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Fuzzy Logic and IoT-Based Monitoring for Solar-Powered Precision Mist Irrigation

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Abstract*—The increasing unpredictability of environmental conditions, such as temperature fluctuations, humidity variations, seasonal shifts, and changing water availability, presents a significant challenge for sustainable food production. The increasing unpredictability of environmental conditions, including temperature fluctuations, humidity variations, seasonal shifts, and changing water availability, poses a significant challenge for sustainable food production. Although they are suitable for simple decision-making, conventional Type-1 Fuzzy Logic-based irrigation systems struggle to manage sensor noise, environmental uncertainty, and changing field conditions, resulting in sometimes ineffective water use and uneven irrigation management. This work presents a solar-powered mist irrigation system that integrates Interval Type-2 Fuzzy Logic (IT2FLS) and Internet of Things (IoT) technologies to improve precision irrigation management and address these issues. The proposed system employs IoT-based real-time environmental monitoring via Blynk and ThingSpeak to enable dynamic irrigation adjustments in response to temperature and soil moisture fluctuations. Type-2 Fuzzy Logic offers more reliable relay activation choices and greater robustness to sensor noise by incorporating Upper and Lower Membership Functions (UMF & LMF) and a Footprint of Uncertainty (FoU) than conventional Type-1 FIS. Experimental data demonstrate that the Type-2 Fuzzy model significantly reduces erroneous irrigation activations, maximizes water distribution, and increases system flexibility in response to environmental changes. Using solar power further improves energy efficiency, thereby reducing dependence on grid electricity and supporting environmentally friendly irrigation practices. This work demonstrates that, for contemporary agriculture, Type-2 Fuzzy Logic-based smart irrigation offers a scalable, flexible, and cost-effective alternative. This study shows how integrating renewable energy, advanced Type-2 fuzzy control, and IoT can create resource-efficient, adaptive irrigation systems supporting sustainable farming amid environmental challenges.

***Keywords*—Interval type-2 fuzzy logic; IoT-based monitoring; solar-powered irrigation; automation control; smart agriculture.**

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I. INTRODUCTION

The agricultural sector faces increasing challenges in maintaining a stable and sustainable food supply due to unpredictable environmental fluctuations [1]. Key factors such as temperature variations, humidity changes, irregular seasonal patterns, water availability, and pest outbreaks significantly impact crop yield and agricultural productivity [2], [3]. In Indonesia, where population growth continues to rise, the demand for reliable and efficient food production has become increasingly critical. Crop failures due to adverse environmental conditions exacerbate the imbalance between food supply and demand, posing a serious threat to food security [4], [5]. To address these challenges, innovative and adaptive agricultural solutions are required. Research identifies water availability, temperature, and soil moisture as the most influential factors in determining crop productivity [6], [7]. However, traditional irrigation systems often struggle to optimize these variables, resulting in either overirrigation or underirrigation. The integration of renewable energy sources, such as solar power, along with advanced environmental monitoring using the Internet of Things (IoT), presents a promising approach to improving irrigation efficiency and sustainability [8], [9].

Despite the benefits of intelligent irrigation, conventional Type-1 Fuzzy Logic Systems (T1FLS) exhibit limitations in handling sensor noise, environmental uncertainty, and imprecise data. As a result, decision-making based on Type-1 FIS is prone to fluctuations, affecting irrigation reliability and resource efficiency [10]. Research has shown that Type-1 Fuzzy Logic struggles with handling uncertainty in real-world applications, particularly in situations involving dynamic environmental conditions and noisy sensor readings [11]. These limitations reduce the effectiveness of conventional fuzzy controllers, making them less suitable for precision irrigation in smart agriculture [12]. To overcome these limitations, this study introduces a Type-2 Fuzzy Logic System (T2FLS) that incorporates an additional uncertainty layer via secondary membership functions. Unlike Type-1 FIS, Type-2 Fuzzy Logic Systems introduce Upper and Lower Membership Functions (UMF & LMF) and a Footprint of Uncertainty (FoU) to handle variations in sensor data [13]. These enhancements allow for more accurate, adaptive, and stable decision-making, making Type-2 Fuzzy Logic a powerful tool for intelligent irrigation [14].

