# Optimizing Plant Watering Efficiency via IoT: Fuzzy Sugeno Method with ESP8266 Microcontroller

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***Abstract* – This research explores automatic plant sprinklers utilizing fuzzy logic with the fuzzy Sugeno method to overcome optimal watering schedules. Developed with ESP8266 microcontroller hardware and Arduino IDE software, the WSN prototype focuses on spinach plants. Watering in the nursery was done twice a day for seedling growth, then reduced to once a day. Soil moisture levels were assessed using a soil analyzer, as well as temperature variations with the HTC-1 device. Python facilitates data analysis, generating fuzzy inference graphs on temperature sensors (10-40°C) and soil moisture values (1-1024 RH). This innovative approach, which integrates fuzzy logic and advanced hardware, offers a promising solution for effective plant care.**

***Keywords* – Spinach plants, watering, fuzzy sugeno, ESP8266 microcontroller.**

## 1. Introduction

Watering is an important activity that requires attention while caring for plants. Knowing when to water a plant is an important part of the growth process.

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The need for water in plants must be considered since optimal plant growth relies on sufficient water supplies at the right time [1]. Plants require water for their growth and development just like humans. Water plays a vital role as an essential component during the processes of photosynthesis and transpiration. Water also provides energy to plants [2]. Lack of water in plants will lead to unhealthy and wilted appearances. As a result, the plants' need for minerals is lowered because water transports minerals from the soil to the plant's top.

As time progresses, most plant owners continue to rely on the conventional method of manual plant watering. This method is considered to have drawbacks, as plant owners may forget or lack the time to meet their plants' water needs. Humidity is another important factor that affects the growth and development of plants. Based on previous research conducted Krishnan [6], this study proposes a smart irrigation system that assists farmers irrigate their agricultural land using the GSM module. This system provides notifications regarding the status of ongoing work, such as soil moisture levels and ambient temperature [3]. Another study, "Adaptive Irrigation System Based on Fuzzy Logic" [4], explores the automation of plant watering. It utilizes an irrigation system based on the Internet of Things (IoT) as well as a proposed system based on a wireless sensors network (WSN) installed in a greenhouse. This watering device sends data from the plant environment, such as soil moisture and temperature, to the server (Raspberry Pi) through radio frequency (RF) communication, and uses the fuzzy logic controller (FLC) process to make intelligent and optimal decisions [4].

Based on the preceding background provided, this watering tool was created to help the owner of the Bayem House garden. The ESP8266 microcontroller serves as the main control function of this automatic watering device. This tool is equipped with an output indicator, which is the LCD screen.

This program uses a local web server running the PhpMyAdmin database along with a website as a monitoring system in addition to allowing direct LCD screen viewing.

In practice, this tool utilizes NodeMCU, which can be connected to the Internet, making it more optimal for monitoring systems. It employs a fuzzy logic method to determine decisions based on various variables and rules concerning automatic watering. Fuzzy logic is a methodology within a system that aids in sensor control. For instance, it affects air humidity and soil moisture [5], [6].

Many researchers are interested in conducting a more in-depth examination of optimizing plant watering efficiency [2]. This study proposes the fuzzy logic method especially the Fuzzy Sugeno method with ESP8266 Microcontroller. The objective is to determine when the system will send a signal to the IoT device to automate plant watering and monitor soil moisture conditions, with the website serving as a monitoring system for sensors based on temperature and soil moisture. These data will later be stored in a database to monitor automatic watering activities. The sentence provided serves as a clear and concise summary of the paper's structure.

## 2. Related Works

Water, an indispensable resource for all living things, often goes to waste due to the negligence of people who forget to turn off their water taps. This wasteful water consumption not only disturbs neighbours when flooding occurs within a dwelling, but it also exacerbates the water shortage issues faced in certain regions of the country. The solution suggested by Mantoro and Istiono [7] involves developing an automated system that can intelligently open and close the water tap to minimize water waste. This study accurately determines higher water levels by monitoring the proximity of the water surface to an ultrasonic sensor. This enables the timely closure of water taps to prevent flooding. The implementation of this study utilizes an Arduino Uno microcontroller and employs a fuzzy logic algorithm [7].

