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The Performance of Water Irrigation Control using Fuzzy-GA Approach

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ABSTRACT

Irrigation in agriculture uses around 70% of freshwater resources globally, but traditional systems often result in ineffective utilization through rigid schedules or skewed decision-making. This article proposes an improved fuzzy logic controller developed using a Genetic Algorithm (GA) to optimize soil moisture control. The GA optimizes the fuzzy membership functions within 50 generations to enhance irrigation efficiency. Simulation and experimental results show that the fuzzy-GA controller maintained soil moisture at values close to the desired value of 25.1% with lower error rates, saving 858 mL more water than manual irrigation and 16 mL more than conventional fuzzy control. The results confirm the potential of fuzzy-GA systems in optimizing irrigation efficiency and ensuring sustainable use of water in agriculture. The fuzzy-genetic algorithm (Fuzzy-GA) improves fuzzy logic control by maintaining soil moisture at a target level of 25.1%, with a very low steady-state error of 0.03783%.

1. INTRODUCTION

About 70% of the freshwater used worldwide is used for agriculture (Perez-Blanco *et al*., 2020). The demand for food and water is anticipated to increase dramatically as the world's population is predicted to reach 10 billion people by 2050 (Ganivet, 2020). But conventional irrigation methods frequently depend on set timetables or farmers' instincts, which results in wasteful water use (Bwambale *et al*., 2022). Both excessive and insufficient irrigation can be caused by these inefficiencies, which pose major risks to crop health and water sustainability (Islam *et al*., 2021; Violino *et al*., 2023).

Over-irrigation wastes water and damages plant growth, while under-irrigation limits nutrient uptake and reduces crop yields (Li *et al*., 2009; Davies & Albrigo, 1983). Since water availability also affects nutrient mobility and uptake, efficient irrigation is necessary to optimize both water and nutrient use efficiency. Irrigation systems, thus, need to consider not only the nutrient content but also the soil water status (Li *et al*., 2009).

To address these issues, recent technologies have focused on smart irrigation technologies. Internet of Things (IoT) technologies enable real-time monitoring of the environment, such as soil moisture, and their use for more effective irrigation decision-making (Liang & Shah, 2023; Saha *et al*., 2021). Most of the IoT-based systems, however, are still manual adjustment-dependent. Fuzzy logic controllers are more autonomous in their approach, controlling irrigation based on parameters like humidity, temperature, and soil moisture (Krishnan *et al*., 2020). They have saved as much as 58% of water compared to flood irrigation and have the potential to increase crop yield by 164% (Jaiswal & Ballal, 2020). Although they are strong, fuzzy controllers heavily depend on the knowledge expertise to define rules and membership functions, limiting their efficiency (Niu *et al*., 2021).

To overcome this limitation, optimization algorithms such as Particle Swarm Optimization (PSO) have been applied, improving soil moisture control and reducing average error compared to non-optimized fuzzy systems (Xie *et al*., 2022). Genetic Algorithms (GAs), in particular, have shown promise due to their ability to avoid local optima through crossover and mutation operations (Bajpai & Kumar, 2010). GAs have been successfully used to optimize fuzzy rules and membership functions in various control applications, leading to enhanced response time and reduced overshoot (Niu *et al*., 2021; Liang *et al*., 2020).

Despite these advancements, there is limited research applying GA-optimized fuzzy logic specifically to irrigation systems. This study addresses that gap by developing a fuzzy logic controller optimized with a Genetic Algorithm for controlling soil moisture. The proposed system aims to improve irrigation efficiency by delivering water more precisely and maintaining soil moisture stability, thereby reducing waste without compromising crop health.

2. MATERIALS AND METHODS

2.1. Hardware

The block diagram of the overall system was shown in figure 1, the input is from a soil moisture sensor and the output is water pump. The soil moisture sensor measures soil capacitance and outputs a corresponding analog signal. The ESP-32 microcontroller converts this signal to a moisture percentage using its ADC and transmits the data to a central server via HTTP. The schematic diagram is shown in Figure 2.

