation constitutes a crucial mechanism that determines the level of harvest success [4]. The traditional irrigation system that has been employed thus far relies on the experience and knowledge of farmers to estimate the optimal timing for watering. This necessitates periodic checks by farmers on soil moisture conditions to ensure that plants do not suffer from water deficiency.

In pursuit of greater time and operational cost efficiency, conventional irrigation systems have evolved into intelligent, Internet of Things (IoT)-based irrigation systems. This transition forms a integral component of the broader concept of smart agriculture. Smart agriculture leverages contemporary information and communication technology within the agricultural sector, offering substantial potential for heightened productivity and sustainable agricultural output through a more precise and efficient allocation of resources. The application of IoT in agriculture is geared towards empowering farmers with decision-making tools and automation technology, expediting the amalgamation of products, knowledge, and services to enhance production quality and ultimately yield greater profits. [5].

One of the concepts in smart agriculture is advanced through the utilization of a Fuzzy Logic Controller (FLC). The Fuzzy Logic Controller (FLC) constitutes an integral component of intelligent control systems rooted in classical control theory and artificial intelligence. It enables the incorporation of expert technological knowledge into logical processes, thereby delineating the parameters and variables to be regulated within a system. [6]. It offers significant advantages in addressing irrigation concerns, notably in terms of enhanced water utilization and optimized maintenance. Parameters employed for monitoring agricultural irrigation encompass factors like water quantity and

quality, meteorological conditions, soil attributes, moisture levels, and fertilizer application. [5].

There are three methodologies for constructing an FLC, namely the Mamdani, Takagi-Sugeno-Kang, and Tsukamoto approaches. The first is renowned for its utilization of linguistic variables, while the latter two rely on mathematical analysis. Nevertheless, all these methods necessitate the incorporation of both fuzzification and defuzzification stages. Given that the Tsukamoto approach facilitates the expression of scientific and technological expertise in terms of concepts rather than numerical values, it is the most fitting choice for the objectives of this study. [6].

While fuzzy control techniques have been employed in various agricultural contexts, there remains a need for studies focusing on their application in rose cultivation, particularly utilizing cost-effective electronic devices to enhance and optimize irrigation systems. [7]. Therefore, this research not only focuses on integrating the FLC concept into an automated irrigation scheme, but also provides recommendations for a cost-effective smart irrigation system.

II. METHODOLOGY

A. System Architecture

Smart irrigation system yang diusulkan melalui penelitian ini menggunakan mikrokontroler NodeMCU ESP32 sebagai pemegang kendali system, mulai dari mendeteksi tingkat kelembapan tanah, mengatur katup air serta menjalankan algoritma Fuzzy Tsukamoto. Desain smart irrigation system ini mengadopsi mekanisme closed-loop control, which represents an alternative and efficient solution to traditional irrigation methods. The main task of these systems is to accurately determine the crop irrigation needs [8].

Initially, the soil moisture sensor identifies the level of moisture in the soil and sends this information to the ESP32. The FLC then utilizes this data as input to produce output data specifying the duration of watering. Following this, the microcontroller triggers the relay, functioning as a connecting switch and power interrupter for the solenoid, which acts as the controller for the water valve. The microcontroller implements the FLC's computed results to activate the mist maker, enabling the automated watering process. To summarize, the operational process of the developed intelligent irrigation system is depicted in Fig. 1.
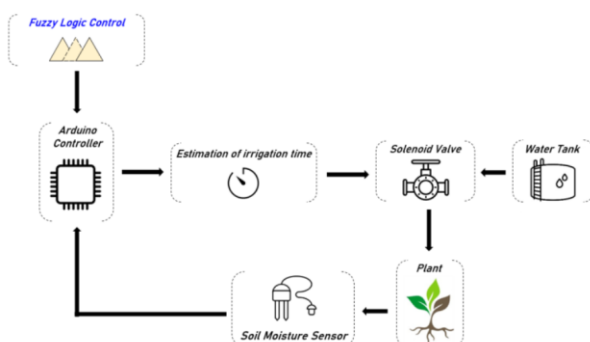

