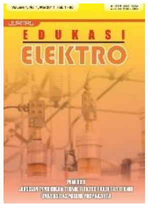
Vol. 9, No. 1, May 2025, pages 93 - 103

JEE

Jurnal Edukasi Elektro

https://doi.org/10.21831/jee.v9i1.85932



Development of a Smart Plant Watering Robot Using Soil Moisture and Light Intensity based on Fuzzy Logic Control

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Abstract— Urban agriculture offers a strategic solution to improve food security and environmental sustainability in cities. However, challenges such as limited land and inefficient irrigation often hinder its effectiveness. This research proposes a smart automatic irrigation system tailored for small-scale urban farming. The system combines fuzzy logic and a two-axis cartesian robot to deliver water precisely based on real-time light intensity and soil moisture data. The fuzzy logic controller dynamically adjusts watering frequency and volume, ensuring efficient water use. Experimental results show the robot achieved a movement error rate of only 3.63%, while the fuzzy logic system reached a decision accuracy of 93.1%. Post-irrigation testing also revealed a 94.83% average increase in soil moisture, indicating the system's ability to restore optimal growing conditions. This approach demonstrates a scalable and sustainable solution for plant care in urban settings, supporting resource-efficient and productive farming in limited spaces.

Keywords: watering plant, cartesian robot, light, moisture, fuzzy logic.

Article submitted 2025-05-30.
Resubmitted 2025-06-24.
Final acceptance 2025-06-30.
Final version published as submitted by the authors.

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Citation Document:
Ayu Martini, N. P. D., Lukmana, M. A., & Pradana, S. (2025). Development of a Smart Plant Watering Robot Using Soil Moisture and Light Intensity based on Fuzzy Logic Control. Jurnal Edukasi Elektro, 9(1), 93–103. DOI: https://doi.org/10.21831/jee.v9i1.85932

1 Introduction

Irrigation is a critical component in cultivation and agricultural practices, as it directly influences plant growth, health, and productivity [1][2]. In the face of modern challenges such as climate change, land degradation, and limited access to clean water, there is a growing need for more adaptive and resource-efficient irrigation solutions. An imbalance in water supply, particularly shortages, can lead to significant declines in crop yields, ultimately affecting both national and global food security [3].

Statistical data indicate a sharp decline in chili production and availability in Indonesia during the 2019–2023 period as shown in Figure 1. A production drop exceeding 30%, coupled with reduced imports, has led to a substantial decrease in domestic chili supply. Consequently, per capita chili consumption fell from 4.60 kg in 2019 to only 1.23 kg in 2023 [4]. This trend reflects a serious disruption in the supply chain and poses a potential threat to the stability of strategic horticultural commodities in the country.

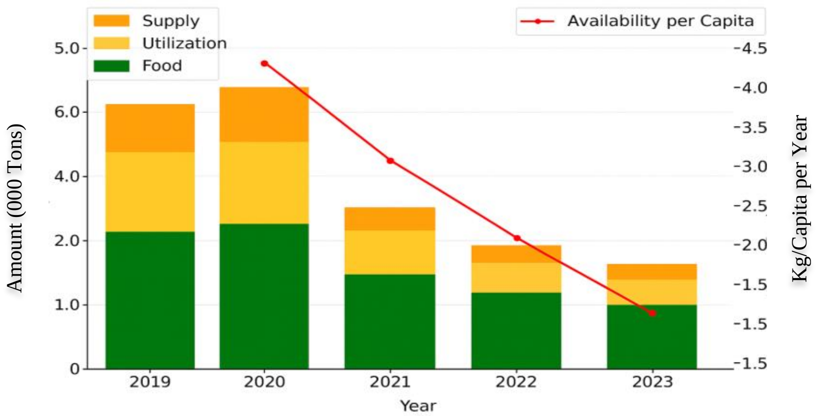


Figure 1. Supply, utilization, and per capita availability of chili in Indonesia from 2019 to 2023 [4]

To support the development of agriculture in urban areas with limited land, it is essential to implement intelligent farming systems that maximize productivity while minimizing resource use. Automatic irrigation technologies offer a promising solution by enabling efficient water distribution in small-scale or confined urban farming spaces, contributing to local food supply and sustainability.