Another significant concern with wireless sensor networks (WSNs) is high power consumption that detrimentally affects the overall network lifetime. To solve this issue, this study focuses on analyzing and addressing three critical routing parameters: the initial power of the nodes, residual power within the nodes, and the routing period. Throughout the routing process, these parameters are carefully taken into account to provide insights that extend the life of the network.

Alkalbani *et al.* [8] made a significant contribution to this subject by examining well-known trust and reputation models for WSNs comprehensively and formally. In the field of data routing, accuracy, scalability, and power consumption emerge as primary challenges. Notably, the detrimental impact of high power consumption on the network's lifetime is emphasized [8]. This study compares trust and reputation models, with a focus on their energy efficiency aspects [8], [9].

The referenced studies encompass various IoT applications in agriculture and related fields, offering valuable insights into optimizing irrigation, improving crop production, and raising environmental awareness. Benyezza et al. [10] proposed a smart irrigation system based on fuzzy control technology and IoT to optimize water and energy usage. Chang *et al.* [11] employed artificial intelligence approaches to predict the growth and quality of lettuce in an IoT-based greenhouse system. Togneri et al. [12] emphasized data-driven water estimation for smart irrigation, highlighting the importance of data analysis. To promote environmental education, Tabuenca *et al.* [13] focus on environmental awareness systems utilizing IoT technology. Murugan *et al.* [14] explored IoT applications in monitoring and controlling desalination plants for efficient water treatment. Kaur *et al.* [15] performed a comparative analysis of IoT-based crop growth monitoring systems for indoor vertical hydroponic farming. Pathmudi *et al.* [16] provided a systematic review of IoT technology for smart and sustainable agricultural applications. Using intelligent IoT sensors, Lakshmi *et al.* [17] proposed a connected smart irrigation model. Castañeda-Miranda and Castaño-Meneses [18] discussed IoT applications in smart agriculture and frost control in greenhouses, enhancing crop production. These studies, which address issues including irrigation, crop growth monitoring, environmental awareness, and control systems, all promote and increase IoT applications in agriculture.

In the study conducted by [19], a comprehensive overview of Ag-IoT applications in crop and environmental monitoring is provided, with an emphasis on their potential to enhance agricultural practices through real-time data collection and analysis. Reference [20] introduces a predictive model based on machine learning algorithms to estimate dissolved oxygen levels in aquaculture water, which contributes to the development of intelligent aquaculture systems.

A study [21] introduced a smart and secure irrigation system that utilizes fuzzy logic and blockchain technology, optimizing irrigation schedules while ensuring IoT system security.

Paper [22] explored the application of hybrid fuzzy techniques in construction and management engineering, addressing decision-making challenges and risk analysis. Additionally, [23] proposed a neuro-fuzzy digital twin model for high-temperature generators, enabling performance prediction and optimization. Lastly, [24] focused on optimizing wireless sensor network-based forest fire monitoring systems using Sugeno fuzzy logic for real-time detection and response.

The strengths of this research lie in its innovative solutions for addressing water wastage and promoting responsible usage. However, a limitation of this study is the lack of information provided in the references. Thus, further research is required to evaluate the scalability and robustness of these proposed solutions across diverse agricultural and environmental contexts. Furthermore, future studies might delve deeper into the integration of emerging technologies such as blockchain and machine learning into existing frameworks, enhancing agricultural systems' efficiency as well as their resistance to unexpected issues such as climate change. The path to sustainable agriculture and resource management through IoT applications can be strengthened by encouraging interdisciplinary collaborations and incorporating stakeholder feedback.

## 3. Research Method

This section describes the research methods and procedures employed in the study, focusing on the application of fuzzy logic in an IoT-based automatic plant watering system.

### *3.1. Fuzzy Logic*

In 1965, Prof. LA Zadeh was known as the originator of the idea of fuzzy logic, which expands upon the concept of crisp sets. A crisp set is typically used to classify individuals into distinct categories, such as members and non-members. When reviewed from the crisp set, there is only two possibility score membership that is zero or one. In use, value membership in this fuzzy set owns a range value of 0 to 1. For example, if x has a score fuzzy membership $\mu A[x] = 0$, p shows that x does not belong to set A. Also valid for $\mu A\ [x] = 1$, p this means that x belongs to in set A as member full.