Fig. 1. Proposed architecture [17]

B. Fuzzy Logic System

Some opinions suggest that the Tsukamoto fuzzy inference is one of the irrigation system decision-making methods designed in combination with the MATLAB application to determine the output of Tsukamoto's fuzzy analysis. In Fig.2 is a commonly known fuzzy logic system (FLS). It consists of three main conceps: fuzzification, fuzzy interference system (knowledge base & interference unit), and
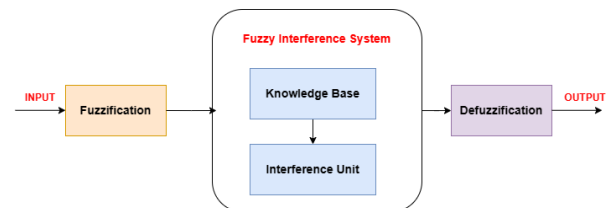

Fig. 2. Fuzzy Logic System [17]

defuzzification [9].

1) Fuzzification

Fuzzification is a crucial step in applying fuzzy logic to systems like a rose irrigation system. It involves the process of converting crisp, precise input values into fuzzy linguistic terms or labels, which represent the qualitative assessment of these values [10]. This step allows us to deal with imprecise or uncertain information regarding factors like soil moisture levels, weather conditions, and plant water requirements.

We use two linguistic labels, that are dry and wet to categorize the soil moisture into qualitative terms. These labels are associated with membership functions that define the degree of membership of a given value to each linguistic term. This means that a specific soil moisture value could partially belong to multiple labels [11].

In order to obtain the right decision, the triangular and trapezoidal membership functions represent a typical choice in the proposed system. Equation (1) and (2) shows the structure of a triangular and trapezoidal adhesion for a two-value fuzzification system. These equations represent fuzzy membership functions for the linguistic terms "dry" and "wet" with respect to a variable x. These functions are used in fuzzy logic to quantify the degree of membership of a given value of x to the sets "dry" and "wet". The membership value varies between 0 (indicating no membership) and 1 (indicating full membership) [12].

$$\mu_{dry}[x] = \begin{cases} 0; & x \geq 70 \\ \frac{70-x}{70-55}; & 55 \leq x \leq 70 \\ 1; & x \leq 55 \end{cases} \quad (1)$$

For *dry*: if x is greater than or equal to 70, the membership value is 0. If x is in the range between 55 and 70, the membership value is given by $\frac{70-x}{70-55}$, which represents a linear decrease in membership from 1 to 0

as x increases from 55 to 70. If x is less than or equal to 55, the membership value is 1, indicating full membership [13].

$$\mu_{wet}[x] = \begin{array}{l} 0; \ x \leq 55 \\ \frac{x-55}{70-55} ; \ 55 \leq x \leq 70 \\ 1; \ x \geq 70 \end{array} \qquad (2)$$

For *wet*: if x is less than or equal to 55, the membership value is 0. If x is in the range between 55 and 70, the membership value is given by $\frac{x-55}{70-55}$, which represents a linear increase in membership from 0 to 1 as x increases from 55 to 70. If x is greater than or equal to 70, the membership value is 1, indicating full membership [13].