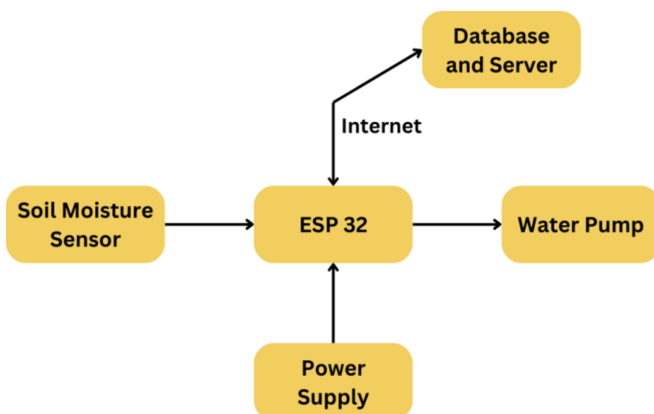


Figure 1. System block diagram

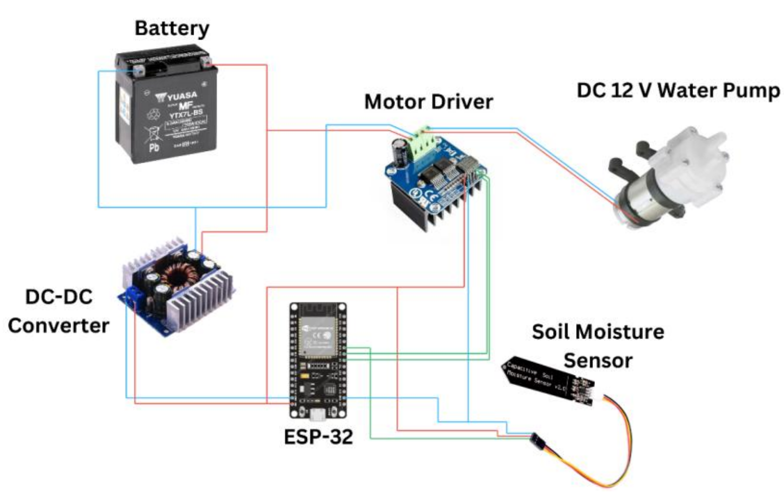


Figure 2. Schematic wiring diagram

On the server, a Fuzzy-Genetic Algorithm (Fuzzy-GA) processes the data to compute a Pulse Width Modulation (PWM) output ranging from 0 to 255. The algorithm determines the PWM value based on the error and derivative error relative to the target soil moisture level. The schematic of the irrigation system is shown on figure 3. The computed PWM value dynamically controls the voltage supplied to the water pump, adjusting its speed to optimize irrigation based on real-time soil moisture. The ESP-32 retrieves the PWM output from the server via HTTP and actuates the pump to maintain the target moisture level.

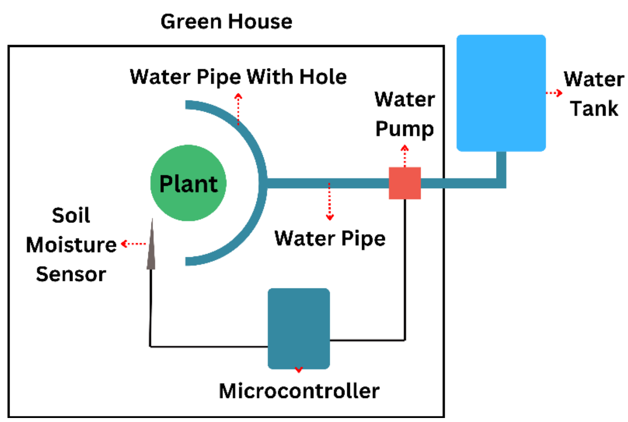


Figure 3. Schematic of irrigation system

2.2. Test Area and Target Setpoint

The experiment was conducted on *Citrus sinensis* (orange) trees at Jl. Kecapi, Serua, Kec. Ciputat, Kota Tangerang Selatan, Banten (latitude: -6.3070420909202625, longitude: 106.71126629234902). The climate of this region is tropical. With a wilting point (WP) of 0.1 m^3/m^3 and a field capacity (FC) of 0.25 m^3/m^3, the soil at the experimental site is categorised as loam. The sensor probe was positioned 30 cm below the citrus tree canopy to precisely measure soil moisture, focusing on the root zone where water uptake is most significant. The experimental setup of the study area is illustrated in Figure 4.

