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An Intelligent IoT-Enabled Vermiculture Monitoring and Control System Based on Fuzzy Inference Approach (Case Studi : Siscamling)

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ABSTRACT Earthworm cultivation requires precise environmental control to sustain optimal growth, reproduction, and substrate integrity. However, existing vermiculture management systems predominantly rely on manual monitoring and fixed-threshold control strategies, which are insufficient for handling the dynamic and uncertain nature of environmental variables such as soil moisture, pH, and temperature. This limitation results in inconsistent habitat regulation, reduced earthworm productivity, and inefficient resource utilization. Furthermore, prior IoT-based agricultural monitoring studies have not adequately addressed adaptive decision-making under environmental uncertainty in the context of vermiculture. This study proposes an intelligent IoT-enabled monitoring and control system integrating a Sugeno fuzzy inference method to overcome these limitations through automated and adaptive environmental management in vermiculture at CV MSS, Lumajang. The system incorporates sensors for soil moisture, temperature, soil pH, water pH, and total dissolved solids, connected to a microcontroller and cloud platform for real-time monitoring and remote oversight via mobile application. Fuzzy logic governs the uncertainty in sensor readings and determines appropriate control actions, including irrigation, nutrient delivery, and ventilation, through a set of 27 IF-THEN inference rules. Experimental results demonstrate that the system effectively maintained substrate moisture within the optimal range of 15–30% and regulated pH values between 6.0 and 7.2. Automated responses — including irrigation activation at 40% moisture threshold and nutrient correction under mildly acidic conditions (pH 5.8) — were accurately triggered across all test scenarios with negligible transmission latency. These findings confirm that the proposed system offers a scalable, adaptive, and sustainable solution for smart vermiculture management, contributing to improved resource efficiency and reduced dependence on manual intervention in earthworm farming..

KEYWORDS: IoT; Fuzzy Logic Controller; Vermiculture; Environmental Monitoring; Smart Agriculture

I. INTRODUCTION

The earthworm is a soil organism that possesses a high competitive ability, a strong adaptive capacity, and relatively rapid dispersal[1]. These traits allow earthworm taxa to prevail across diverse terrestrial ecosystems. Besides sustaining ecosystem equilibrium, earthworms enhance soil structure via their burrowing activities and the decomposition of organic materials [2]. This procedure improves soil aeration, augments nutrient availability, and fosters beneficial microbial activity that facilitates plant growth [3].

The cultivation of earthworms is regarded as a strategic method for enhancing productivity, namely through the optimization of growth rates, reproduction, and population density [4]. Efficient and sustainable earthworm production can be achieved through the implementation of suitable cultivation techniques, including the regulation of environmental moisture, the provision of high-quality organic feed, and the correct management of substrate quality [3]. In addition to its ecological advantages, earthworm farming possesses economic significance, since earthworms can be employed for organic fertilizer, animal feed, and as raw materials in agriculture and aquaculture.

Regulating earthworm productivity is an essential component of the farming process. An effective strategy involves employing Internet of Things (IoT) technologies to monitor and regulate environmental conditions in real time [5]. Monitoring nutrient levels, soil pH, and moisture is

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crucial, as these elements significantly affect earthworm viability and reproductive behavior. Farmers can swiftly implement corrective measures in response to environmental changes that may diminish productivity, utilizing sensors and automated systems. The utilization of this technology enhances crop management efficiency and fosters a more stable environment, facilitating optimal growth and development of earthworms[6].

The habitat for earthworm cultivation must satisfy several environmental parameters to ensure optimal growth and reproduction. A shady location with air temperatures between 15–25°C is essential, as extreme temperatures can impair earthworm metabolism [7]. Furthermore, optimal air and soil moisture levels should be maintained between 15% and 30%, substrate acidity must be kept at a pH of 6.0 to 7.2, and an adequate supply of organic matter is essential as a nutrition source. Failure to meet these variables may subject earthworms to environmental stress, diminish habitat suitability, and increase the risk of reduced productivity or mortality [5].

