A PRECISION AGRICULTURE FRAMEWORK FOR STRAWBERRY CULTIVATION USING IOT-BASED SOIL MOISTURE MONITORING AND TSUKAMOTO FUZZY INFERENCE

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ABSTRACT: Strawberry cultivation requires precise soil moisture management to maintain optimal growth conditions and prevent yield reduction. Traditional manual monitoring and irrigation methods are labor-intensive, time-consuming, and prone to inefficiencies that may result in crop failure. This study presents a precision agriculture framework that integrates Internet of Things (IoT) technology with Tsukamoto fuzzy inference to enable real-time soil moisture monitoring and intelligent irrigation control for strawberry farming. The system employs a capacitive soil moisture sensor connected to a NodeMCU ESP8266 microcontroller, which transmits data to the ThingSpeak cloud platform for remote access and visualization. The Tsukamoto fuzzy method processes sensor readings to determine the optimal irrigation duration based on predefined moisture thresholds. Experimental results show that the system achieved a soil moisture range of 44–85%, with an average of 80.9%, and a user satisfaction score of 68.49%. This approach demonstrates the potential to reduce water usage, minimize crop failure risks, and improve overall efficiency in high-value crop production. The proposed framework offers a scalable solution for sustainable agriculture, particularly in resource-constrained farming environments.

KEYWORDS: *Precision Agriculture; Internet of Things; Soil Moisture Monitoring;*

Tsukamoto Fuzzy Inference; Smart Irrigation; Strawberry Cultivation

1.0 INTRODUCTION

Strawberry (Fragaria Ananassa) is a high-value horticultural crop widely cultivated for its nutritional and economic importance. Optimal growth of strawberries requires specific environmental conditions, including an air temperature of 17–20 °C, relative humidity of 80–90%, and soil moisture levels between 40% and 85%[1], [2]. In many strawberry-producing regions, particularly in highland areas, maintaining these conditions is challenging due to climatic variability, water scarcity, and suboptimal irrigation practices[3]. Traditional irrigation methods in strawberry farming often rely on manual observation, which is labor-intensive, time-consuming, and prone to human error, leading to water wastage and reduced yield[4].
In Indonesia, strawberry production has shown a significant decline from 58,884 tons in 2014 to only 8,531 tons in 2018. Largely due to prolonged droughts, extreme temperatures, and inadequate irrigation management[5], [6]. Similar challenges are observed globally, where inefficient water management is identified as one of the leading causes of reduced agricultural productivity[7], [8]. Addressing these challenges requires the adoption of precision agriculture practices that integrate sensor technologies, automation, and data-driven decision-making[9], [10].

Water quality monitoring in hydroponic cultivation requires accurate and continuous observation to ensure that critical parameters remain within acceptable thresholds. In large-scale hydroponic facilities, manual monitoring becomes inefficient due to the extensive cultivation area, unlike in smaller setups where direct observation is more feasible. To address this limitation, predictive models such as Seasonal Autoregressive Integrated Moving Average (SARIMA) can be employed to forecast water quality based on parameters including temperature, pH, and total dissolved solids (TDS)[11]. Meanwhile, the Internet of Things (IoT) has emerged as a transformative tool in modern agriculture, offering capabilities for real-time monitoring, advanced data analytics, and automated control of environmental factors[12], [13], [14]. In irrigation management, IoT-based solutions have been effectively implemented to monitor variables such as soil moisture and temperature, thereby enhancing water efficiency and crop productivity[15]. In the previous model, there were several weaknesses, such as a lack of fuzzy capability to determine the moisture level in human-understandable indicators. The next problem is the lack of pump control in the previous model. Many models only have high or off configurations.

To address these limitations, this study proposes an IoT-based soil moisture monitoring and irrigation control system for strawberry cultivation, integrating the Tsukamoto fuzzy inference method to enhance decision-making accuracy. The fuzzy Tsukamoto inference method offers a flexible approach to decision-making under uncertainty. Unlike conventional control methods, fuzzy logic can handle imprecise input data and produce precise control actions based on linguistic rules. The Tsukamoto method is particularly well-suited for scientific applications such as irrigation control due to its ability to generate crisp outputs of monotonic membership functions. This property ensures precise, consistent, and smooth adjustments to water delivery, which is critical for maintaining optimal soil moisture and improving agricultural efficiency[16]. Previous studies have demonstrated the effectiveness of fuzzy logic in optimizing irrigation schedules for various crops[17], [18], but few have specifically explored its application in strawberry cultivation within the context of an IoT-enabled system. The proposed model employs a capacitive soil moisture sensor, NodeMCU ESP8266 microcontroller, and ThingSpeak cloud platform for data acquisition, processing, and visualization. By combining IoT connectivity with fuzzy-based control, the proposed framework aims to reduce the risk of crop failure, optimize water usage, and support sustainable high-value crop production.