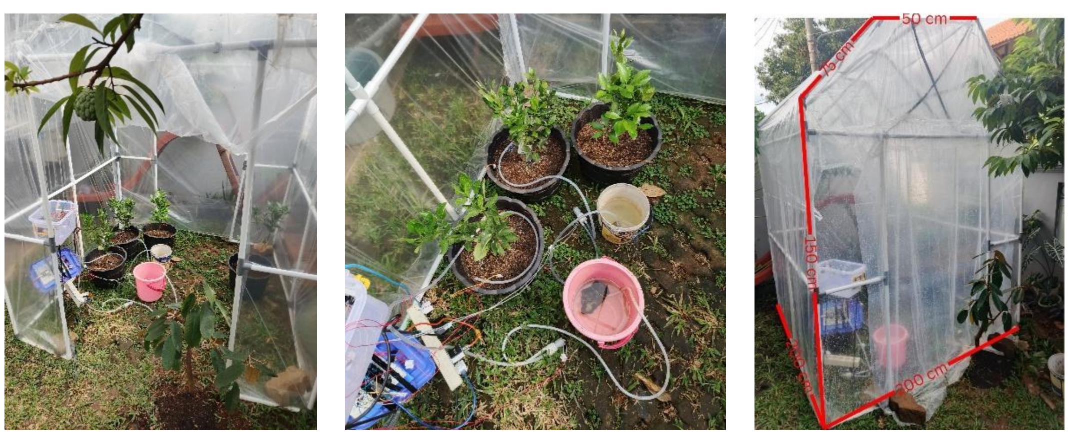


Figure 4. Location of citrus area

To determine the soil moisture setpoint for Fuzzy-GA control, specific formulas were utilized. The first step involved calculating the Total Available Water (TAW), which represents the amount of water a crop can extract from its root zone. The magnitude of TAW depends on field capacity, wilting point of soil, and rooting depth. The formula was shown in Equation 1 (Allen *et al*., 1998).

$$TAW = 1000(FC - WP) \times Zr \tag{1}$$

where FC is field capacity, WP is wilting point, and Zr is the rooting depth. Using Equation 1, the Readily Available Water (RAW) can then be determined. RAW refers to the portion of TAW that crops can utilize before experiencing significant water stress, which may lead to yield or quality reduction. The formula was shown in Equation 2.

$$RAW = p \times TAW \tag{2}$$

where p is the allowable depletion fraction, representing the proportion of soil water content that can be depleted without causing crop stress, and TAW is the total available water. The p value for Citrus sinensis is 33% (Allen & MacAdam, 2020; Kadyampakeni *et al*., 2017). Using equation 2, the target soil moisture was determined by subtracting FC from RAW. The formula is shown in Equation 3.

$$Target = FC - \left(\frac{RAW}{1000 * Zr}\right) \tag{3}$$

2.3. Fuzzy Control

The fuzzy input system comprised two variables: soil moisture error (SME) and the rate of change of soil moisture error (SMECR). The output variable, designated as u, represents the control signal. The block diagram of the control system was shown in Figure 5.