Set conventional normal used as operation fuzzy set. Several operations have a specific meaning with purpose i.e. combine and transform fuzzy set. An α-predicate is a commonly used term because it has a membership value resulting from the operation of two sets. Some basic operators results of Zadeh's works include AND operators, OR operators, and NOT operators.

Function implication refers to rules that exist on the line of vague and possessing knowledge connection with fuzzy relationship. Next is the general ratio of function implication.

*IF x is A THEN y is B* (1)

Antecedents is a commonly used term that symbolizes relationship after IF. Meanwhile, consequent is a term commonly used to symbolize a relationship after THEN. These propositions can be developed using fuzzy operators such as the following:

*IF (x1 is A1) • (x2 is A2) • (x3 is A3) •.... • (xN is AN) • THEN y is B* (2)

### *3.2. Fuzzy Sugeno*

The Sugeno method is included in one fuzzy logic method. This method was introduced in 1985 by Takagi-Sueno Kang. The fuzzy Sugeno system overcomes the shortcomings of a pure fuzzy system by incorporating basic calculus concepts into THEN. This change results in weighing the average value of the fuzzy system in parts of fuzzy IF-THEN rules. The weakness of the Sugeno fuzzy system lies in the THEN section. For example, the existence of mathematical calculations can provide an experiential framework for presenting real knowledge to humans [24].
Fuzzy logic uses method Sugeno which is implemented in several stages. There are 4 stages used i.e. as follows:

### *3.3. Establishment Fuzzy Set*

This research utilized two variables: soil moisture and a temperature sensor. Each fuzzy set has a domain value that is within the scope of the universe of discourse. It is acceptable to operate on a fuzzy set. The universe of discourse for the fuzzy sets is presented in Table 1.

*Table 1. Fuzzy set*

| Function | Variable | Fuzzy Set | Universal Set | Domain |
|---|---|---|---|---|
| Inputs | Land | Wet | 0 – 1024 | 0 – 400 |
| | | Moist | 0 – 1024 | 200 – 800 |
| | | Dry | 0 – 1024 | 600 – 1024 |
| | Temperature | Cold | 15 – 40 | 15 – 25 |
| | | Normal | 15 – 40 | 20 – 35 |
| | | Hot | 15 – 40 | 30 – 40 |
| Output | Water Pump | No Flush | 0 – 1 | 0 – 0.5 |
| | | Flush | 0 – 1 | 0.5 – 1 |

Membership functions are created after the formation of fuzzy sets. In fuzzy sets, these membership functions map input data to degrees/membership values.

The interval used for membership values is from 0 to 1. In this study, the function approximation is obtained from the membership functions. The trapezoidal representation function is used in this research. The membership function for the soil moisture sensor is shown in Figure 1, while the membership function for the temperature sensor is shown in Figure 2.