2.0 LITERATURE REVIEW

The Internet of Things (IoT) has emerged as a transformative technology in precision agriculture, enabling real-time monitoring, data analysis, and automated control of farming operations[19], [20]. In irrigation management, IoT-based systems integrate wireless sensor networks, microcontrollers, and cloud platforms to optimize water consumption and improve crop productivity [21], [22]. For instance, Fatoni (2020) developed a smart gardening system employing a Wemos D1 ESP8266 microcontroller, DHT22 sensors, and Tsukamoto fuzzy inference to automate strawberry irrigation, successfully applying fuzzy rules for decision-making and remote web-based monitoring[23]. Similarly, Satrio et al. (2020) utilized moisture probes with fuzzy logic for irrigation timing [24], while Budi Sugandi et al.

(2021) implemented Arduino Uno-based fuzzy control with minimal temperature and humidity measurement errors [25]. Although such systems demonstrate effective integration of sensing and intelligent control, many depend on general-purpose platforms like Blynk, which may lack the analytical capabilities of cloud services such as ThingSpeak. Soil moisture is a vital factor affecting plant growth, nutrient uptake, and yield quality [26]. Capacitive soil moisture sensors, favored for their corrosion resistance and measurement stability [27], are particularly relevant in strawberry cultivation, where optimal moisture ranges between 40–60% [28]. IoT-based monitoring allows remote oversight and data-driven irrigation. Demonstrated a LoRa-enabled system for pH and moisture monitoring in strawberries, highlighting significant environmental variability [29]. Fuzzy logic, especially the Tsukamoto method, effectively handles agricultural decision-making under uncertainty by generating crisp outputs for precise irrigation control [30], [31].

Despite successful integration of IoT sensing devices and fuzzy Tsukamoto inference for automated irrigation, previous models face key limitations. Many rely on general-purpose platforms like Blynk, which lack advanced analytics and scalable data storage, restricting long-term evaluation and optimization compared to robust cloud-based services like ThingSpeak. Most studies use single-node or small-scale deployments that fail to capture spatial variability in soil moisture and environmental conditions, an important factor in agriculture due to microclimatic differences. Furthermore, Tsukamoto rules are often based on limited expert knowledge or fixed thresholds, reducing adaptability to changing seasons, soil differences, and crop stages. Prior research typically considers only basic parameters such as soil moisture or temperature, neglecting critical factors like evapotranspiration, soil texture, and crop water needs, which may lower inference accuracy. While Tsukamoto inference produces precise irrigation outputs, few studies compare it to other intelligent or baseline methods, limiting quantitative assessment of its agricultural value.

Addressing this gap, the present study develops an IoT-based soil moisture monitoring and irrigation control system using Tsukamoto fuzzy inference with ThingSpeak integration, aiming to improve water efficiency, reduce crop loss, and enhance sustainable strawberry production.

3.0 METHODOLOGY AND SYSTEM DESIGN

This research employed an experimental approach based on the Waterfall development model, including requirement analysis, design, implementation, and evaluation stages. Primary data were collected from capacitive soil moisture sensors and farmer feedback, while secondary data were obtained from literature on IoT and fuzzy inference. The system integrates NodeMCU ESP8266, capacitive soil moisture sensor.