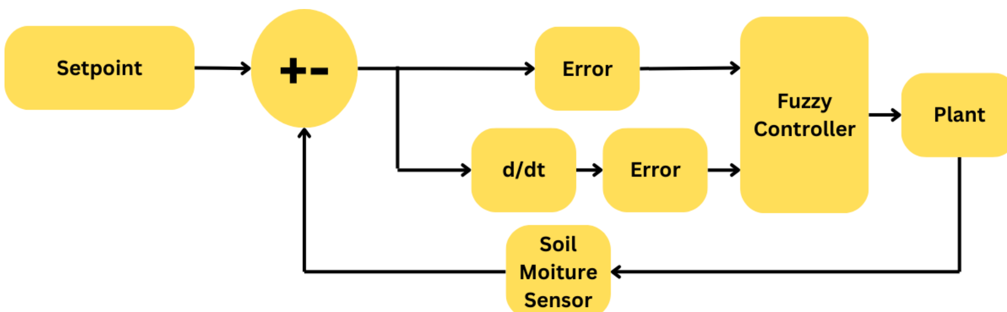
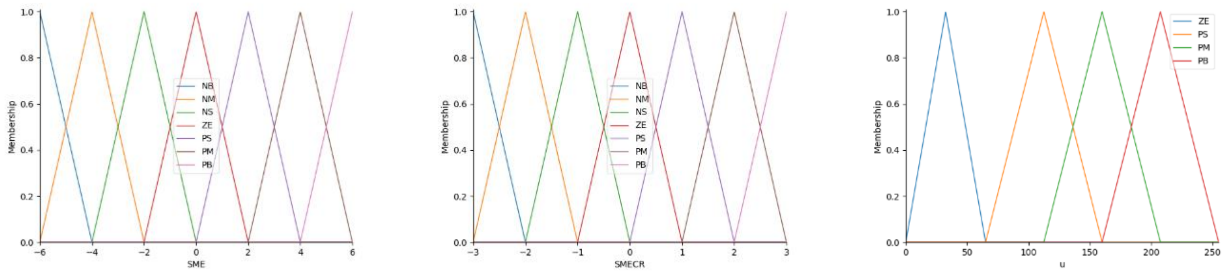


Figure 5. Block diagram of fuzzy control

All three linguistic variables were quantized into 13 levels (Xie *et al*., 2022). The fuzzy theoretical domain for SME spans [-8.8], for SMECR it ranges between [-4.4], and for u, the range is [0.255] with an actuator dead zone of 0 –65. The input linguistic variable was defined by seven fuzzy subsets: Positive Big (PB), Positive Middle (PM), Positive Small (PS), Zero (ZE), Negative Small (NS), Negative Middle (NM), and Negative Big (NB) as for the output linguistic variable is defined by four fuzzy subsets Zero(ZE), Positive Small (PS), Positive Middle (PM), and Positive Big (PB). For this study, triangular membership functions, known for their simplicity and computational efficiency, were employed to represent these subsets (Sutikno *et al*., 2021). The analytical formulation of the triangular membership function was presented in Equation 4 (MathWorks, 2024).

$$f(x,a,b,c) = \begin{cases} 0 & x \le a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{c-x}{c-b} & b \le x \le c \\ 0 & x \ge c \end{cases} \tag{4}$$

where a, b, and c are critical parameters that define the morphology of the membership functions. These parameters ensure that the membership functions are properly aligned with the fuzzy domain by dictating their shape and distribution. The specific distribution of the membership functions was illustrated in Figure 6.



a b c

Figure 6. a) Membership function of SME, b) Membership function of SMECR, c) Membership of u

A fuzzy controller's design principle was to maximize output when the error is large, minimize output when the error is small, and carefully consider system stability and overshoot to ensure optimal performance (Xie *et al*., 2022). The rules of the fuzzy controller consisted of 49 rules, as shown in Table 1. The rules in Table 1 adhered to the format: "If SME x and SMECR y, then *u* z."

Table 1. Table of fuzzy rules

SME	**SMECR**						
	NB	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
NB	PB	PB	PM	PM	PM	PS	ZE
NM	PB	PB	PM	PM	PS	ZE	ZE
NS	PB	PM	PM	PS	ZE	ZE	ZE
ZE	PM	PM	PS	ZE	ZE	ZE	ZE
PS	PM	PS	ZE	ZE	ZE	ZE	ZE
PM	PS	ZE	ZE	ZE	ZE	ZE	ZE
PB	ZE	ZE	ZE	ZE	ZE	ZE	ZE

Table 2. Equations of the performance metrics

Performance Metrics Equations	**Number**
$Error = System\ Input - System\ Output$	(5)
$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Error_i)^2}$	(6)
$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert Error_i\rvert$	(7)
$IAE = \sum_{i=1}^{n}\lvert Error_i\rvert \times \Delta t$	(8)
$ITAE = \sum_{i=1}^{n}(t_i \times \lvert Error_i\rvert)\Delta t$	(9)
$fitness = \mid RMSE \mid + \mid MAE \mid + \mid IAE \mid + \mid ITAE \mid$	(10)

2.4. Fuzzy Genetic Algorithm

In this study, a fuzzy genetic algorithm (Fuzzy-GA) was employed to optimize fuzzy control by altering the range of triangular membership functions. The membership functions of the fuzzy controller were encoded into chromosomes to form the initial population. These chromosomes were then subjected to simulation, where the output was evaluated using performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Integral Absolute