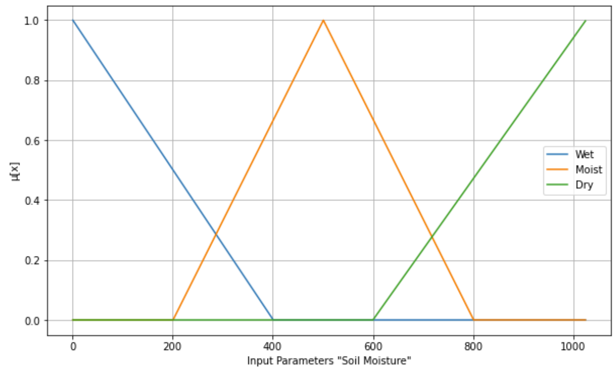


*Figure 1. Soil moisture variable curve*

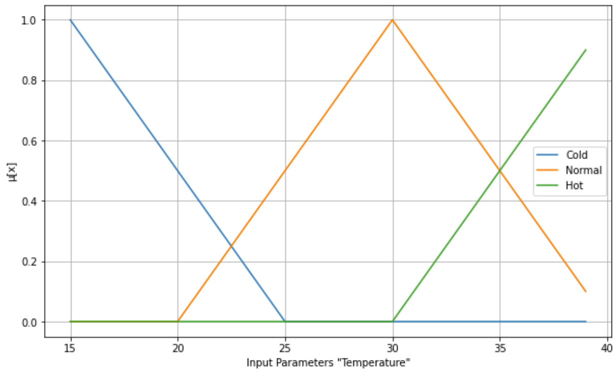


*Figure 2. Temperature variable curve*

Table 1 shows that there is a soil moisture sensor variable divided into 3 fuzzy sets: wet, moist, and dry. Meanwhile, the temperature sensor is divided into 3 fuzzy sets, including cold, normal, and hot. The dry variable is represented by a left shoulder-shaped curve in the soil moisture sensor. On the other hand, the right shoulder-shaped curve is used to represent the wet variable. For the soil variable, the input values are shown on the x-axis with a percentage unit. The degree of membership for the input values is denoted by the symbol μ(x). The temperature sensor uses a left shoulder-shaped curve for the cold variable, a trapezoidal curve for the normal variable, and a right shoulder-shaped curve for the hot variable. The x°C axis represents the input values in degrees Celsius for the temperature variable, while μ (x°C) represents the degree of membership for the input values of the temperature sensor.

### *3.4. Functions Implications*

The application of implication functions using the MIN function is found in the inference stage function. The following is how the implication function is calculated:

$$ai = \mu Ai\,(x) \cap \mu Bi\,(x) = \min\,(\,\mu Ai\,(x), \mu Bi\,(x)) \qquad (3)$$

where:
$ai$ = Minimum value of rule i in fuzzy sets A and B
$\mu$Ai(x) = Fuzzy set A with membership degree x for rule i
$\mu Bi(x)$ = Fuzzy set B with membership degree x for rule i

### *3.5. Composition of Rules*

This is the stage when fuzzy rules are developed. The creation of fuzzy rules requires determining the output based on the variables used in the study, namely soil moisture and temperature. The method used in this stage is the Sugeno method. These rules are meant to represent the relationship between the input and output, which will then be combined into nine different rule combinations. The following table shows the rule compositions for the output.

*Table 2. Fuzzy rules*

| Code | Rule |
|---|---|
| R1 | IF wet soil AND cold temperature THEN water pump not irrigate |
| R2 | IF wet soil AND normal temperature THEN water pump not irrigate |
| R3 | IF wet soil AND hot temperature THEN water pump not irrigate |
| R4 | IF moist soil AND cold temperature THEN water pump not irrigate |
| R5 | IF moist soil AND normal temperature THEN water pump not irrigate |
| R6 | IF moist soil AND hot temperature THEN water pump not irrigate |
| R7 | IF dry soil AND cold temperature THEN water pump irrigate |
| R8 | IF dry soil AND normal temperature THEN water pump irrigate |
| R9 | IF dry soil AND hot temperature THEN water pump irrigate |

### *3.6. Defuzzification*

The input from the defuzzification process is a fuzzy number derived from the composition of fuzzy rules. The output obtained is a number within the fuzzy domain set. If the fuzzy set is given within a certain range, it must be capable of producing a certain crisp value as an output. Defuzzification can be accomplished by calculating the weighted average value using the Sugeno method as follows:

$$WA = \frac{\sum_{i=1}^{9} A_i X_i}{\sum_{i=1}^{9} A_i} \quad (4)$$

where:
$WA$ = Weighted average value
Ai = a-predicate for rule i
Xi = consequent for rule i

## 4. System Requirements

In building the system, hardware devices are required. The selection of the following hardware devices was made after considering the functional system requirements and conducting literature studies. The required hardware devices are as follows: (1) NodeMCU ESP8266 LUA WiFi v3 4MB 32MBits CH530, (2) NodeMCU v3 BaseBoard Base Plate, (3) Sensor YL-69 Soil Moisture, (4) Sensor DHT-11 Temperature, (5) Mini Pump Motor Submersible Horizontal DC 3v-5v, (6) LCD 1602 Char Blue Backlight with I2C Serial Interface Module, (7) Relay Module Single Channel 1ch 10A 250VAC 30VDC Modul DC-AC Arduino, (8) Female-Female Jumper Cables, (9) 5/16-inch Fiber Thread Water Hose, (10) Micro USB 2A Data Cable, and (11) X6 Arduino Electronic Box.