In summary, these membership functions describe how "dryness" and "wetness" are quantified based on the value of x. The functions provide a smooth transition in membership values as x changes within the specified ranges. Fig.3 shows the membership function of the fuzzy logic controller inputs in this study [13].
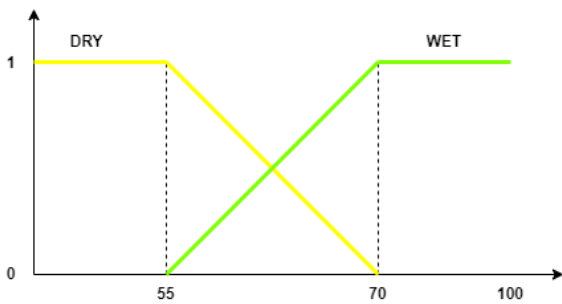

Fig. 3. Membership Function Input

In the Tsukamoto fuzzy model, membership functions play a pivotal role in quantifying linguistic variables like "dryness" and "wetness". These functions graphically depict the degree to which a given input value belongs to a particular linguistic category. In the case of dryness, the membership function typically starts at 1 for low values of the variable (indicating high dryness) and gradually decreases to 0 as the value increases. This reflects the gradual transition from complete membership to non-membership as dryness diminishes. Conversely, for wetness, the membership function starts at 0 and ascends to 1, signifying the shift from non-membership to full membership as wetness intensifies. The curves of these membership functions are crucial in defining the behavior of fuzzy rules and, subsequently, in making decisions within a fuzzy logic system. They serve as a bridge between crisp, numerical data and linguistic variables, enabling the system to process and respond to imprecise information in a meaningful way [10].

2) Fuzzy Rule Base (Knowledge Base)

The Fuzzy Rule Base, also known as the Knowledge Base in fuzzy logic, is a critical component of a fuzzy logic system. It consists of a collection of rules that describe the relationship between inputs and outputs in a fuzzy system. These rules are typically expressed in the form of conditional statements that link linguistic variables. Each rule comprises two main parts: an antecedent (or premise) and a consequent [10].

Antecedent (Premise) establishes the conditions or criteria based on which a decision or action is made. It involves linguistic variables and their corresponding membership functions, representing the input values of the system. While c*onsequent* specifies the resulting action or output based on the conditions set in the antecedent. It involves linguistic variables and their corresponding membership functions representing the output values of the system [13].

In this study, we consider sensor condition as main premises in building the rules: dry and wet. We used two soil sensors that placed in different places in order to get data more accurately. We structured the sensor conditions as input into four rules that generate output in the form of irrigation duration classified as either long or short. This approach allows for a nuanced response to varying soil moisture levels, ensuring an appropriate and timely watering regimen for the plants. This rule is based on discussions with experts (rose farmers association) in the Batu, Indonesia. Table 1 represents the knowledge base in this study.

3) Defuzzification

Defuzzification is a crucial step in fuzzy logic systems where the final fuzzy output is transformed into a crisp, numerical value that can be used for practical control or decision-making. In other words, it converts a

Table 1. The Fuzzy Rules for Rose Watering System

Rules	Soil Sensor 1 Level	Soil Sensor Level 2	Watering Duration
1	Dry	Dry	Long
2	Dry	Wet	Short
3	Wet	Dry	Short
4	Wet	Wet	Short

fuzzy set or fuzzy value into a specific, actionable response [10].

We used center weighted average method in defuzzification process, which involves taking a weighted sum of the output values based on their membership values. The weights are determined by the membership values of each fuzzy value, as shown in Equation (3) [14].

$$Z = \frac{\sum_{i}^{n} \propto_i . Z_i}{\propto_i} \qquad (3)$$

Where Z represents the final defuzzified value, which is essential for making practical decisions or control actions. The variable n refers to the number of fuzzy sets or rules contributing to the output. The coefficients $\propto_i$ represent the membership values associated with each rule, indicating the level of influence or importance of that rule's output. Z_i denotes the individual fuzzy outputs generated by each rule. The

numerator calculates the weighted sum of these fuzzy outputs, while the denominator normalizes the result by dividing by the total weight. This ensures that the final defuzzified value accurately reflects the overall contribution of the rules [10].