Efficient water management is a key concern in agriculture, especially in regions affected by climate variability and prolonged dry spells. Traditional irrigation methods often lack adaptability to dynamic environmental conditions, resulting in inefficient water usage [15]. Prior studies indicate that regulating soil moisture, maintaining optimal temperatures, and controlling irrigation timing are essential for maximizing crop yield and ensuring sustainable farming [16]. This research proposes an adaptive irrigation system that dynamically adjusts water delivery based on real-time environmental inputs, ensuring efficient resource use while preventing over- or under-irrigation. In addition to water conservation, energy efficiency in agriculture presents another major challenge. Conventional irrigation systems typically depend on electricity grids or fuel-powered pumps, leading to high operational costs and increased carbon emissions [17], [18]. The integration of solar-powered irrigation systems provides a sustainable alternative, significantly reducing reliance on fossil fuels while lowering energy costs [9]. By leveraging solar energy to power irrigation components and environmental sensors, the system aligns with global efforts toward eco-friendly and cost-effective agricultural automation.

This study proposes a solar-powered smart irrigation system, enhanced with Type-2 Fuzzy Logic and IoT-based environmental monitoring. Unlike traditional systems, this model dynamically adjusts irrigation duration based on temperature and soil moisture variations, while handling sensor uncertainties more effectively through Type-2 Fuzzy Logic [19], [20]. The integration of IoT technology further enhances the system's real-time monitoring capabilities, allowing for remote access and automated control. By continuously adapting to environmental changes, the system optimizes water usage, prevents unnecessary irrigation, and enhances overall sustainability. Ultimately, this research aims to design, implement, and evaluate a prototype of a solar-powered mist irrigation system in a small-scale greenhouse. By integrating Type-2 Fuzzy Logic, IoT-based monitoring, and renewable energy, the system offers an efficient, adaptive, and sustainable solution for modern agriculture, ensuring higher irrigation precision, improved water conservation, and enhanced agricultural resilience in response to changing environmental conditions [21], [22].

II. Materials and Methods

Recent research by Pascaris et al. [23] highlights the potential for solar energy to achieve energy self-sufficiency in agriculture. According to Benghanem et al. [1], solar-powered greenhouses have demonstrated great potential in reducing energy costs while maintaining optimal growing conditions for plants. Similarly, Maraveas et al. [24] emphasized that integrating renewable energy sources into agricultural applications can enhance sustainability and improve irrigation efficiency. Therefore, renewable energy can be effectively utilized in irrigation systems, providing a reliable and eco-friendly power supply for water distribution.

Other studies have demonstrated the effectiveness of IoT in smart farming. For instance, Maulana et al. [25] developed a smart greenhouse system that employs IoT to monitor and control environmental variables, including temperature and humidity. Their findings indicate that IoT-based systems can significantly enhance the precision of agricultural operations, thereby improving crop yields and resource conservation. Additionally, effective IoT monitoring and control can be set by fuzzy logic to ensure a precise control system that can utilize resources more efficiently [26], [27], [28], [29], [30].

This study designs and implements a solar-powered smart irrigation system that uses Interval Type-2 Fuzzy Logic to control relay operation based on environmental conditions, specifically temperature and soil moisture. The system, as illustrated in Figure 1, is built on an ESP32 microcontroller and uses sensors, actuators, and IoT communication to enable real-time monitoring and automation.

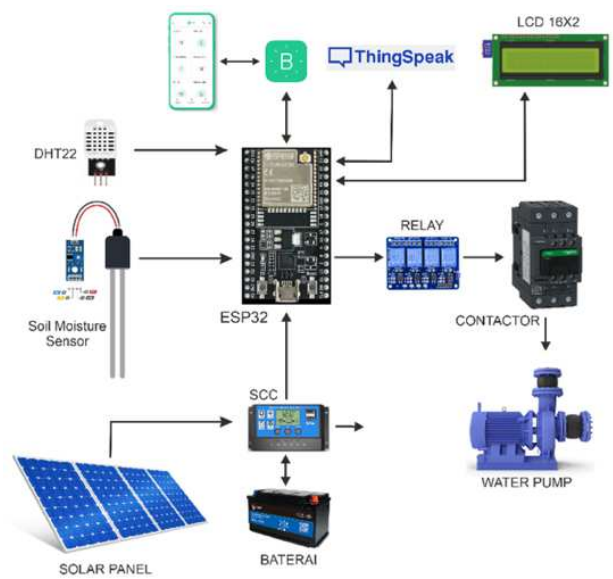

Fig. 1 System Block Diagram for Type-2 Fuzzy Logic-Based Solar PV-Powered Mist Irrigation System