3.1 Block Diagram Design Schematic

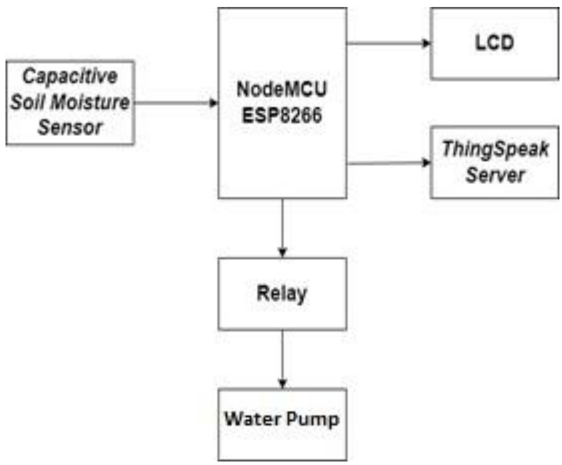

Figure 1: Block Diagram Design Schematic

Figure 1 presents the schematic of the IoT-based soil moisture monitoring and irrigation system. It highlights the system's closed-loop control mechanism. A capacitive soil moisture sensor functions as the main input device and transmits data to the NodeMCU ESP8266 microcontroller. The NodeMCU displays real-time values on an LCD for local monitoring. It also sends the data to the ThingSpeak server for remote access and analysis. Irrigation is regulated via a relay-controlled water pump. The pump activates when moisture drops below a threshold and deactivates upon reaching the desired level. This operation ensures efficient and sustainable water management.

3.2 Flowchart Diagram

A flowchart shows the sequential workflow of a system. This visual makes process comprehension easier, helps identify potential issues, and documents procedures clearly, as seen in Figure 2. The system flowchart includes two modes: automatic and manual. In automatic mode, the capacitive soil moisture sensor detects moisture levels. The pump activates if values fall below 45%. Meanwhile, the NodeMCU sends data to ThingSpeak for monitoring. In manual mode, users operate the pump using specific buttons. The NodeMCU still sends real-time performance and status data to the cloud platform.

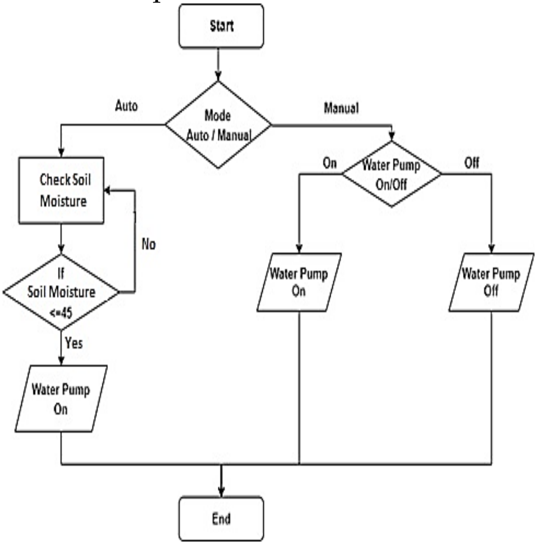

Figure 2. Block Diagram Design Schematic

3.3 Hardware Design

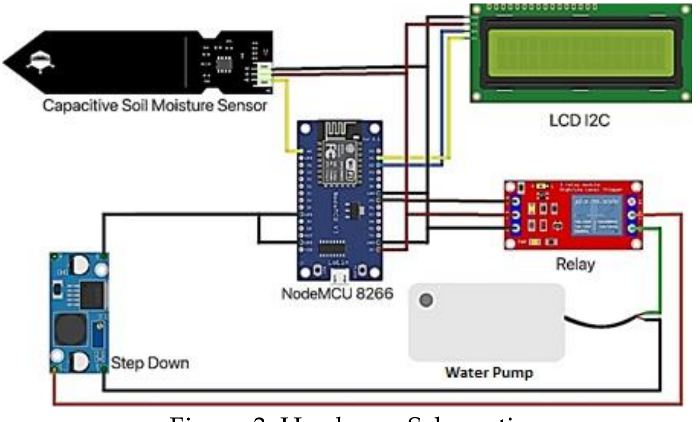

Figure 3: Hardware Schematic

The hardware design stage focuses on developing an IoT-based system for soil moisture monitoring in strawberry cultivation. Several circuit configurations were created to ensure proper functionality, with the overall scheme illustrating component integration with the main controller.

As shown in Figure 3, the prototype combines moisture monitoring with automated irrigation. A capacitive sensor measures soil water content, while the NodeMCU ESP8266 processes data and transmits it to ThingSpeak. Additionally, a 16×2 I2C LCD displays readings, and a water pump provides irrigation when required.