The output, which represents the suggested watering duration, is obtained by taking the weighted average of the fuzzy values produced by the rules. We determined values between 0 and 200 seconds for watering duration, which is represented in Fig. 4. This allows for precise control actions in response to varying input conditions, making Tsukamoto's method a valuable tool in fuzzy logic applications.
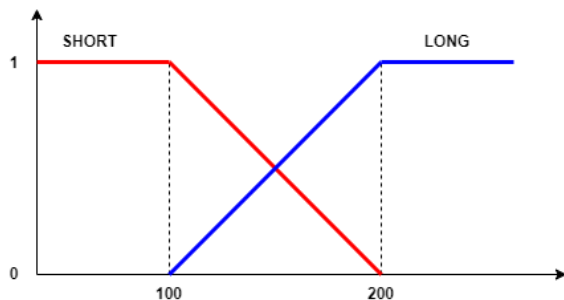

Fig. 4. Membership Function Output

In the Tsukamoto method, the membership function for a fuzzy set is typically represented using a linear function [13]. For this case, we used 2 types of linear function, that are ascending (long) and descending (short). The equation for both linear membership functions in the Tsukamoto method can be expressed as Equation (4) and Equation (5).

$$\mu_{ascending}[x] = \begin{array}{l} 0;\ x \leq 100 \\ \frac{x-100}{200-100};\ 100 \leq x \leq 200 \\ 1;\ x \geq 200 \end{array} \qquad (4)$$

This membership function behaves as follows: for x values less than or equal to 100, the membership grade is 0, signifying a weak association with the set. When x falls within the range of 100 to 200, the membership grade is determined by the linear function $\frac{x-100}{200-100}$, where 100 and 200 are parameters representing the lower and upper bounds of this range, respectively. This means the membership grade gradually increases from 0 to 1 as x moves from 100 to 200, indicating a strengthening association with the "ascending" set. Finally, for x values greater than or equal to 200, the membership grade is a full 1, indicating a strong association with the set.

$$\mu_{descending}[x] = \begin{array}{l} \frac{200-x}{200-100};\ 100 \leq x \leq 200 \\ 0;\ x \geq 200 \end{array} \qquad (5)$$

This membership function behaves as follows: for x values between 100 and 200 (inclusive), the membership grade is given by $\frac{200-x}{200-100}$, which denotes a linear decrease in membership grade as x moves from 100 to 200. This indicates a weakening association with the "descending" set within this range. For x values greater than or equal to 200, the membership grade is set to 0, indicating no membership with the set beyond this point.

III. RESULTS AND DISCUSSION

In order to assess the performance of the Fuzzy Tsukamoto model in optimizing watering durations for our rose cultivation system, a series of experiments were conducted. For the purpose of initial evaluation, dummy data was generated to simulate varying soil moisture levels for both soil sensors.

A. Fuzzy Logic Procedures

The proposed work has been programmed using MATLAB simulation tool and Arduino programming. Soil moisture Arduino module hygrometer YL-69 is used to collect the information about the humidity level. It is used because of cost effectiveness and fast response while monitoring the temperature and humidity data. Correspondingly, this sensor also used to collect the data regarding the humidity content of soil in the agricultural field [15].

As an illustrative instance, we employed dummy data for the initial trial: sensor 1 registered a reading of 56, while sensor 2 recorded 60. Subsequently, we conducted computations utilizing our Fuzzy Tsukamoto modelling approach to ascertain the output, which manifests in the form of the rose watering duration.

1) *Fuzzification:* the process of determining membership degrees for each sensor is pivotal. For Sensor 1, the computed results yield $\mu_{dry}[56] = 0,93$ and $\mu_{wet}[56] = 0,06.$ Meanwhile, for Sensor 2, the computed values indicate $\mu_{dry}[56] = 0,66$ and $\mu_{wet}[56] = 0,3.$

2) *Fuzzy rule base*: processes the crisp input values, mapping them to fuzzy linguistic values through membership functions, and subsequently applies fuzzy rules to generate the output. We used 4 rules (see Table I) to generate the output.