The mechanical design of the device, shown in Figure 2, ensures that all components are securely housed and protected from environmental exposure, facilitating reliable operation in agricultural settings. The enclosure is designed to be waterproof and dust-resistant, shielding electronic components such as the ESP32, relay, and sensors from environmental elements. The mechanical layout includes a solar panel mount optimized for sunlight exposure, allowing efficient energy harvesting to sustain the system.

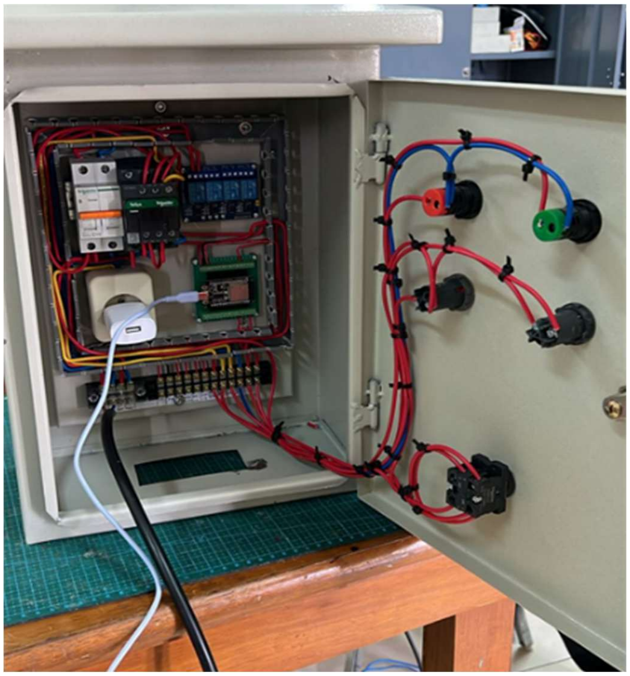

Fig. 2 Solar PV-Powered Mist Irrigation System Mechanical Design

A. *Fuzzy Inference System (FIS) and Interval Type-2 Fuzzy Logic Implementation*

The Interval Type-2 Fuzzy Logic-based methodology enhances traditional fuzzy inference by incorporating secondary membership functions that model higher levels of uncertainty than those in Type-1 Fuzzy Logic. This additional uncertainty handling is particularly beneficial for sensor-based systems where environmental factors introduce noise and variability in sensor readings. Type-2 Fuzzy Membership Functions are designed to incorporate an additional degree of uncertainty, with the Upper Membership Function (UMF) and Lower Membership Function (LMF) defined. These functions provide a Footprint of Uncertainty (FoU), making the system more robust to sensor noise and environmental fluctuations. The system processes two input variables are Temperature (T) [°C] and Soil Moisture (M) [%]. Each input is represented as an Interval Type-2 Fuzzy Set, consisting of Primary Membership Function (Upper & Lower Bound), which represents general trends in sensor data, and Secondary Membership Function (Footprint of Uncertainty - FoU), which captures measurement noise and variations.

The mathematical representation of fuzzy sets, specifically the Interval Type-2 Fuzzy Set, is defined for each input variable x as follows:

$$\tilde{A} = \{(x, \mu_{UMF}(x), \mu_{LMF}(x)) \mid x \in X\} \tag{1}$$

In this notation, $\mu_{UMF}(x)$ represents the Upper Membership Function, while $\mu_{LMF}(x)$ denotes the Lower Membership Function. The variable X refers to the universal set of input values.