Several previous studies have explored the implementation of IoT and fuzzy logic technologies in smart agriculture and vermiculture systems. Musyafa' et al. developed a fuzzy logic-based humidity control system for earthworm cultivation using Wemos D1 R2, which successfully automated substrate moisture regulation; however, the system was limited to single-parameter control without integrating additional environmental indicators. Kusuma [8] proposed an automatic nutrient delivery prototype for earthworm cultivation using fuzzy logic and solar power technology, yet the study mainly focused on nutrient automation and lacked real-time cloud monitoring capabilities. Rianto et al [5] introduced an ESP32-based smart farming system integrated with a website platform for earthworm cultivation monitoring, but the system primarily emphasized monitoring functions rather than adaptive decision-making mechanisms. Furthermore, Kurniasari et al [3] implemented an intelligent IoT-based fuzzy logic controller for hydroponic plant automation, demonstrating the effectiveness of fuzzy inference in environmental control; nevertheless, the application was limited to hydroponic agriculture and not specifically designed for vermiculture environments.

Compared with previous studies, the proposed research offers several advantages by integrating multi-parameter environmental monitoring, including soil moisture, soil pH, water pH, temperature, and total dissolved solids (TDS), within a unified IoT ecosystem. In addition, the implementation of the Sugeno fuzzy inference method enables adaptive and autonomous decision-making for irrigation [8], nutrient regulation, and ventilation control in real time. The integration of cloud-based monitoring and automated control mechanisms provides a more scalable, responsive, and sustainable solution for smart vermiculture management compared to existing systems that mainly focus on monitoring or single-variable automation.

However, previous studies on earthworm cultivation monitoring systems have primarily focused on single-parameter observation, such as soil moisture control, without integrating comprehensive environmental parameters including soil pH, water pH, temperature, and nutrient concentration within a unified intelligent control framework [9]. In addition, limited research has implemented adaptive fuzzy Sugeno-based decision-making combined with IoT cloud monitoring to enable autonomous and real-time environmental regulation for sustainable vermiculture management [10].

The management of earthworm habitats is predominantly executed manually by cultivators. This method frequently encounters difficulties as decision-making predominantly relies on estimation, including the time of substrate replacement and the evaluation of soil moisture levels. To preserve moisture, cultivators generally apply water intermittently; nevertheless, this method may prove ineffectual if the volume of water used is inadequate. Excessively moist soil can diminish oxygen levels, whilst overly dry soil might impede earthworm activity, both of which may result in reduced productivity.

To address these constraints, the implementation of technology-based sensors can enhance the accuracy of habitat status monitoring. A frequently utilized instrument is the soil moisture sensor, which functions by producing an electrical output signal in reaction to the presence of water between cylindrical capacitor plates. This sensor comprises two probes that transmit electrical current through the soil and assess resistance to ascertain moisture levels. Increased water content enhances the soil's electrical conductivity, while dry soil demonstrates elevated electrical resistance [11].

Fuzzy logic was selected in this research due to its capability to handle uncertainty, nonlinearity, and imprecise environmental conditions commonly found in vermiculture systems [6]. Unlike conventional threshold-based control methods, which rely on rigid parameter boundaries, fuzzy logic enables gradual and adaptive decision-making based on linguistic variables such as "dry," "optimal," or "wet." This characteristic is particularly important in earthworm cultivation, where environmental parameters continuously fluctuate and cannot always be represented using exact mathematical models [12].

Compared with PID controllers, fuzzy logic does not require an accurate mathematical model of the system and performs effectively in dynamic environments with multiple interacting variables,

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such as soil moisture, temperature, and pH. In addition, machine learning approaches generally require large training datasets, higher computational resources, and longer training processes, making them less practical for low-cost embedded IoT systems. Therefore, the Sugeno fuzzy inference method provides a more efficient, interpretable, and computationally lightweight solution for real-time environmental monitoring and autonomous control in smart vermiculture applications.