Error (IAE), and Integral Time Absolute Error (ITAE). The formula for the performance metrics was shown in Table 2. In the table, n is the number of observations, $error_i$ is the error for the i^{th} observation, Δt is is the time step ($\Delta t = time\_steps[1] - time\_steps[0]$)8, and t_i is the i-th time step value. The evaluation values were inputed into a fitness function in Equation 10, and the resulting fitness scores were used to select the best membership functions through a tournament selection method with a size of three.

In this method, three individuals were randomly selected, and the one with the best fitness is chosen as a parent for the next generation. Tournament selection was employed due to its efficiency and rapid iteration capability (Razali & Geraghty, 2011). The selected genes were then recombined using Blend Crossover (BLX-α). For each gene in the parent chromosomes, a child gene was generated by sampling uniformly from an interval around the parent genes (Tebbal & Hamida, 2023). Small, random mutations were introduced into the genes to maintain genetic diversity and prevent premature convergence. The next generation was formed by replacing less fit individuals while employing elitism. The elitism retained the best individuals from the current generation, ensuring that the optimal solution was preserved despite variations introduced during selection, crossover, or mutation. The flowchart of the Fuzzy-GA was shown in Figure 7. The genetic algorithm was configured to produce an output after 50 generations.

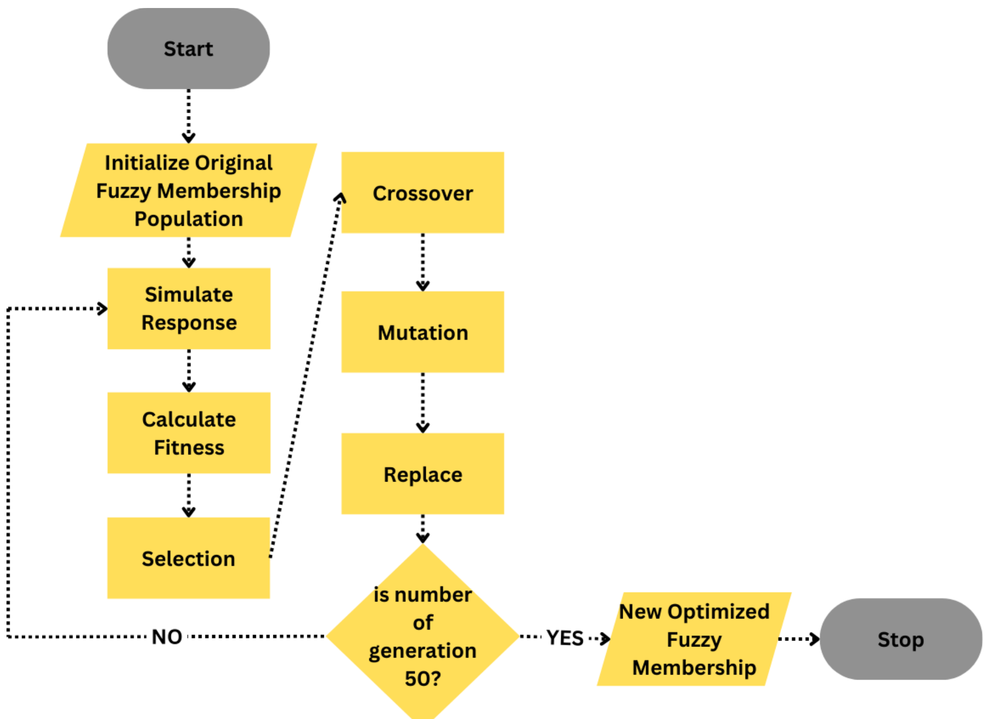


Figure 7. Flowchart of genetic algorithm optimization process

2.5. Simulation

The simulation for the Fuzzy-GA system was modeled as a first-order system, with its mathematical expression presented in Equation 11.

$$G(s) = \frac{288.1953}{1905.60\ s + 1} \tag{11}$$

The Fuzzy-GA controller was compared to conventional fuzzy control in simulation. In field experiments, the Fuzzy-GA controller is evaluated against the FAO standard manual irrigation method, as represented in Equation 12.