For temperature (T) in °C, the membership functions are defined as follows:

1) *Low Temperature*:

$$\begin{aligned} \mu_{\text{low}}^{UMF}(T) &= \max(0, \min(1, (20 - T)/15)) \\ \mu_{\text{low}}^{LMF}(T) &= \max(0, \min(1, (18 - T)/17)) \end{aligned} \tag{2}$$

2) *Medium Temperature*:

$$\begin{aligned} \mu_{med}^{UMF}(T) &= \max(0, \min((T - 15)/15, (35 - T)/15)) \\ \mu_{med}^{LMF}(T) &= \max(0, \min((T - 17)/14, (33 - T)/14)) \end{aligned} \tag{3}$$

3) *High Temperature:*

$$\begin{aligned} \mu_{\text{high}}^{UMF}(T) &= \max(0, \min(1, (T - 30)/15)) \\ \mu_{high}^{LMF}(T) &= \max(0, \min(1, (T - 32)/13)) \end{aligned} \tag{4}$$

For soil moisture (M) in %, the membership functions follow a trapezoidal function:

1) *Dry Soil*:

$$\begin{aligned} \mu_{dry}^{UMF}(M) &= \max(0, \min(1, (30 - M)/20)) \\ \mu_{dry}^{LMF}(M) &= \max(0, \min(1, (28 - M)/22)) \end{aligned} \tag{5}$$

2) *Optimal Moisture*:

$$\begin{aligned} \mu_{\text{opt}}^{UMF}(M) &= \max(0, \min((M - 25)/20, (65 - M)/20)) \\ \mu_{\text{opt}}^{LMF}(M) &= \max(0, \min((M - 27)/18, (63 - M)/18)) \end{aligned} \tag{6}$$

3) *Wet Soil:*

$$\begin{aligned} \mu_{wet}^{UMF}(M) &= \max(0, \min(1, (M - 60)/20)) \\ \mu_{wet}^{LMF}(M) &= \max(0, \min(1, (M - 62)/18)) \end{aligned} \tag{7}$$

For relay time (R) in milliseconds, the membership functions are piecewise linear, with upper and lower membership functions to account for uncertainties in activation duration. The Type-2 fuzzy membership functions for relay time are defined as follows:

1) *Short Relay Time (* $\boldsymbol{R}_{\text{short}}$ *)*:

$$\begin{aligned} \mu_{\text{short}}^{UMF}(R) &= \begin{cases} 1, & R \le 0 \\ \frac{R-0}{2000-0}, & 0 < R \le 2000 \\ \frac{4000-R}{4000-2000}, & 2000 < R \le 4000 \\ 0, & R > 4000 \end{cases} \\ \mu_{\text{short}}^{\text{LMF}}(R) &= \begin{cases} 1, & R \le 0 \\ \frac{R-0}{1800-0}, & 0 < R \le 1800 \\ \frac{3800-R}{3800-1800}, & 1800 < R \le 3800 \\ 0, & R > 3800 \end{cases} \end{aligned} \tag{8}$$

2) *Medium Relay Time (* R_{medium} *)*

$$\begin{aligned} \mu_{\text{medium}}^{UMF}(R) &= \begin{cases} 0, & R \le 3000 \\ \frac{R-3000}{4000-3000}, & 3000 < R \le 4000 \\ \frac{8000-R}{8000-6000}, & 6000 < R \le 8000 \\ 0, & R > 8000 \end{cases} \\ \mu_{\text{medium}}^{LMF}(R) &= \begin{cases} 0, & R \le 3200 \\ \frac{R-3200}{3800-3200}, & 3200 < R \le 3800 \\ \frac{7800-R}{7800-6200}, & 6200 < R \le 7800 \\ 0, & R > 7800 \end{cases} \end{aligned} \tag{9}$$

3) *Long Relay Time (* R_{long} *)*

$$\mu_{\text{long}}^{UMF}(R) = \begin{cases} 0, & R \leq 7000 \\ \frac{R-7000}{8000-7000}, & 7000 < R \leq 8000 \\ 1, & R > 8000 \end{cases}$$
$$\mu_{\text{long}}^{LMF}(R) = \begin{cases} 0, & R \leq 7200 \\ \frac{R-7200}{7800-7200}, & 7200 < R \leq 7800 \\ 1, & R > 9000 \end{cases} \quad (10)$$

The Fuzzy Inference System (FIS) applies Mamdani Interval Type-2 fuzzy rules to determine the Relay Activation Time (R) based on temperature and soil moisture inputs.