3.4 Thingspeak Dashboard Monitoring

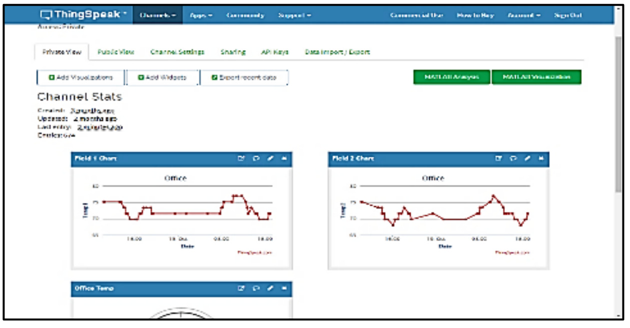

Figure 5: ThingSpeak Dashboard

Figure 5: monitoring platform with Arduino IDE. The NodeMCU ESP8266 program connects to ThingSpeak, which can be used on web, mobile, or desktop devices. Users sign up and create a channel to get unique API keys, making communication between hardware and server secure. ThingSpeak shows soil moisture, how long irrigation lasts, and monitoring results for easy and accurate IoT-based cloud control.

4.0 RESULTS AND DISCUSSIONS

4.1 Prototype Model of an IoT-Based Soil Moisture Monitoring System for Strawberry Cultivation

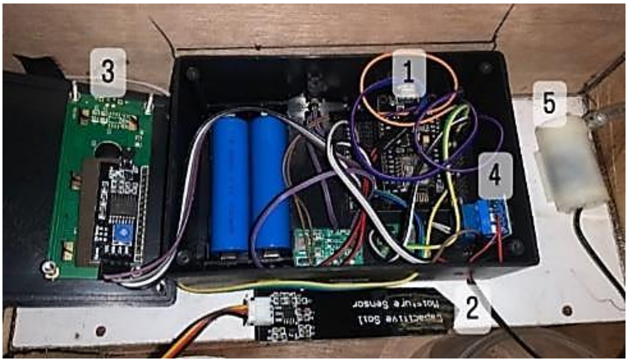

Figure 6: Model of a tool for monitoring soil moisture

Figure 6 presents the overall circuit design without the prototype, consisting of five main components. The NodeMCU ESP8266 serves as the central microcontroller, executing programmed instructions, managing the soil moisture sensor and LCD, and transmitting data to ThingSpeak via Wi-Fi. The soil moisture sensor measures soil humidity, with results processed by the microcontroller and displayed on the 16×2 I2C LCD. A relay operates as a switch to control the water pump, which functions as an actuator, delivering irrigation based on real-time sensor readings. The real implementation of the proposed model is shown in Figure 7.


Figure 7: Prototype of IoT-Based Soil Moisture Monitoring and Irrigation System for Strawberry Cultivation

Figure 7 illustrates a prototype IoT-based soil moisture monitoring and irrigation system applied to strawberry cultivation. A capacitive sensor embedded in the soil measures moisture levels, while a NodeMCU-based controller regulates water flow from a pump. This integration demonstrates a practical implementation of Tsukamoto fuzzy inference for precision agriculture.

4.2 Testing System

The testing phase applies Tsukamoto fuzzy logic to IoT-based soil moisture monitoring in strawberry cultivation. Four categories, shown in Table 1, guide irrigation control. Tsukamoto is selected for its ability to produce precise outputs, enabling efficient and adaptive water regulation rather than binary on–off decisions.

$$\text{IF soil moisture is } A_i \text{ THEN irrigation intensity is } C_i \qquad (1)$$

where A_i represents the fuzzy set of soil moisture conditions and C_i corresponds to the irrigation response. Since the Tsukamoto method requires monotonic membership functions in the consequents, each irrigation decision (e.g., *low flow*, *moderate flow*, *high flow*) is represented by monotonic fuzzy sets.

For every active rule, the firing strength (αi) is calculated based on the soil moisture membership values. Subsequently, a crisp output (z_i) is generated for each rule through the inverse of the consequent's membership function. The overall irrigation decision is obtained by aggregating the outputs of all rules using the weighted average formula:

$$Z = \frac{\sum_{i=1}^{n} a_i - z_i}{\sum_{i=1}^{n} a_i} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

This ensures that the irrigation intensity is precisely adjusted to the real-time soil moisture level.

By integrating IoT-based sensing with the Tsukamoto fuzzy inference system, the framework enhances water use efficiency and maintains optimal soil conditions for strawberry growth. This intelligent control mechanism not only reduces water wastage but also contributes to consistent yield quality in precision agriculture settings.