3) *Defuzzification*: process of converting a fuzzy set or fuzzy output into a decision for controlling the systems. This is achieved by determining the value of min and z for each pre-established rule. The defuzzification process are defined below.

[R1] IF S1=dry AND S2=dry THEN duration=LONG
$$\alpha_1 = min\ (\mu_{dry}[56] \cap \mu_{dry}[60]) = min\ (0,93; 0,66) = 0,66$$
$$\mu[z_1]:\ \alpha_1 = \frac{z_1-100}{200-100};\ 0,66 = \frac{z_1-100}{100};\ z_1 = 166$$

[R2] IF S1=dry AND S2=wet THEN duration=SHORT

$\alpha_2 = min\ (\mu_{dry}[56] \cap \mu_{wet}[60]) = min\ (0,93; 0,3) = 0,3$

$\mu[z_2]\colon \alpha_2 = \frac{200-z_2}{200-100}\ ; 0,3 = \frac{200-z_2}{100}\ ; z_2 = 170$

[R3] IF S1=wet AND S2=dry THEN duration=SHORT

$\alpha_3 = min\ (\mu_{dry}[56] \cap \mu_{dry}[60]) = min\ (0,06; 0,66) = 0,06$

$\mu[z_3]\colon \alpha_3 = \frac{200-z_3}{200-100}\ ; 0,06 = \frac{200-z_3}{100}\ ; z_3 = 194$

[R4] IF S1=wet AND S2=wet THEN duration=SHORT

$\alpha_4 = min\ (\mu_{dry}[56] \cap \mu_{wet}[60]) = min\ (0,06; 0,3) = 0,06$

$\mu[z_4]\colon \alpha_4 = \frac{200-z_4}{200-100}\ ; 0,06 = \frac{200-z_4}{100}\ ; z_4 = 194$

Final defuzzied value computation using Equation (3):

$$Z = \frac{(\alpha_1 \times Z_1) + (\alpha_2 \times Z_2) + (\alpha_3 \times Z_3) + (\alpha_4 \times Z_4)}{\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4}$$

$$Z = \frac{(0,66 \times 140) + (0,3 \times 170) + (0,06 \times 194) + (0,06 \times 194)}{0,66 + 0,3 + 0,06 + 0,06}$$

$$Z = 174,94$$

In this scenario, Sensor 1 and Sensor 2 provided respective readings of 56 and 60, indicating measurements related to specific environmental parameters. These readings were then processed through a fuzzy Tsukamoto-based automatic watering system. The system's output, represented by the **Z** value of 174.94, corresponds to the recommended watering duration. This means that, based on the combined input from both sensors and the fuzzy logic algorithm, the system suggests a watering duration of approximately 174.94 second. This application of fuzzy logic in automatic watering systems allows for nuanced, adaptive decisions, taking into account multiple sensor inputs to optimize the watering process for the specific conditions detected by the sensors.

B. Performance Evaluation

The proposed work has been programmed using Arduino programming in NodeMCU ESP32 Microcontroller. Soil moisture module hygrometer YL-69 is used to collect the information about the humidity level. It is used because of cost effectiveness and fast response while monitoring the temperature and humidity data. Correspondingly, this sensor also used to collect the data regarding the humidity content of soil in the agricultural field [15].

A comprehensive experimental setup was established, to facilitate accurate data collection and assessment of the model's performance. Both soil moisture sensors were strategically placed at varying depths within the rose bed to provide real-time measurements of soil moisture content. We created some conditions in order to make humidity data variation, then evaluated the FLC's ability to interpret input data, and generate appropriate watering decisions.