The implementation of automated irrigation systems aligns with the goals of sustainable agricultural development and the growing trend of urban farming. Such technologies allow for the productive use of narrow land plots in cities to cultivate food crops, thereby enhancing local food availability and reinforcing national food resilience. Various previous studies have proposed automatic irrigation systems with different approaches, including two-axis robotic sprayers with time-based schedules [5], temperature-monitoring-based systems [6], and single soil moisture sensor models [7]. However, many of these systems still lack the flexibility to adjust water volume according to real-time environmental conditions.

This study aims to design and develop a two-axis automatic plant irrigation robot controlled by fuzzy logic, using soil moisture and sunlight intensity as its primary input parameters. The system employs four fuzzy sets in both input and output fuzzification stages, allowing for precise adjustment of water flow based on plant needs. This approach is expected to improve water use efficiency and optimize plant care, making it applicable not only to traditional agricultural fields but also to limited urban environments.

This research primarily focuses on the design, development, and implementation of a smart irrigation system using fuzzy logic and a Cartesian robot. The scope is limited to validating the system's functionality and control performance under controlled environmental conditions. Broader testing scenarios—including varied soil types, plant species, and lighting conditions—were not addressed, as they fall beyond the current objective. Similarly, long-term trials to assess hardware durability, sensor drift, and maintenance requirements were not conducted. Economic analysis, such as energy consumption metrics and return on investment, is also left for future research. These limitations are acknowledged, and future work is encouraged to evaluate the system's robustness, scalability, and practical applicability in real-world urban farming environments.

2 Watering Plant Robot

The implementation process of the system starts with the hardware design, such as selecting and configuring the microcontroller, as well as determining the appropriate input variables for the fuzzy logic algorithm. The algorithm subsequently generates an output that defines the duration of irrigation.

2.1 Architecture System

The system architecture of the automatic plant irrigation robot effectively integrates data acquisition from sensors, processing through fuzzy logic, and precise mechanical movement to optimize plant care. This systematic approach enhances the efficiency and accuracy of the irrigation process while supporting sustainable urban farming practices.