Method

The technology to be built is intended to monitor and autonomously regulate habitat conditions. The diagram is fundamentally divided into three primary components: input, process, and output. This paradigm emulates the nervous system of real animals, with sensors representing the senses, the microcontroller functioning as the brain, and actuators acting as the muscles that implement the microcontroller's choices.

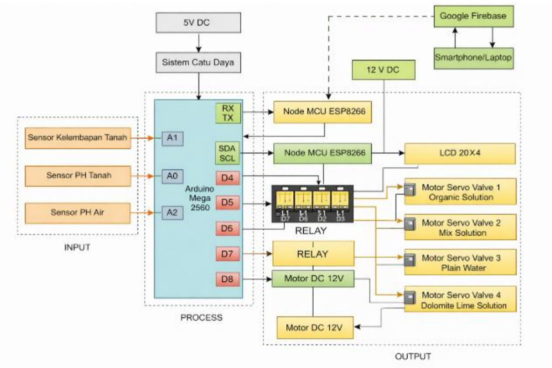

Figure 1 Sensor Model

Three sensor types in the input part yield complementing data: a soil moisture sensor, a soil pH sensor, and a water pH sensor. These devices gather environmental data crucial for earthworm comfort and cutaneous respiration, whereas pH levels affect the stability of enzymes and microorganisms in the substrate. The chosen input variables—soil moisture, soil pH, and water pH—directly influence habitat appropriateness and earthworm productivity [5]. Analog data from these sensors is transferred via pins A0–A2 to the Arduino Mega 2560 for subsequent processing.

In the processing phase, the Arduino Mega 2560 analyzes the sensor data prior to relaying it to the NodeMCU ESP8266, which facilitates internet connectivity and permits data transmission to Google Firebase for real-time monitoring using a smartphone or laptop [10]. The system utilizes fuzzy logic to address uncertainty and environmental variability that cannot always be accurately delineated. Each input is classified into fuzzy sets, including moisture (dry, optimum, wet) and pH (acidic, neutral, alkaline), and the sensor data are subjected to fuzzification to ascertain their degree of membership. The system employs IF–THEN rules; for example, IF moisture is dry, THEN the water pump activates, or IF pH is neutral and moisture is ideal, THEN no action is executed. The Sugeno approach yields a constant output for each rule, denoting the degree of control action, whereas a weighted average of all active rules produces a singular decision value. The system is energized by two sources: a 5V DC supply for the microcontroller and sensors, and a 12V DC supply for higher-power components, guaranteeing stable operation.

The output portion utilizes relays to drive actuators, such as a servo motor and a DC motor, which manage the distribution of water and fertilizer solution based on the requirements of the growth medium. The fuzzy system's decision value is utilized by the microcontroller to autonomously run actuators, including the activation of pumps and the adjustment of water valves. A 20×4 LCD also presents habitat condition data to facilitate on-site monitoring [13]. This integrated mechanism ensures environmental stability in the cultivation habitat, diminishes dependence on manual control, and has the potential to improve the efficiency and production of earthworm farming.

B FUZZY SUGENO

The reasoning process of the Sugeno fuzzy logic approach resembles that of the Mamdani method, especially in the fuzzification and inference phases that utilize IF–THEN rules [4]. The primary distinction resides in the system output: the Mamdani technique yields a fuzzy set necessitating defuzzification, whereas the Sugeno method gives outputs as constant values or linear equations, thereby streamlining the computational process and enhancing efficiency. The Sugeno model use the height technique, or weighted average, to ascertain the ultimate output value by initially determining the firing strength (α_i) of each rule and subsequently amalgamating them using the following equation [14]:

$$Z = \frac{\sum(\alpha_i \cdot z_i)}{\sum \alpha_i}$$

where α_i indicates the firing strength of the i-th rule, Z is the ultimate output value, and z_i is the consequent value of each rule, usually represented as a linear equation or a constant. Moreover, the output variables in the Sugeno approach employ singleton membership functions—individual values that denote each rule consequent—facilitating a more expeditious defuzzification process[15]. This approach is ideally suited for automated control systems necessitating rapid reactions and minimal computational load.