$$ETc = Kc + ETo \tag{12}$$

where *ETc* is the crop evapotranspiration (mm/day), *Kc* is the crop coefficient, and *ETo* is the reference crop evapotranspiration (mm/day). According to the FAO 56 guidelines, the *Kc* value for citrus in the late season with 50% canopy coverage is 0.60, and the *ETo* is reported as 2159 mm/year (Marganingrum & Santoso, 2019). Based on these values, the *ETc* for citrus sinensis is calculated to be 3.9 mm/day.

$$Volume = ETc \times Area \tag{13}$$

The volume of water required for the plant was determined using the evapotranspiration (*ETc*) value, as described by Equation 13. In this calculation, the area represents the soil surface where the plant is cultivated, which is measured as 706.5 cm². By applying the appropriate formula, the estimated daily water requirement was determined to be 275 mL. The irrigation schedule for manual control was set at an interval of every two days. This schedule was designed based on the calculated daily water requirement of 275 mL, ensuring that the plant receives adequate moisture.

3. RESULTS AND DISCUSSION

3.1. Sensor Calibration

Sensor calibration was performed on the sensors used in this experiment to ensure accurate measurement of soil moisture in the field. The calibration process was conducted to minimize errors and improve measurement reliability, the calibration is done on 200ml of soil. The results of the sensor calibration are presented in Table 3. Based on these results, a polynomial regression analysis was conducted to derive the calibration equations, as presented in Eq. (14).

$$f(x) = (4 * 10^{-5})x^2 - (0.185)x + 207.76 \tag{14}$$

where x is the sensor value, Equation 14 has a fit of 96.95%. The graphical representation of the calibration curve is shown in Figure 8, illustrating the correlation between the measured and predicted values.

Table 3. Sensor calibration output

Sensor Read	2110	1860	1690	1598	1410	1325	1110	955	947
Soil Moisture (%)	0	1.1	5.5	14.3	23.1	44.0	55.0	64.9	67.1

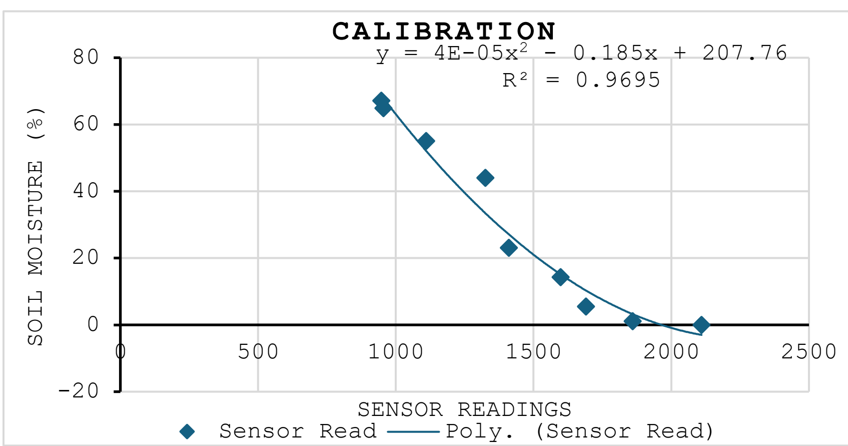


Figure 8. Equation fit from calibration

3.2. Control Result

The simulation was conducted using the Python programming language, with a target soil moisture level of 25.01%, as calculated using Equation 3. The results of the simulation are presented in Figure 9. From the figure, it can be observed that the fuzzy GA approach achieves a stable value with reduced steady-state error. The system response of the GA-optimized system includes a steady-state error of 0.03783%, an overshoot of 0.4920%, a settling time of 1.301

seconds, a root mean square (RMS) error of 1.6416%, and a mean absolute error (MAE) of 0.37588%. This occurs because the Genetic Algorithm (GA) continuously searches for optimal membership parameters and evaluates the system response over 50 generations. Upon reaching the 50th generation, a new membership function is generated and applied to the system, resulting in improved fuzzy control performance and enhanced irrigation optimization.