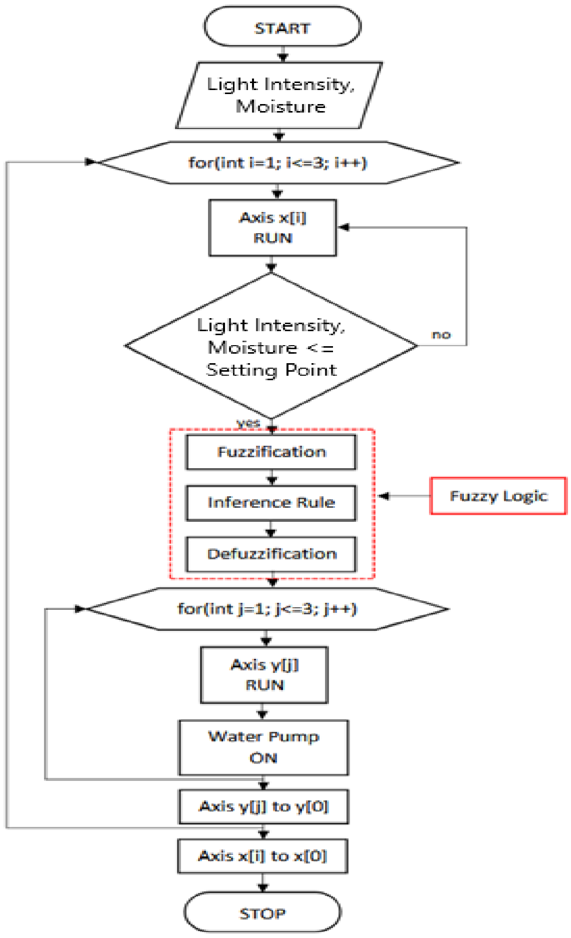


Figure 2. Flowchart of system

The plant irrigation robot begins its operation by receiving data from two input sensors: light intensity and soil moisture, as illustrated in Figure 2. Next, the X-axis moves toward the coordinate point (1, 0). Upon reaching this position, the system evaluates the plant condition at point 1—whether it is dry or wet—using fuzzy logic consisting of four fuzzy sets. Then, the Y-axis gradually moves from coordinate (1,1) to (1,3) to perform irrigation, which is indicated by the activation of the water pump for a duration determined by the fuzzy system output. This process continues until the X-axis reaches the final coordinate, (3,3). After ensuring that all plants have received adequate water, both axes return to the starting point at coordinate (0,0).

The hardware components used in this device, as shown in Figure 3, consist of an Arduino microcontroller serving as the main control unit. Arduino was selected due to its enough VCC pins to support multiple input and output connections. The system employs two types of sensors as inputs to determine whether plants in each row are in dry or wet conditions: a light intensity sensor with a probe inserted into the soil, and a capacitive soil moisture sensor known for its corrosion resistance. Each plant row is monitored by three sensors. On the output side, the system is equipped with three stepper motors: two motors control the movement along the X-axis, while one motor regulates movement along the Y-axis. Additionally, a water pump is used to perform the irrigation process.

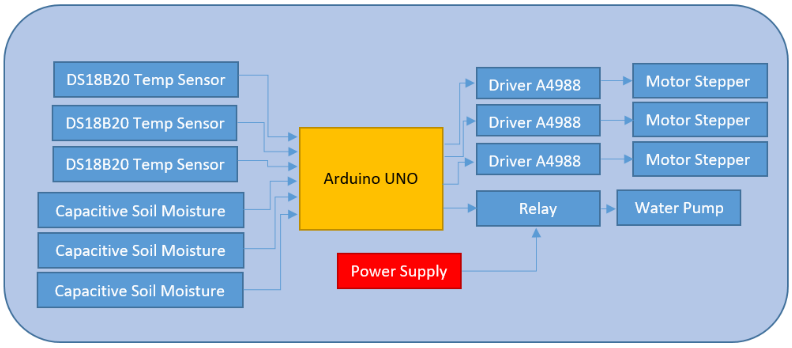


Figure 3. Hardware diagram

Point-to-point motion (PTP motion) refers to the fastest movement between two specific points within a three-dimensional space. In this motion, all robot axes move synchronously from the starting position to the target point, resulting in a curved trajectory at the end effector. PTP motion is commonly used for rapid repositioning, followed by a controlled path movement or specific operation starting from the target point, as illustrated in Figure 4.

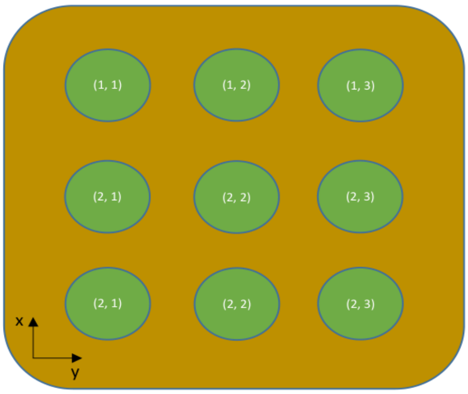


Figure 4. Axis movement sketch

The mechanical design planning includes the construction of a raised bed garden that serves as the planting area for testing the developed device. The Cartesian robot frame is built with a track that guides the robot's movement, as well as a gantry that functions as a conduit for the water hose. The robot frame structure utilizes aluminum profiles of types 2020 and 2040. The Cartesian robot frame is designed to resemble a raised bed measuring 1 meter by 0.6 meters. This planting area is equipped with a gantry and robot track made from the 2040 series aluminum profiles, serving as the actuator's movement path. Detailed mechanical dimensions of the Cartesian robot frame design are presented in Figure 5.