The soil moisture categories in Table 1 are modeled as fuzzy sets with overlapping ranges to represent gradual transitions between dry, slightly dry, ideal, and wet conditions. Within the Tsukamoto fuzzy inference system, each category is described using a monotonic membership function that transforms sensor data into membership degrees. For instance, at 40% soil moisture, the degrees are 0.5 for slightly dry and 0.33 for ideal, producing crisp outputs of 50% and

13.3%. A weighted average aggregation yields a final irrigation recommendation of 35.3%.

Table 1: Variables *Fuzzy Logic* Soil Moisture

Moisture (Input 1)	
Humidity	Information (%)
Dry	0 – 35
A little dry	25 – 45
Ideal	35 – 65
Wet	55 – 100

The second input variable, difference humidity, denotes the deviation between actual soil moisture and its reference level, expressed linguistically as not much (−35% to −15%), a little less (−25% to −5%), DNormal (−15% to 15%), and Excess (5–35%). Each category is modeled as a fuzzy set with overlapping intervals to ensure smooth transitions. Using the Tsukamoto method, monotonic membership functions assign firing strengths for each rule, generating crisp outputs through inverse functions. The watering time variable, serving as the system output, is expressed in four fuzzy categories—off (0 s), a moment (0–2 s), currently (1–5 s), and long (4–6 s)—allowing flexible and precise irrigation adjustments, as summarized in Table 2.

Table 2: Variables *Fuzzy Logic* Difference humidity

Difference Humidity (Input 2)	
Difference	Information
Not much	(-35) – (-15)%
A little less	(-25) – (-5)%
DNormal	(-15) – 15%
Excess	5 – 35%

Table 3 defines the fuzzy logic output variable for watering time within the proposed precision agriculture framework. It categorizes irrigation durations into four linguistic terms: off (0 s), a moment (0–2 s), currently (1–5 s), and long (4–6 s). These categories enable flexible, gradual irrigation control, supporting efficient strawberry cultivation through IoT-based soil moisture monitoring and Tsukamoto fuzzy inference.

Table 3: Variables *Fuzzy Logic* Watering Time

Watering Time	
Watering	Description (seconds)
Off	0

A moment	0 – 2
Currently	1 – 5
Long	4 – 6

Table 4 presents the fuzzy rules governing the Tsukamoto fuzzy inference system applied in precision agriculture for strawberry cultivation. It links soil moisture conditions, from dry to wet, with irrigation actions of different durations, including long, short, and irregular. This rule structure enables proportional water distribution, minimizing risks of under- or over-irrigation. By combining IoT-based soil monitoring with fuzzy logic, the system supports real-time, adaptive water control, ensuring resource efficiency while promoting optimal growth and productivity in strawberry farming.

Table 4: *Fuzzy Rule*

	Dry Soil Moisture	Soil Moisture Slightly Dry	Ideal Soil Moisture	Wet Soil Moisture
Not much	Long	Currently	A moment	Off
A little less	Currently	A moment	Off	Off
Normal	A moment	Off	Off	Off
Excess	Off	Off	Off	Off

Table 5 presents the soil moisture test results, illustrating the system's ability to maintain stable conditions through IoT-based monitoring and Tsukamoto fuzzy inference. Initially, soil moisture was low (44%), triggering a short watering action of 0.23 seconds. Subsequently, moisture stabilized at 85% with a consistent difference of 35%, leading to no further irrigation. The average values confirm effective regulation, demonstrating that the framework ensures precise water delivery while preventing excess irrigation, thereby supporting optimal strawberry cultivation.

Table 5: Test Results Soil Moisture

Time (minutes)	Moisture (%)	Difference (%)	Watering Time (second)
10	44%	-6%	0.23

20	85%	35%	0
30	85%	35%	0
40	85%	35%	0
50	85%	35%	0
60	85%	35%	0
70	85%	35%	0
80	85%	35%	0
90	85%	35%	0
100	85%	35%	0
Average	80.9%	32.1%	0.023

5.0 CONCLUSION

Based on the experimental results and analysis, it can be concluded that the IoT-based soil moisture monitoring system for strawberry cultivation operates effectively and as intended. The system successfully achieved an average soil moisture of 80.9%, an average difference of 32.1%, and an average watering duration of 0.023s, with real-time data displayed via LCD and ThingSpeak server despite a 2-second delay. Respondent satisfaction reached 68.49%, confirming practical usability. However, limitations remain in the Tsukamoto method and prototype design. Future studies should focus on improving soil moisture accuracy through advanced sensors and integrating real-time mobile notifications.

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