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C. SYSTEM DEVELOPMENT

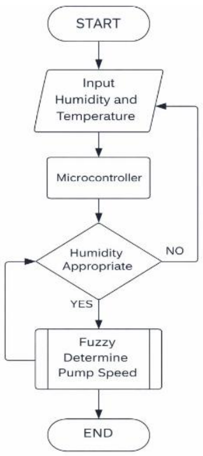

Figure 2 Flowchart System Development

Figure 2 illustrates the workflow of the IoT-based fuzzy logic control system designed for monitoring and regulating environmental conditions in vermiculture cultivation. The process begins with the initialization stage (*Start*), followed by the acquisition of environmental data through humidity and temperature sensors. These sensors continuously measure the condition of the cultivation media to ensure that the environmental parameters remain within the optimal range required for earthworm growth and reproduction.

The collected sensor data are then transmitted to the microcontroller, which acts as the central processing unit of the system. The microcontroller evaluates whether the measured humidity conditions are appropriate according to the predefined threshold values. If the humidity level is not suitable, the system returns to the monitoring stage and continuously reads new environmental data until the required conditions are achieved.

When the humidity level is identified as appropriate, the fuzzy logic controller is activated to determine the appropriate pump speed. The fuzzy inference process analyzes the environmental input variables and generates adaptive control actions based on predefined fuzzy rules. The pump speed is then adjusted automatically to maintain stable environmental conditions within the cultivation medium. This automated mechanism enables efficient water management, minimizes manual intervention, and improves the stability of the vermiculture environment. Once the control action has been executed, the process reaches the final stage.

II. RESULT AND DISCUSSION

The soil pH sensor was evaluated to ascertain the precision of the readings utilized in the system. The testing procedure entailed comparing the measurements acquired by a stick-type soil pH sensor with the pH values recorded by a reference device, specifically the 4-in-1 Soil Survey Instrument. This assessment was performed on many soil samples exhibiting diverse acidity levels to illustrate sensor efficacy across various environmental circumstances.

The measurement results were evaluated by computing the percentage error to determine the discrepancy between the values recorded by the sensor and the actual values from the reference equipment. The error computation was executed utilizing the subsequent equation:

$$error = \left(\frac{True\ Value - \ measured\ value}{True\ Value}\right) \text{x } 100\%$$

A minimal error number signifies that the sensor possesses high accuracy and is appropriate for the soil monitoring system, whereas a substantial error value indicates the necessity for calibration or other modifications. The objective of this testing is to ensure that the soil pH sensor generates dependable data, which will facilitate more precise and efficient decision-making within the control system, for linguistic variable for soil and temperature variables :

Tabel 1 Membership Function Parameters of Fuzzy Inference System

Variable	Linguistic Set	MF Type	Parameters	ange
Soil Moisture (%)	Dry	Trapezoid	[0, 0, 10, 18]	0 – 50%
	Normal	Triangle	[10, 22, 35]	0 – 50%
	Wet	Trapezoid	[28, 38, 50, 50]	0 – 50%
Soil pH	Acidic	Trapezoid	[4.0, 4.0, 5.5, 6.7]	4.0 – 9.0
	Neutral	Triangle	[5.5, 6.5, 7.6]	4.0 – 9.0
	Alkaline	Trapezoid	[6.8, 7.8, 9.0, 9.0]	4.0 – 9.0
Temperature (°C)	Cold	Trapezoid	[5, 5, 13, 20]	5 – 40°C
	Normal	Triangle	[13, 20, 27]	5 – 40°C
	Hot	Trapezoid	[22, 28, 40, 40]	5 – 40°C
Water pH	Acidic	Trapezoid	[4.0, 4.0, 5.5, 6.7]	4.0 – 9.0