Software is also required for building the system. The software that was chosen has been examined in light of the research requirements and references from pertinent literature. The software used includes Arduino IDE, XAMPP, Visual Studio Code, Python, and Diagrams Net.

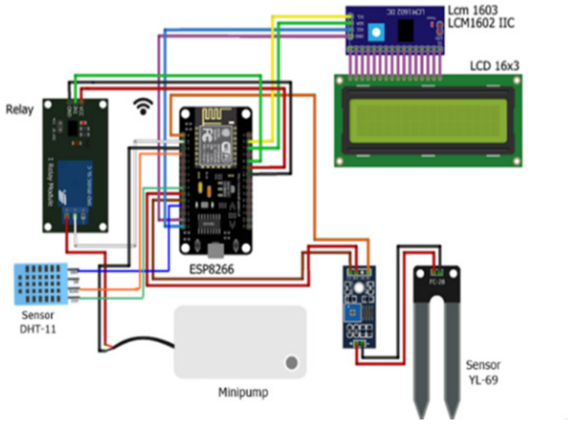


*Figure 3. Circuit system requirements*

### *4.1. Block Diagrams*

The purpose of creating this block diagram is to design the required components as shown in Figure 4. Another objective is to explain the correlation between components in a system. The sensors in the system, specifically the soil moisture sensor and temperature sensor, will be directly connected to the NodeMCU ESP8266, with computations conducted on the microcontroller.

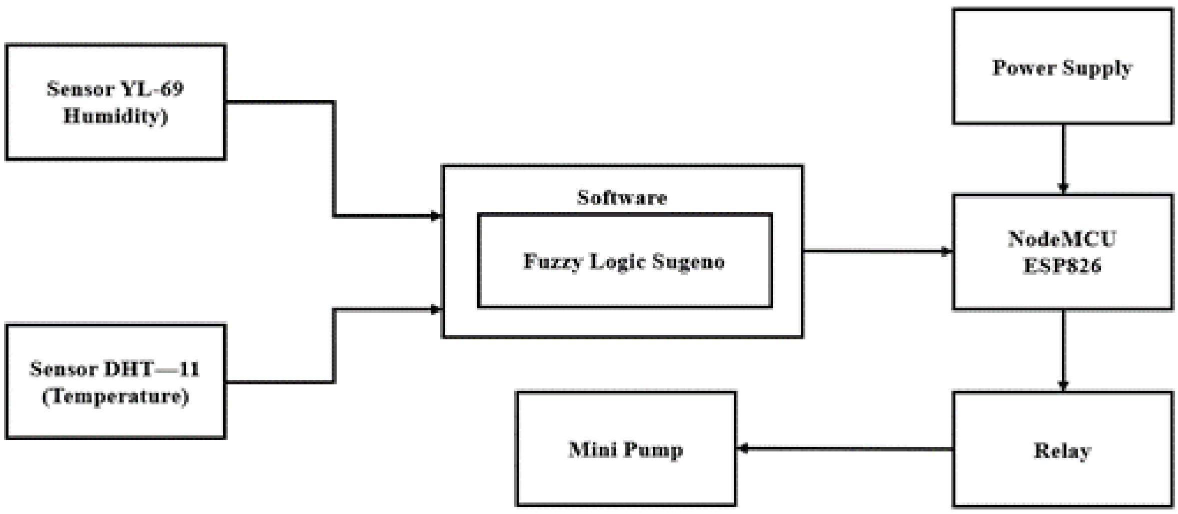


*Figure 4. Irrigation block diagram*

The computed results will be used to determine whether the water pump should be switched on or off. The water pump requires more current than the NodeMCU ESP8266 can provide. Therefore, an additional current source is needed. A relay serves as an intermediary, controlling the on and off states of this current.

### *4.2. Fuzzy Construction Flow*

The required stages in fuzzy construction are as follows. First, determine the boundaries of fuzzy input sets. These boundaries can be derived from the input sensor limits.

Communication with the garden owner can help determine the graph or membership functions. Alternatively, the sensor results can be compared to the actual conditions in the garden.