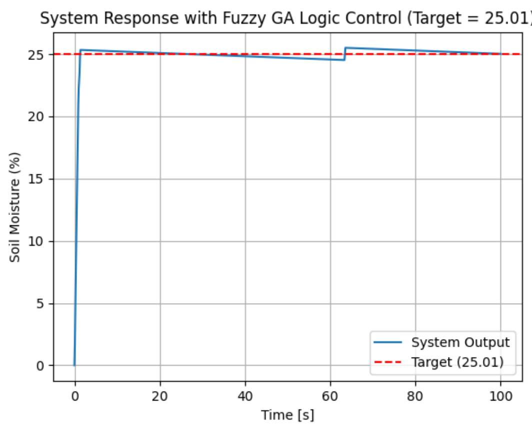


Figure 9. Response of fuzzy GA control

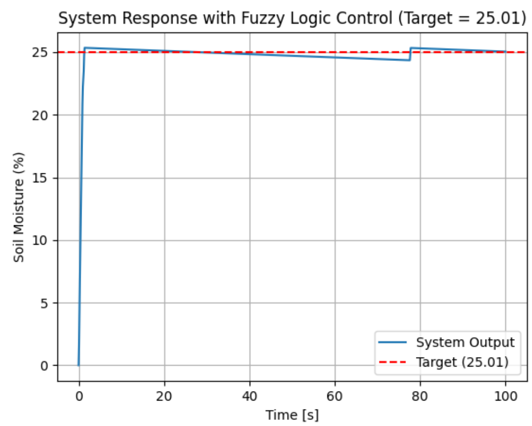
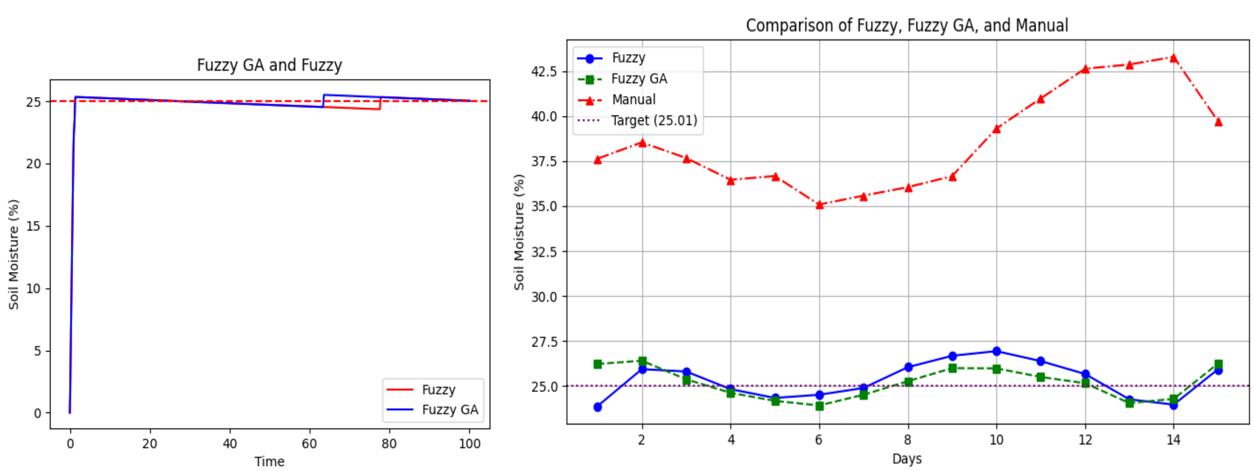


Figure 10. Response of fuzzy logic control

In contrast, the standard fuzzy controller's system response, shown in Figure 10, reveals a steady-state error of 0.091%, an overshoot of 0.331%, a settling time of 1.301 seconds, a root mean square (RMS) error of 1.648%, and a mean absolute error (MAE) of 0.403%. These performance metrics suggest that, although the fuzzy controller manages soil moisture levels, it displays a relatively higher steady-state error and less overshoot. This variance from the intended setpoint is attributed to the suboptimal performance of the membership function, highlighting the necessity for controller optimization to improve accuracy and stability in agricultural applications. The comparison between fuzzy logic and fuzzy GA is depicted in Figure 11a. The fuzzy and fuzzy GA controllers, tested in a greenhouse experiment on Citrus sinensis, produced results consistent with those obtained from the simulation. The results are represented in Figure 11b.