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Variabl e	Linguis tic Set	MF Type	Parame ters	ange
	Neutral	Triangl e	[5.5, 6.5, 7.6]	4.0 – 9.0
	Alkalin e	Trapez oid	[6.8, 7.8, 9.0, 9.0]	4.0 – 9.0
Output (Control Action)	Monito ring	Singlet on	z = 5	0 – 40
	Waterin g	Singlet on	z = 20	0 – 40
	Add Nutrien ts	Singlet on	z = 25	0 – 40
	Activat e Fan	Singlet on	z = 30	0 – 40
	Combin ed Action	Singlet on	z = 35	0 – 40

Table 1 delineates the linguistic variables of the soil moisture sensor, utilized as input parameters in the fuzzy logic system. The membership functions are categorized into three states: dry, normal, and moist. Soil is deemed dry when its moisture content falls below 15%, signifying the necessity for supplementary water to sustain optimal conditions. The typical group denotes moisture levels ranging from 15% to 30%, indicating that the soil possesses adequate water content to maintain environmental stability. Concurrently, soil is classified as wet when moisture levels above 30%, indicating a rather substantial water content that may not necessitate further watering. These classifications assist the system in identifying suitable control measures to sustain equilibrium in soil conditions.

Figure 3 IoT Tools for automation

The IoT-based monitoring system has undergone comprehensive testing across many environmental conditions. The employed sensors—temperature, humidity, soil moisture, pH, and TDS—transmit data in real-time to an ESP32 board linked to the cloud, facilitating remote monitoring. The test findings indicate that the sensors deliver reliable and precise readings, while intermittent network outages have impacted the data transfer process. Nonetheless, these disturbances were negligible and could be promptly rectified.

Under a variety of environmental conditions, the IoT-based monitoring system was subjected to a rigorous evaluation of its reliability and performance. Sensors gauging temperature, humidity, soil moisture, pH, and TDS relayed real-time data to the ESP32 board, which was linked to a cloud platform for remote surveillance. The results demonstrated that the sensors reliably generated precise measurements, while occasional minor network disruptions impacted data transmission. The faults were minor and handled swiftly, illustrating the system's stability.

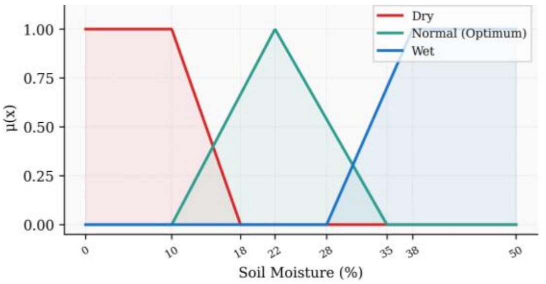

Figure 4 Membership Function - Soil Mosture

Soil Moisture and pH Regulation: At 7:00 AM, the soil moisture sensor recorded a value of 40%, activating the automatic irrigation system. Concurrently, the pH level decreased to 5.8, signifying mildly acidic circumstances, necessitating an adjustment in nutrient delivery by the system. The data validate that the IoT system consistently upheld adequate soil moisture and nutrient equilibrium, consequently improving the efficacy of the hydroponic environment.

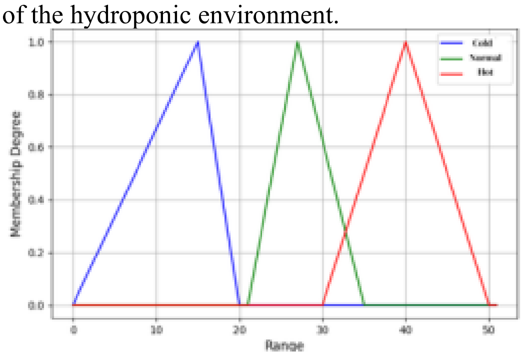

Figure 5 Membership Function Of Temperature

The fuzzy logic component was thoroughly assessed to guarantee correct operation throughout all phases, including fuzzification, rule evaluation, aggregation, and defuzzification. Various test scenarios were developed by altering environmental

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parameters including temperature, humidity, soil moisture, pH, and total dissolved solids (TDS). These differences facilitated a comprehensive evaluation of the system's capacity to handle real-time sensor data and engage suitable actuators, including fans and misting devices.