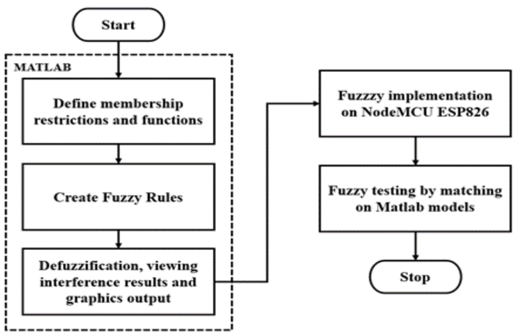


*Figure 5. Fuzzy logic construction flow*

The next stage is to determine the fuzzy inference rules. These rules are determined by irrigation occurring when the soil is dry and the temperature is moderate, or when the soil is dry and the temperature is high. Irrigation is not done under any other circumstances. In the last stage, defuzzification is performed using the Sugeno method and the weighted average formula. The fuzzy results can be observed in Python and are ready for code implementation within the NodeMCU ESP8266.

### *4.3. Determination of Soil Moisture Range*

Membership set for wet condition

$$\mu\text{Wet}(x) = \begin{cases} 0\ , & x > 400 \\ \dfrac{400 - x}{400 - 0}, & 0 < x < 400 \\ 1\ , & x < 400 \end{cases}$$

Membership set for moist condition

$$\mu\text{Moist}(x) = \begin{cases} 0\ , & x < 200 \text{ or } x > 800 \\ \dfrac{x - 200}{400 - 200}, & 200 < x < 400 \\ \dfrac{800 - x}{800 - 600}, & 600 < x < 800 \end{cases}$$

Membership set for dry condition

$$\mu\text{Dry}(x) = \begin{cases} 0\ , & x < 600 \\ \dfrac{x - 600}{1024 - 600}, & 600 < x < 1024 \\ 1\ , & x > 1024 \end{cases}$$

### *4.3. Determination of Temperature Range*

Membership set for cold condition

$$\mu\text{Cold}(x) = \begin{cases} 0\ , & x > 25 \\ \dfrac{25 - x}{25 - 15}, & 15 < x < 25 \\ 1\ , & x < 25 \end{cases}$$

Membership set for normal condition

$$\mu\text{Normal}(x) = \begin{cases} 0\ , & x < 25 \text{ or } x > 35 \\ \dfrac{x - 20}{25 - 20}, & 20 < x < 35 \\ \dfrac{35 - x}{35 - 30}, & 30 < x < 35 \end{cases}$$

Membership set for hot condition

$$\mu\text{Hot}(x) = \begin{cases} 0\ , & x < 30 \\ \dfrac{x - 30}{4 - 30}, & 30 < x < 40 \\ 1\ , & x > 40 \end{cases}$$

### *4.4. Fuzzy Sugeno Calculation*

For instance, if the soil moisture data is 362 and the temperature is 29.8, this falls under rule 3 and can be calculated as follows:

[R3] IF wet soil AND hot temperature THEN water pump does not irrigate

| | |
|---|---|
| Soil Moisture | Min = (362-0)/(800-0)= 62/800=0.4525 |
| Temperature | Min = (29.8-20)/(35-20)=9.8/15=0.6533 |
| Defuzzification | WA = (0.4525+0.6533)/2=0.447083333 (No Flush) |

### *4.5. Implementation of Automatic Irrigation Device*

To test the devices on a single plant, namely a green spinach plant in the spinach garden house, place the device next to the plant's pot. The device initiates the watering process based on the soil moisture condition determined by the microcontroller system. These trials were recorded three times a day (morning, afternoon, and evening) during the 7-day monitoring, with approximately 20 trials recorded. In this case, the experiment was controlled and monitored for 60 days.

*Figure 6. Implementation of the device*

### *4.6. Blackbox Testing*

The primary focus of black box testing is on whether or not the system has been designed to meet the specified requirements. This study tests the unit and evaluates how well it adheres to the design process after it has been put into practice.