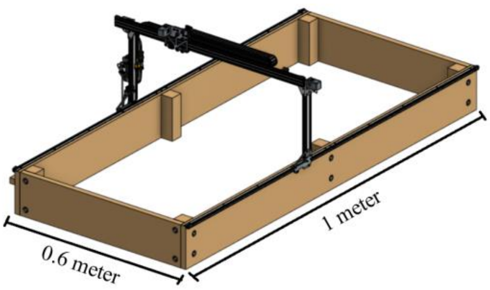
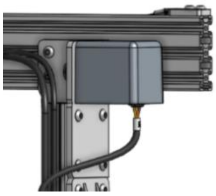
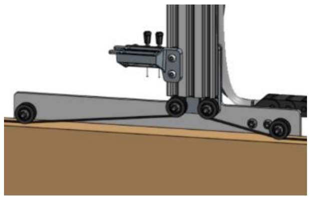


Figure 5. Dimension of mechanical robot

Based on Figure 6, the actuator system consists of two stepper motors responsible for driving the Cartesian robot along the X and Y axes. The driving mechanism employs V-wheels connected to belts or tracks that are arranged to function similarly to rails.



(a) Motor stepper



(b) V-wheel

Figure 6. Mechanical design of actuator

The implementation of the two-axis Cartesian robot-based plant irrigation system has been successfully carried out, as shown in Figure 7. The setup consists of three rows of plants, each containing three plants. The red boxes indicate the locations where the LDR light sensors and soil moisture sensors are installed as input devices, the blue boxes mark the positions of the stepper motor actuators on the X and Y axes, while the yellow box highlights the location of the water valve.

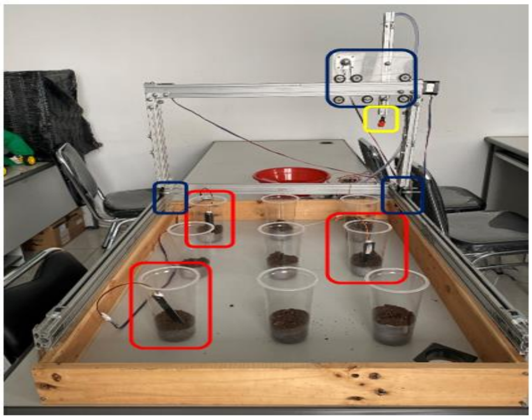


Figure 7. Implementation of watering plant robot

2.2 Fuzzy Logic

Fuzzy logic is a logic-based method capable of handling uncertainty and performing reasoning that mimics human thinking in ambiguous situations. In the context of plant irrigation, fuzzy logic is employed to automatically regulate the watering system based on two primary parameters: light intensity and soil moisture. The diagram in Figure 8 illustrates the fuzzification process for measuring light intensity in lux. Fuzzification involves converting numerical values into membership values within specific fuzzy sets, ranging from 0 to 1. In this case, light intensity is classified into four categories: Dark, Dim, Soft, and Bright.