The performance evaluation of the Fuzzy Tsukamoto

Table 2. Comparative Results of Proposed System

Soil Sensor 1 Level (^{0})	Soil Sensor 2 Level (^{0})	Watering Duration (second)		Absolute Error
		Calculation	Real Measurement	
35	37	200	198.53	0.009934
40	50	200	196.44	0.020149
42	48	200	197.52	0.020756
50	56	193.06	197.48	0.024884
56	60	170.22	179.56	0.022854
75	78	100	77.78	0.275381
70	72	100	76.66	0.274852
63	65	160.15	123.43	0.281579
60	60	168.3	148.99	0.141492
59	60	168.94	155.32	0.088820
			Total	1.20486

model involved a comparison between calculated watering recommendations generated by the system and the actual water applied under real-world conditions. The results obtained from the experiment are summarized at Table 2.

Overall, it is evident that the model tends to provide recommendations that are generally in close proximity to the actual amounts of water applied. This is particularly notable in trials 2, 3, and 4, where the model's suggestions were very closely aligned with the real-world application. This indicates a relatively high level of accuracy in the model's calculations, suggesting that it has a good grasp on the optimal watering requirements for the rose plants in these specific scenarios.

However, as observed in trials 6 and 7, there were instances where the model's recommendations significantly deviated from the actual watering amounts. In these cases, the model appeared to underestimate the required water, resulting in a notable shortfall in the applied volume. This discrepancy could potentially be attributed to factors not accounted for in the model's calculations, such as variations in soil type or localized environmental conditions.

Conversely, trials 5, 8, 9, and 10 demonstrated cases where the model's recommendations exceeded the actual water applied. This suggests that in these instances, the model may have been overly cautious, potentially leading to slight over-watering. This tendency could be indicative of a conservative approach in the model's decision-making process, which could be further refined to achieve an optimal balance between water conservation and plant hydration.

To quantitatively assess the accuracy of these recommendations, the *Mean Absolute Percentage Error* (MAPE) was computed. This statistical measure offers a comprehensive evaluation, quantifying the average percentage deviation between the calculated and actual values. The Mean Absolute Percentage Error (MAPE) is calculated using the Eauqtion (6) [16]:

$$MAPE\ (\%) = \frac{1}{n} \sum_{n=1}^{i} \left| \frac{A_i - F_i}{A_i} \right| \times 100\ \% \qquad (6)$$

Where A_i represents the actual value (real condition), F_i represents the forecasted value

(calculation data) and n is the total number of data points. Given the calculation data and real conditions from Table 2, we get the MAPE value defined as follows.

$$MAPE\ (\%) = \frac{1.20486}{10} \times 100\% \approx 12.05\%$$

Our proposed system gives error result approximately 12.05%, indicates a valuable quantitative measure of the model's performance, enabling growers to make informed decisions about implementing our scheme in their cultivation. With ongoing refinement and calibration, it's likely that the model's accuracy could be even further improved, potentially leading to more precise watering recommendations in practical applications.

IV. CONCLUSION

This research endeavors to advance the field of smart agriculture, specifically in the domain of rose cultivation. By integrating the Fuzzy Logic Controller (FLC) concept into an automated irrigation scheme, we have demonstrated the potential for enhancing water management practices in a cost-effective manner. The utilization of low-cost electronic devices in conjunction with the FLC has shown promise in optimizing irrigation systems, thereby offering a viable solution for farmers seeking to improve their cultivation practices. These findings underscore the significance of harnessing advanced control techniques and affordable technology in bolstering agricultural sustainability and productivity. As smart agriculture continues to evolve, this study contributes a practical framework for the implementation of intelligent irrigation systems, not only in rose cultivation but potentially in various other agricultural contexts as well.

To further advance this research, several avenues for future exploration are recommended. Firstly, a comprehensive field trial encompassing a diverse range of environmental conditions and soil types would provide a more robust assessment of the FLC-based irrigation system's performance. Additionally, incorporating real-time data from weather forecasts and soil sensors could enhance the model's predictive capabilities. Moreover, investigating the potential integration of other advanced control techniques, such as machine learning algorithms, could lead to even more refined and adaptable irrigation systems.

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