*Table 3. Blackbox testing*

| No | Testing Subject | Testing Name |
|---|---|---|
| 1 | Automatic Irrigation Device | Sensor Moisture Level Error Testing for YL-69 compared to 3 Way Soil Meter |
| | | Temperature Sensor Error Testing for DHT-11 compared to HTC-1 |
| 2 | Fuzzy Logic | Suitability of Fuzzy Logic Sugeno Method in ESP8266 Automatic Irrigation Device with |
| 3 | Database | Connection with Website |
| | | Connection with NodeMCU ESP8266 |
| | | Database receives moisture and temperature sensor values |

*Table 4. Accuracy testing*

| No | YL-69 SENSOR | | | | DHT-11 SENSOR | | | |
|---|---|---|---|---|---|---|---|---|
| | Sensor YL-69 | Soil Meter Device | Deviation | | Sensor DHT-11 | HTC-1 Device | Deviation | |
| | Soil Moisture (RH) | Soil Moisture (RH) | Value (RH) | Percentage (%) | Temperature (ºC) | Temperature (ºC) | Temperature (ºC) | Percentage (%) |
| 1 | 1024 | 1000 | 24 | 2,400 | 29,8 | 30,1 | 0,3 | 0,750 |
| 2 | 920 | 900 | 20 | 2,200 | 28,5 | 29 | 0,5 | 1,250 |
| 3 | 719 | 700 | 19 | 2,714 | 30,2 | 30,5 | 0,3 | 0,750 |
| 4 | 831 | 900 | 69 | 7,666 | 31,2 | 30,9 | 0,3 | 0,750 |
| 5 | 690 | 700 | 10 | 1,428 | 29,8 | 29,6 | 0,2 | 0,500 |
| 6 | 459 | 500 | 41 | 8,200 | 30,8 | 30,7 | 0,1 | 0,250 |
| 7 | 367 | 400 | 27 | 6,750 | 32,3 | 31,7 | 0,6 | 1,500 |
| 8 | 390 | 400 | 10 | 2,500 | 31,3 | 31,1 | 0,2 | 0,500 |
| 9 | 799 | 800 | 1 | 0,125 | 29,3 | 29,4 | 0,1 | 0,250 |
| 10 | 585 | 600 | 15 | 2,500 | 28,5 | 28,7 | 0,2 | 0,500 |
| 11 | 663 | 700 | 37 | 5,285 | 31,9 | 32,3 | 0,4 | 1,000 |
| 12 | 797 | 800 | 3 | 0,375 | 28,9 | 29 | 0,1 | 0,250 |
| 13 | 512 | 600 | 88 | 14,666 | 27,1 | 27,5 | 0,4 | 1,000 |
| 14 | 428 | 500 | 72 | 14,400 | 33 | 33,4 | 0,4 | 1,000 |
| 15 | 403 | 500 | 97 | 19,400 | 29,9 | 30,3 | 0,4 | 1,000 |
| 16 | 378 | 400 | 22 | 5,500 | 30,4 | 30,6 | 0,2 | 0,500 |
| 17 | 346 | 400 | 54 | 13,500 | 31,2 | 31,3 | 0,1 | 0,250 |
| 18 | 460 | 500 | 40 | 8,000 | 32,2 | 32,3 | 0,1 | 0,250 |
| 19 | 473 | 500 | 27 | 5,400 | 32,5 | 32,9 | 0,4 | 1,000 |
| 20 | 468 | 500 | 32 | 6,400 | 31,7 | 31,8 | 0,1 | 0,250 |
| | Average | | 35,40 | 6,470 | Average | | 0,27 | 0,675 |

The accuracy testing revealed a strong correlation between the YL-69 soil moisture sensor and the soil meter device, with thirty tests completed. The readings show an average moisture level of 35.4 relative humidity (RH) units, with a minimal percentage difference of 6.47%. This suggests that that when it comes to accurately monitoring soil moisture levels, the YL-69 sensor and the soil meter devices function comparably.

Similarly, based on thirty test results, there is a close correlation in the comparison between the DHT-11 temperature sensor and the HTC-1 device. The average difference between the temperature readings of the two sensors is only 0.27 ºC, with a percentage difference of merely 0.675%. These findings imply that the DHT-11 sensor provides temperature measurements that closely align with those of the HTC-1 device.

Even though we had initially included an analysis with a table of test results, we decided not to display the table to maintain focus on the core aspects of this research and adhere to page limitations. On the other hand, our test findings indicate that the implementation of the fuzzy logic method with the Sugeno method on ESP8266 has an error rate of 0.0375. We expected that the twenty test results would match the Python calculations.

### *4.7. Irrigation Device Testing*

Before proceeding to the testing phase, irrigation device testing was conducted to evaluate its performance.