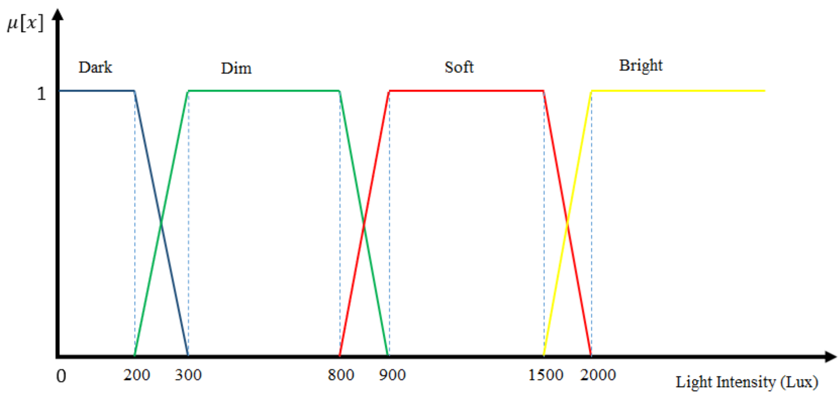


Figure 8. Membership function of light intensity

The figure depicts the membership function graph of light intensity in the fuzzy logic system. There are four levels: Dark (0–300 lux), Dim (200–900 lux), Soft (800–1500 lux), and Bright (1500–2000+ lux). Each level features overlapping ranges to enable smoother transitions, allowing the system to adaptively adjust the irrigation response according to environmental light changes. This approach helps manage uncertainty in classifying light intensity, thereby facilitating more flexible decision-making within the fuzzy logic-based system.

The diagram in Figure 9 illustrates the fuzzification process for soil moisture measurement expressed as a percentage (%). Moisture levels are classified into four fuzzy sets: Dry, Moist, Wet, Full. The horizontal axis represents moisture percentage, while the vertical axis shows the membership degree (μ[x]) ranging from 0 to 1.

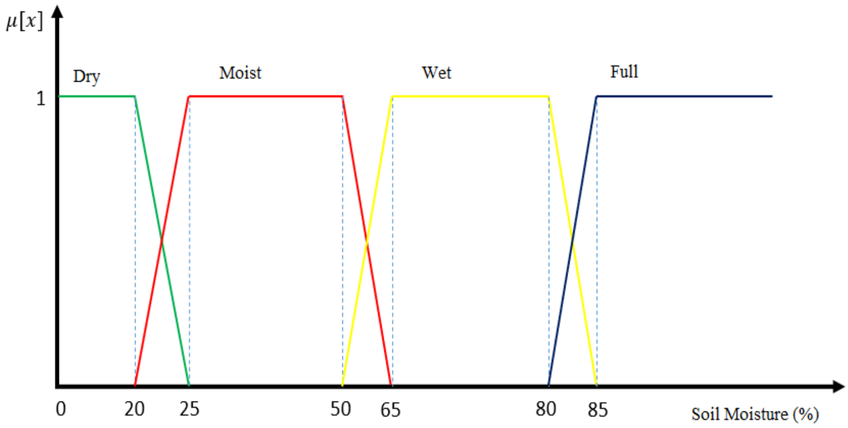


Figure 9. Membership function of soil moisture

The figure illustrates the membership function graph for the soil moisture variable within the fuzzy logic system. Moisture is divided into four categories: Dry (0–25%), Moist (20–50%), Wet (50–80%), and Full (80–100%). Each category has overlapping areas to allow smooth transitions between conditions, enabling the system to more accurately and adaptively determine irrigation needs based on soil conditions. This facilitates the fuzzy logic system in handling uncertainty in moisture classification, resulting in more flexible decision-making.

Table 1 presents the Fuzzy Inference Rules used to determine the automatic irrigation duration based on two environmental parameters: soil moisture level (rows) and light intensity (columns). Each combination of these parameters yields a fuzzy decision regarding irrigation duration: Fast, Moderate, Brief and Long. The drier the soil and the brighter the light, the longer the watering duration. Conversely, when the soil is wet, irrigation is performed instantly regardless of light intensity. These rules enhance the system's efficiency and responsiveness to environmental conditions.

Table 1. Inference Rule

Light / Moisture	**Dark**	**Dim**	**Soft**	**Bright**
Dry	Brief	Moderate	Long	Long
Moist	Brief	Brief	Moderate	Moderate
Wet	Fast	Fast	Brief	Brief
Full	Fast	Fast	Fast	Fast

The fuzzy membership-function graph illustrating the irrigation duration is divided into several categories: Fast, Moderate, Brief and Long. Each represented by different colored graphs as shown in Figure 10.