(a) (b)

Figure 11. (a) Comparison of fuzzy and fuzzy GA, and (b) Experimental results of fuzzy, fuzzy GA, and manual

The experimental setup demonstrated a higher Mean Absolute Error (MAE) for both the fuzzy and fuzzy-GA models, measuring 0.9138% and 0.7695%, respectively. This rise in error is linked to environmental noise factors like fluctuations in temperature and air humidity, leading to discrepancies in sensor readings. Furthermore, the system's sensor placement influences the readings, particularly if the sensor is not adequately in contact with the soil. Despite these challenges, the results indicate that the fuzzy GA controller demonstrated greater stability compared to the standard fuzzy controller. The manual control method recommended by the FAO maintains an average soil moisture level of 38.61%, which remains within a reasonable range to adequately support plant growth. The FAO method results in higher soil moisture levels due to its reliance on a fixed irrigation schedule rather than real-time soil moisture measurements. As a result, irrigation is applied even when the soil still has sufficient water to support plant growth.

3.3. Water Usage and Plant Growth

The water usage and plant growth in this experiment was recorded and analyzed, with the results presented in Table 4. The results indicate that fuzzy control achieves more optimized water utilization compared to manual methods, with further improvements when the fuzzy GA approach is utilized. This enhanced efficiency stems from the adaptive characteristics of fuzzy control, which respond dynamically to actual soil moisture levels rather than following a fixed irrigation schedule. Consequently, irrigation occurs only when soil moisture falls below the target level, thus eliminating waste from excessive water application.

Table 4. Water usage and plant growth

Citrus Sinensis Tree	Manual Control	Fuzzy Control	Fuzzy GA Control
Plant Water Usage	4125 mL	3283 mL	3267 mL
Plant Height Growth	0.4 cm	0.3 cm	0.3 cm
Stem Width Growth	0 cm	0 cm	0 cm

With minimal water usage, plant growth remains unaffected, as evidenced by the data presented in Table 14. The results indicate that plant growth under the fuzzy and fuzzy GA control methods is either comparable to or only slightly different from that observed under the scheduled irrigation control recommended by the FAO. This outcome suggests that the optimized irrigation approach successfully maintains soil moisture within the optimal range for plant growth. Since the minimum water requirement for optimal growth is met, plant development proceeds similarly to that of plants irrigated using the conventional schedule. This demonstrates that adaptive irrigation strategies, such as fuzzy and fuzzy GA control, can lead to substantial water conservation without compromising crop health and yield. The unchanged stem width observed in the experiment is likely due to the short duration of the study, which was insufficient to capture measurable growth changes. Given the natural growth rate of stem width, the experimental period may not have been long enough to allow for meaningful comparisons.

4. CONCLUSION

This study shows that using a fuzzy-genetic algorithm (Fuzzy-GA) improves fuzzy logic control by maintaining soil moisture at a target level of 25.1%, with a very low steady-state error of 0.03783%. Compared to both manual control and a standard fuzzy controller, the Fuzzy-GA method reduces water usage by 858 mL and 16 mL respectively making it more efficient. These findings indicate that Fuzzy-GA offers a promising approach for precision irrigation, particularly in applications where resource optimization and system responsiveness are critical. The observed improvements in both accuracy and efficiency underscore its potential for deployment in automated agricultural environments. However, a key limitation of this study is that the system can only maintain soil moisture when it falls below the target threshold. If soil moisture exceeds the target level, the system merely waits for natural evaporation instead of actively reducing moisture levels. Consequently, this approach is most suitable for controlled environments such as greenhouses. Moreover, sensor placement and stability may influence measurement accuracy, which can affect control reliability.

Future research should address this limitation by incorporating actuators capable of artificially reducing soil moisture, such as adding an aerator to ventilate the system more effectively and enhance adaptability. Additionally, it could explore sensor placement strategies to ensure continuous contact with the probe, possibly by incorporating an anchor mechanism. Investigating different optimization algorithms, such as the Grey Wolf Optimizer or hybrid methods that combine various algorithms, may enhance performance. Furthermore, extending the experiment duration would provide a more comprehensive evaluation of system performance.

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