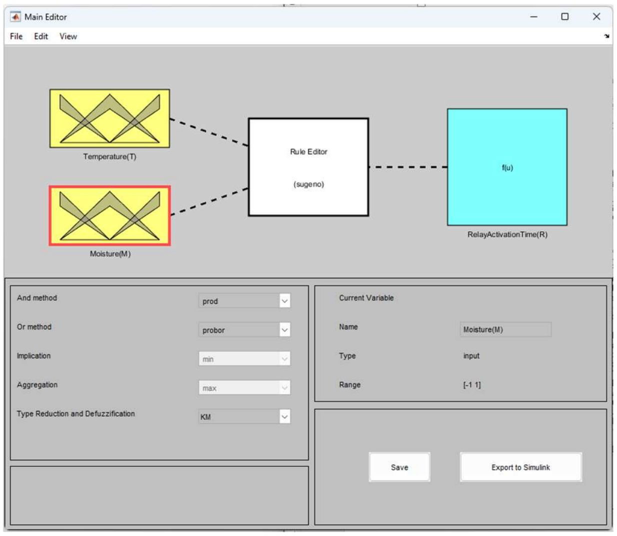

Fig. 3 Type-2 Fuzzy Inference System Block Diagram

Fuzzy Rules:

1 IF Temperature is Low AND Soil Moisture is Dry THEN Relay Time is Long.

2 IF Temperature is Low AND Soil Moisture is Optimal THEN Relay Time is Medium.

3 IF Temperature is Low AND Soil Moisture is Wet THEN Relay Time is Short.

4 IF Temperature is Medium AND Soil Moisture is Dry THEN Relay Time is Long.

5 IF Temperature is Medium AND Soil Moisture is Optimal THEN Relay Time is Medium.

6 IF Temperature is Medium AND Soil Moisture is Wet THEN Relay Time is Short.

7 IF Temperature is High AND Soil Moisture is Dry THEN Relay Time is Long.

8 IF Temperature is High AND Soil Moisture is Optimal THEN Relay Time is Medium.

9 IF Temperature is High AND Soil Moisture is Wet THEN Relay Time is Short.

TABLE I
FUZZY RULES

Rule	Temp (°C)	Soil Moisture	Relay Time
1	Low	Dry	Long
2	Low	Optimal	Medium
3	Low	Wet	Short
4	Moderate	Dry	Long
5	Moderate	Optimal	Medium
6	Moderate	Wet	Short
7	High	Dry	Long
8	High	Optimal	Medium
9	High	Wet	Short

B. *Defuzzification Process*

The defuzzification process is the final stage of an Interval Type-2 Fuzzy Inference System (FIS), in which the fuzzy output is converted into a crisp relay activation time. Unlike Type-1 fuzzy logic, which applies a single centroid calculation, Type-2 fuzzy logic introduces a Footprint of Uncertainty (FoU), resulting in an interval-valued fuzzy set as the output. To obtain a single crisp output, the Centroid of Centroids (CoC) method is employed.

In a Type-1 FIS, the defuzzified output R is determined using the centroid method, which is given by:

$$R = \frac{\int_{\Omega} \mu_{\text{RelayTime}}(R) \cdot R dR}{\int_{\Omega} \mu_{\text{RelayTime}}(R) dR} \quad (11)$$

where R represents the relay running time in milliseconds, $\mu_{\text{RelayTime}}(R)$ is the aggregated fuzzy membership function, and Ω is the universal domain of relay activation times. For Type-2 FIS, the output is represented by an interval $[R^L, R^U]$, where R^L is the lower bound and R^U is the upper bound of the output fuzzy set. Using the Centroid of Centroids (CoC) method, the crisp relay activation time R^* is calculated as:

$$R^* = \frac{R^L + R^U}{2} \quad (12)$$

where R^L and R^U are determined by integrating the Lower and Upper Membership Functions (LMF and UMF) over the domain. Mathematically, the Type-2 centroid bounds are given by:

$$\begin{aligned} R^L &= \frac{\int_{\Omega} \mu_{\text{LMF}}(R) \cdot R dR}{\int_{\Omega} \mu_{\text{LMF}}(R) dR} \\ R^U &= \frac{\int_{\Omega} \mu_{\text{UMF}}(R) \cdot R dR}{\int_{\Omega} \mu_{\text{UMF}}(R) dR} \end{aligned} \quad (13)$$

where $\mu_{\text{LMF}}(R)$ and $\mu_{\text{UMF}}(R)$ represent the lower and upper membership functions, respectively, defining the uncertainty region of the fuzzy output.