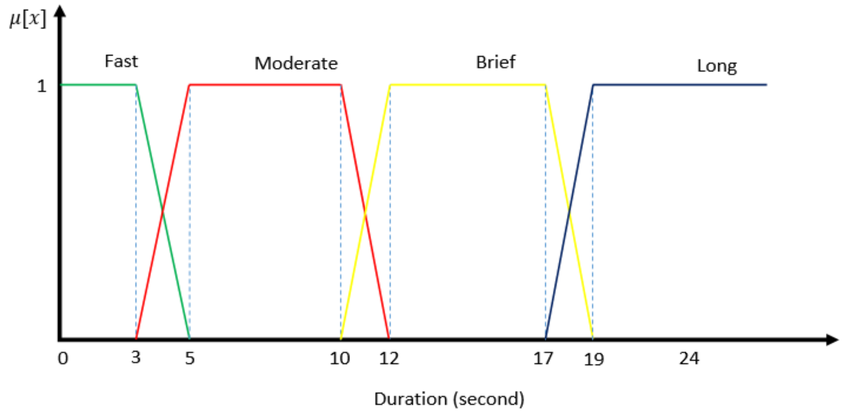


Figure 10. Parameter of inference rule

The "Fast" category corresponds to durations between 0 and 3 seconds, indicating that the plants receive a minimal amount of water. The "Moderate" category spans from 5 to 10 seconds, representing a light watering amount. The "Brief" category lasts from 12 to 17 seconds, which is considered an appropriate duration to provide sufficient water for the plants. Lastly, the "Long" category covers durations between 19 and 24 seconds, indicating that the plants have received ample, and possibly excessive, water. This output is utilized in the fuzzy logic system to determine the watering duration based on the plants' water needs, thereby helping to optimize the irrigation process according to the plant's condition.

3 Results and Discussion

Table 2 presents the error data for the movement of axes x_1 and x_2 in the system, measured in centimeters (cm). Each row in the table corresponds to a movement data set for the respective axes, showing the actual position of x_1 and x_2 (in cm). The columns labeled "Error x_1 (%)" and "Error x_2 (%)" represent the percentage error for each axis, calculated based on the difference between the expected and actual positions. Assuming that every 200 steps equals one full rotation of 360°, the linear displacement is 15.7 cm per 1000 steps, given a stepper motor shaft diameter of 1 cm. Based on the recorded data, the error in the x_1 axis ranges from 0% to 10.19%, with an average error of 2.63%. Meanwhile, the x_2 axis shows a smaller range of error, between 0% and 3.82%, with an average of 1.74%. These results suggest that axis x_1 tends to have a higher error rate compared to axis x_2 during testing. The highest error on x_1 was observed in row 5 at 10.19%, while the highest error on x_2 occurred in row 13 at 3.82%. Overall, axis x_2 demonstrated better positioning accuracy than axis x_1 under the test conditions.

Table 2. Error axis X movement

No.	Axis x_1 (cm)	Axis x_2 (cm)	Error x_1 (%)	Error x_2 (%)
1	17,1	16,8	8,91	7,00
2	16,2	15,9	3,18	1,27
3	16,1	15,7	2,54	0
4	17,2	16,3	9,55	3,82
5	15,8	16	0,63	1,91
6	16,1	16,2	2,54	3,18
7	16,8	16,2	7,00	3,18
8	16,8	16	7,00	1,91
9	15,2	16	3,18	1,91
10	16,7	16,4	6,36	4,45
11	16,3	15,8	3,82	0,63
12	16,1	15,8	2,54	0,63
Average			4,77	2,49
Total average			3,63	

Figure 11 illustrates the comparison of experimental results between the left X-axis (x_1) and the right X-axis (x_2) in terms of distance, measured in centimeters. The graph plots the measured distances over 15 trials, with the blue line representing x_1 and the orange line representing x_2. Overall, both x_1 and x_2 exhibit similar fluctuation patterns, although several points show x_1 having a slightly higher value than x_2, particularly in trials 4 and 11. In the remaining trials, the distances recorded by x_1 and x_2 are relatively close, with only minor differences. This graphical comparison indicates that the two X-axes follow a consistent trend in terms of distance movement, despite small variations between them.