The results of these tests are then presented in Table 5, which displays the data and outcomes of various tests conducted on the irrigation device.

*Table 5. Irrigation device testing*

| No | Soil Moisture (RH) | Temperature (ºC) | Fuzzy Logic | Pump Condition |
|---|---|---|---|---|
| 1 | 1024 | 29,8 | 1 | ON |
| 2 | 920 | 28,5 | 1 | ON |
| 3 | 719 | 30,2 | 0,75 | ON |
| 4 | 831 | 31,2 | 1 | ON |
| 5 | 690 | 29,8 | 0,679 | ON |
| 6 | 459 | 30,8 | 0,5 | OFF |
| 7 | 367 | 32,3 | 0,433 | OFF |
| 8 | 390 | 31,3 | 0,48 | OFF |
| 9 | 799 | 29,3 | 0,5 | ON |
| 10 | 585 | 28,5 | 0,5 | OFF |
| 11 | 663 | 31,9 | 0,619 | ON |
| 12 | 797 | 28,9 | 0,989 | ON |
| 13 | 512 | 27,1 | 0,5 | OFF |
| 14 | 428 | 33 | 0,5 | OFF |
| 15 | 403 | 29,9 | 0,5 | OFF |
| 16 | 378 | 30,4 | 0,456 | OFF |
| 17 | 346 | 31,2 | 0,388 | OFF |
| 18 | 460 | 32,2 | 0,5 | OFF |
| 19 | 473 | 32,5 | 0,5 | OFF |
| 20 | 293 | 31,7 | 0,264 | OFF |

Based on the implementation results, thirty test results are expected to be equal to the calculations produced by the ESP8266. This indicates that the irrigation device is functioning as expected.

### *4.8. Database Testing*

Similarly, database testing was carried out to assess the functionality and reliability of the database system.

The results of these tests are summarized in Table 6, providing insights into the performance and effectiveness of the database under various conditions

*Table 6. Database testing*

| No | Testing Name | Expected Result | Result |
|---|---|---|---|
| 1 | Website Connection | Database connected to website monitoring | Successful |
| 2 | Hardware Connection | Database connected to irrigation device using GET Method API | Successful |
| 3 | Sensor Values (Soil Moisture and Temperature) | The Database can be retrieved data from the irrigation device | Successful |

The results of the database testing indicate that the website connection, the irrigation device connection, and the data retrieval from the automated plant watering device were all functioning according to plan.

## 5. Discussion

The results indicate that the irrigation system effectively manages water supply, with sufficient accuracy in adjusting irrigation according to plant needs. Likewise, the evaluation of the database testing revealed that the database system maintains data integrity and consistency well, efficiently handling workloads. This discussion also highlights challenges encountered during development and testing, such as resource limitations and technical complexities, which might serve as focal points for future enhancements.

## 6. Conclusion

This study has successfully developed an innovative automatic plant sprinkler system using fuzzy logic with the fuzzy Sugeno method. Utilizing a WSN prototype with ESP8266 microcontroller hardware and Arduino IDE software, this research focused on spinach plants and effectively adjusted watering schedules during both the nursery and seedling growth periods. By integrating soil moisture analysis and temperature sensors, the system made accurate watering decisions, simplifying plant care practices.

The key findings and conclusions derived from the results and discussions are as follows: Firstly, the automatic plant watering device implemented the Sugeno method for fuzzy logic with a low error rate of 0.0375. Secondly, the incorporation of soil moisture and temperature sensors enabled seamless activation and deactivation of the water pump based on preset conditions, with sensor readings transmitted to a monitoring website for logging purposes. Thirdly, the device met all required specifications as confirmed by black box testing.

Moving forward, future work might focus on developing more sophisticated fuzzy logic models to further enhance the system's accuracy and efficiency, as well as explore its applicability to various plant species to broaden understanding of watering needs.

Furthermore, integrating IoT technology using real-time data collection and analysis could enhance remote monitoring and control capabilities, offering a comprehensive solution for efficient plant irrigation management. As the overall objective of this research is to give readers a constructive and insightful understanding of automatic plant sprinkler systems, opening the way for improvements in agricultural technology and environmentally friendly plant care practices.

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