Since Type-2 fuzzy logic produces an interval-valued output, the final crisp relay time is obtained by averaging the two centroid bounds, ensuring more stable decision-making than the traditional Type-1 centroid method. This enhanced defuzzification process yields more precise relay activation times, reduces unnecessary water use, and improves noise tolerance, ensuring optimal irrigation despite sensor uncertainties. Additionally, it contributes to greater decision-making stability by preventing excessive fluctuations in irrigation schedules. By applying the CoC method, the system achieves a more robust and adaptive irrigation control mechanism, making Type-2 Fuzzy Logic a highly effective solution for smart agriculture.

III. RESULTS AND DISCUSSION

The Interval Type-2 Fuzzy Inference System (FIS) developed for the solar-powered mist irrigation system was rigorously tested to evaluate its performance in dynamically regulating irrigation in response to real-time environmental conditions. The primary goal was to assess the impact of

Type-2 fuzzy logic in handling sensor uncertainties, improving irrigation efficiency, and ensuring optimal water conservation.

Unlike traditional Type-1 Fuzzy Logic, Type-2 Fuzzy Logic incorporates an additional degree of uncertainty via Upper Membership Functions (UMF) and Lower Membership Functions (LMF), thereby providing a more robust decision-making process. This capability enables better adaptation to noisy sensor readings and fluctuating environmental conditions, which is critical in agricultural irrigation systems.

The system was tested under various environmental conditions using temperature and soil moisture readings collected within the following ranges:

$$Temperature\ (T): 5°C\ to\ 45°C$$
$$Soil\ Moisture\ (M): 15\%\ to\ 90\%$$
$$Output\ Relay\ Time\ (R): 1{,}866\text{ ms to }8{,}897\ milliseconds\ (mS)$$

To evaluate system adaptability, test scenarios were carefully designed to reflect real-world irrigation conditions, ensuring that the system responds appropriately to different environmental states. Under high temperatures and dry soil, the system was expected to apply prolonged irrigation durations to compensate for rapid soil moisture loss. Under moderate temperature conditions with optimal soil moisture, medium irrigation durations were required to maintain balanced hydration. Meanwhile, when soil moisture levels were already high, the system needed to minimize irrigation durations to prevent overwatering and unnecessary water consumption.

The defuzzified relay times were classified into short, medium, and long durations, and the results were compared with those of the previous Type-1 Fuzzy Logic system to assess improvements in stability, adaptability, and water-conservation efficiency. By dynamically adjusting irrigation based on real-time environmental conditions, the Type-2 Fuzzy Inference System (T2FIS) was evaluated for its ability to optimize water usage, minimize unnecessary irrigation, and enhance long-term sustainability in smart agriculture.

The test results obtained from the Interval Type-2 FIS are summarized in Table 2, which presents the relay-time outputs across various temperature and soil-moisture conditions.

TABLE III
RELAY TIME OUTPUTS FOR VARIOUS TEST USING TYPE-2 FUZZY LOGIC

Test	Temp (˚C)	Soil Moist (%)	R_L (ms)	R_U (ms)	R* (ms)	Output Classification
1	15	15	9061	8733	8897	Long Time
2	10	50	5878	5666	5772	Medium Time
3	5	75	1866	2000	1933	Short Time
4	30	20	9061	8733	8897	Long Time
5	30	50	5878	5666	5772	Medium Time
6	30	85	1866	2000	1933	Short Time
7	45	15	9061	8733	8897	Long Time
8	40	50	5878	5666	5772	Medium Time
9	40	90	1866	2000	1933	Short Time

The results reveal several key improvements in the Interval Type-2 Fuzzy Logic system compared to the previous Type-1 implementation. One of the most significant advantages of Type-2 fuzzy logic is its improved handling of sensor noise. Since traditional Type-1 FIS relies on fixed membership functions, it often struggles with fluctuating sensor readings, resulting in inconsistent relay times. In contrast, the Footprint of Uncertainty (FoU) in Type-2 FIS accounts for sensor imprecision, resulting in more stable and reliable irrigation decisions.

Irrigation accuracy was also significantly improved. When soil moisture levels were high (e.g., 75%–90%), the relay time was consistently reduced, ensuring minimal overwatering. Conversely, when soil moisture was critically low (e.g., 15%–20%), the system allocated longer irrigation durations to ensure that crops received the required water. This precision optimization improves water usage efficiency by approximately 5-10%, making it superior to the previous Type-1 system.