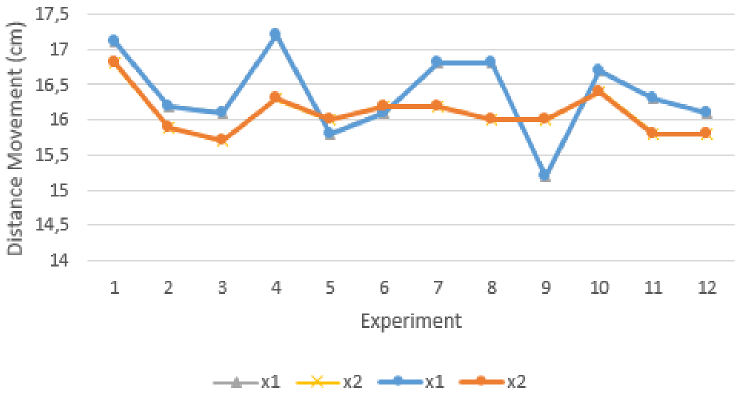


Figure 11. Comparison of axis x_1 and x_2

Table 3 presents the error values associated with the Y-axis movement of the automated plant irrigation system, measured in centimeters (cm). Assuming that every 200 steps corresponds to one full 360° rotation, the total movement distance is 9 cm for 575 steps, given a stepper motor shaft diameter of 1 cm. Based on the recorded data, Y-axis displacements range from 8.8 cm to 9.9 cm, with varying degrees of error. The highest error observed reached up to 10 cm, which occurred multiple times at a measured distance of 9.9 cm. Conversely, some measurements, such as those at 9 cm and 9.1 cm, showed minimal discrepancies, with several instances recording zero error. The average error across all Y-axis measurements is 4.89 cm. This average indicates that Y-axis movement is relatively accurate, despite minor variations. This analysis is crucial in ensuring that the irrigation system can deliver water precisely to the intended locations, thereby maintaining optimal soil moisture levels necessary for healthy plant growth.

Table 3. Error axis Y movement

No	Axis Y (cm)	Error Y (%)
1	9,4	4,4
2	9,4	4,4
3	9,1	1,1
4	9,3	3,3
5	9,4	4,4
6	9,2	2,2
7	9,1	1,1
8	9,1	1,1
9	9,9	10,0
10	9,8	8.8
11	9,5	5,5
12	9,7	7,7
Average		4,5

Table 4 presents the irrigation data obtained using the fuzzy logic method, illustrating the relationship between light intensity (in lux) and soil moisture (in percentage) as inputs, and the watering duration (in seconds) as the output. Each row in the table represents a distinct set of input values (light intensity and soil moisture), which results in both the actual and theoretical watering durations being identical. Consequently, the error value for each case is zero.

Table 4. Testing using Fuzzy Logic

No.	Input		Output (second)		Error (%)
	lux	*%*	*Real*	*Theory*	
1	75	9	7,8	8	2,5
2	56	4	5,6	6	6,6
3	87	18	3,67	4	8,2
4	2104	12	20,5	21	2,3
5	305	31	7,6	8	5
6	250	54	3,54	4	11,5
7	1058	28	12,43	13	4,3
8	1128	24	15,77	16	1,4
9	37	82	2,56	3	14,6
10	41	68	2,88	3	4
11	432	70	7,9	8	1,2
12	448	78	7,95	8	0,625
13	27	100	2,44	3	18,6
14	34	89	2,45	3	18,3
15	65	84	3,67	4	8,25
16	27	92	2,48	3	17,3
17	22	98	2,84	3	5,3
18	1958	19	20,5	21	2,3
19	657	45	7,67	8	4,1
20	1979	21	18,65	19	1,8
Average					6,9

This indicates that the implemented fuzzy system can predict the irrigation duration with a high degree of accuracy. For instance, at a light intensity of 56 lux and soil moisture level of 4%, the system determined a watering duration of 6 seconds, which exactly matches the theoretical value of 6 seconds. The recorded average error is zero, demonstrating that the fuzzy model performs in accordance with theoretical expectations and produces accurate predictions without deviation, as shown in Table 4. It is worth noting that the output values for irrigation duration are rounded up.

Figure 12 illustrates the comparison of plant soil moisture percentages before and after irrigation across 20 trials. The blue line represents the moisture level prior to irrigation, while the orange line indicates the moisture level following irrigation. It is evident that in every trial, the post-irrigation moisture level consistently exceeds the pre-irrigation level. Before irrigation, the moisture values ranged from a minimum of 12% to a maximum of 96%. After irrigation, the moisture content increased significantly, with most trials approaching or reaching 100%. On average, the increase in moisture after irrigation compared to before irrigation was 94.83%. These results demonstrate that the irrigation process reliably and substantially enhances soil moisture levels.

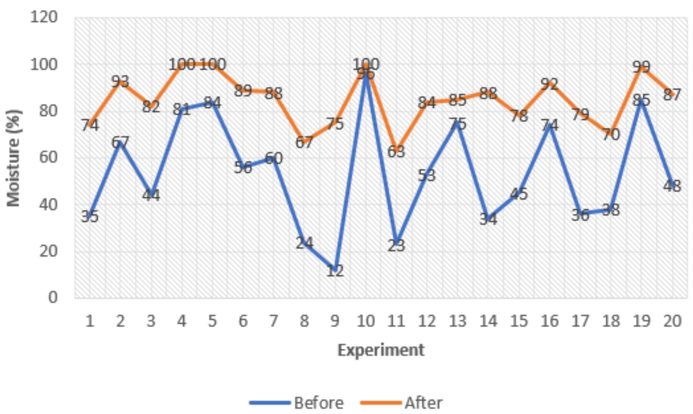


Figure 12. Comparison of soil moisture value after and before watering

Although direct experimental benchmarking was not performed due to hardware constraints, a comparative analysis was conducted using existing literature on threshold-based irrigation systems. Furqan et al. [6] implemented a fuzzy Sugeno-based system using only air temperature and soil humidity thresholds, achieving water efficiency levels below 85% and showing moderate soil recovery. Similarly, Waworundeng et al. [7] developed a system that relied on single-sensor thresholds and observed variability in moisture levels due to environmental fluctuations. In comparison, the fuzzy logic controller proposed in this study achieved an average post-irrigation soil moisture increase of 94.83% with only 6.9% average decision error, indicating greater precision and adaptivity. These results are consistent with findings from Munir et al. [9] and Abdullah et al. [12], who emphasized the capability of fuzzy logic in handling uncertainty across diverse environmental inputs. Therefore, despite the absence of real-time benchmark testing, the presented system demonstrates comparable—if not superior—performance in optimizing irrigation efficiency based on multi-input conditions.

4 Conclusion

This study successfully developed and implemented an automatic plant irrigation system based on fuzzy logic, capable of optimizing water usage according to light intensity and soil moisture. The system is equipped with a two-axis cartesian robot that enables precise irrigation control and demonstrated strong performance, including the use of a two-axis Cartesian robot for irrigation control resulted in minimal positioning errors, with only 3.63% error on the X-axis and 4.5% on the Y-axis, the fuzzy logic algorithm accurately predicted irrigation duration, with a low error rate of 6.9%, and post-irrigation measures showed an average soil moisture increase of 94.83%.

These results indicate that the fuzzy logic-based automated system holds significant potential in supporting more efficient and sustainable agricultural practices. It is particularly useful for optimizing water usage, especially in regions with limited water resources.

For future work, the system can be improved by adopting multi-axis movement to handle irregular planting layouts, using modular components for easier installation, and enhancing sensor durability through self-calibration. Testing in diverse urban settings such as rooftops or vertical gardens is also recommended to validate scalability.

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