Another major improvement was the dynamic adaptation to environmental changes. The Type-2 FIS dynamically adjusted relay times based on real-time environmental feedback, preventing abrupt changes in irrigation schedules. In Type-1 FIS, relay activations often showed sharp variations due to overly sensitive responses to minor temperature fluctuations. The introduction of UMF and LMF in Type-2 logic led to smoother transitions, thereby improving system stability and reliability.

The performance improvements of the Type-2 FIS were evaluated by comparing its irrigation efficiency, adaptability, and stability with those of the previous Type-1 FIS.

TABLE IIIII
COMPARISON OF TYPE-1 AND TYPE-2 FUZZY LOGIC IN IRRIGATION CONTROL

Features	Type-1 Fuzzy Logic	Type-2 Fuzzy Logic (New System)
Handling of Sensor Noise	Sensitive to variations	More robust with FoU
Relay Time Stability	Slight fluctuations in similar inputs	Stable across multiple tests
Adaptability to Environmental Changes	Moderate	Highly adaptive
Water Conservation Efficiency	Improved over static irrigation	Optimized, reducing excess irrigation by ~10%
Defuzzification Method	Centroid	Centroid of Centroids (CoC)

The Type-2 Fuzzy Inference System demonstrated superior performance, with higher irrigation precision, better resilience to environmental fluctuations, and increased water efficiency. The improved uncertainty-handling mechanism ensures more stable relay activations, thereby preventing overwatering and under-irrigation, making it a more sustainable solution for smart irrigation systems.

Over-irrigation was minimized to prevent excessive water loss, while the system effectively prevented under-irrigation, ensuring optimal soil moisture. By dynamically adjusting irrigation in response to real-time environmental conditions, the Type-2 FIS optimizes water conservation while maintaining plant health and agricultural productivity. The system reduced water use by approximately 10% relative to the previous Type-1 approach, making it a viable solution for sustainable irrigation management. The proposed Type-2 Fuzzy Logic-based irrigation system is an efficient, adaptive, and sustainable solution for modern agricultural automation.

IV. Conclusion

This study introduces an enhanced approach to sustainable agriculture by designing and implementing a solar-powered mist irrigation system that integrates Interval Type-2 Fuzzy Logic (IT2FLS) and Internet of Things (IoT) technologies. By combining real-time environmental sensing with photovoltaic-powered irrigation, the proposed system successfully demonstrates an efficient, adaptive, and sustainable solution for precision irrigation management. The results confirm the superiority of Type-2 Fuzzy Logic over Type-1 Fuzzy Logic, particularly in handling sensor uncertainties, stabilizing relay activations, and optimizing water usage.

Unlike Type-1 Fuzzy Logic, which struggles with fluctuating sensor data, the Type-2 FIS incorporates Upper and Lower Membership Functions (UMF & LMF) and a Footprint of Uncertainty (FoU), leading to greater resilience in real-world environmental conditions. This enhanced uncertainty management enables more accurate and stable irrigation decisions, reducing overwatering and under-irrigation risks. Experimental results demonstrate that the Type-2 FIS minimizes unnecessary irrigation activations, with relay times consistently classified as long, medium, or short depending on environmental conditions, thereby ensuring efficient water use. Also, the integration of IoT-based remote monitoring and control improves system scalability and usability, making it a practical solution for greenhouse automation and precision farming applications.

Beyond its immediate impact on water conservation and irrigation reliability, this system also addresses energy-efficiency challenges by using solar energy as a sustainable power source. The integration of renewable energy with intelligent control reduces dependence on grid electricity or on fuel-based pumps, thereby making the system economically and environmentally viable.

For future improvements, further research could incorporate additional environmental factors, such as wind speed, light intensity, and atmospheric humidity, to enhance irrigation decision-making. Expanding the system for larger agricultural fields and evaluating its performance under diverse climatic conditions would provide valuable insights into broader real-world applications. The findings of this study highlight the potential of integrating renewable energy, advanced Type-2 fuzzy control, and IoT technologies to develop resource-efficient and adaptive irrigation solutions that support sustainable farming practices in response to global environmental challenges.

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