Table 2 presents sample environmental monitoring data used in the fuzzy logic testing process for the vermiculture monitoring system. The parameters include soil moisture, temperature, and total dissolved solids (TDS), which are essential variables influencing earthworm habitat quality and productivity. The data are categorized into several environmental conditions to evaluate the fuzzy inference system's capability in generating adaptive control actions.

Tabel 2 Enviromental Research Data

No	Time	Soil Moisture (%)	Temperature (°C)	TDS (ppm)	Environmental Condition	Fuzzy Output / Action
1	2025-01-01 07:00	12	18	350	Dry & Cold	Activate Water Pump
2	2025-01-01 09:00	18	22	420	Normal	Monitoring Mode
3	2025-01-01 11:00	28	27	500	Optimal	No Action
4	2025-01-01 13:00	35	31	650	Wet & Hot	Activate Fan
5	2025-01-01 15:00	14	29	700	Dry & High Nutrient	Watering + Ventilation
6	2025-01-01 17:00	22	24	450	Stable Condition	Monitoring Mode
7	2025-01-01 19:00	10	20	300	Very Dry	Maximum Pump Speed
8	2025-01-01 21:00	32	26	580	Moist Condition	Reduce Irrigation
9	2025-01-02 07:00	20	23	430	Ideal Condition	Monitoring Mode
10	2025-01-02 10:00	16	30	620	Dry & Hot	Activate Pump and Fan

Based on the fuzzy membership classification, soil moisture values below 15% are categorized as "Dry," values between 15%–30% as "Normal," and values above 30% as "Wet." Temperature values are classified into "Cold," "Normal," and "Hot" categories, while TDS values represent nutrient concentration levels within the cultivation substrate. The fuzzy inference system processes these environmental parameters simultaneously to determine adaptive control actions, including irrigation activation, ventilation control, and monitoring status.

No	Temperature (°C)	Humidity (%)	Soil Moisture (%)	TDS (ppm)	Temperature Fuzzy Set	Moisture Fuzzy Set	TDS Fuzzy Set	Rule Evaluation	Defuzzification Output	System Action
1	18	82	12	350	Cold	Dry	Low	R1	28	Activate Water Pump
2	22	75	18	420	Normal	Normal	Medium	R2	10	Monitoring Mode
3	27	70	28	500	Normal	Normal	Medium	R3	12	No Action
4	31	60	35	650	Hot	Wet	High	R4	32	Activate Fan
5	29	65	14	700	Hot	Dry	High	R5	35	Watering + Ventilation

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6	24	76	22	450	Normal	Normal	Medium	R6	10	Monitoring Mode
7	20	80	10	300	Cold	Dry	Low	R7	38	Maximum Pump Speed
8	26	72	32	580	Normal	Wet	High	R8	18	Reduce Irrigation
9	23	74	20	430	Normal	Normal	Medium	R9	8	Stable Monitoring
10	30	62	16	620	Hot	Dry	High	R10	34	Activate Pump and Fan

Table 7 encapsulates the outcomes of the fuzzification and rule evaluation processes based on the environmental data collected during system testing. Each parameter was transformed into linguistic variables using predefined fuzzy membership functions. The fuzzy inference engine then evaluated the active rules and generated defuzzification outputs to determine the most appropriate control action for maintaining optimal vermiculture environmental conditions.

The results in Table 7 validate the dependability of the fuzzy logic system in regulating environmental parameters. Through the analysis of real-time data, the controller effectively implemented requisite measures, such as activating fans, commencing irrigation, and modifying nutrient levels in accordance with consolidated fuzzy assessments.

The data further illustrates the system's flexibility to fluctuating environmental conditions. On January 1, 2025, at 13:00:00, when the temperature attained 31.2°C and humidity decreased to 60%, the system accurately recognized the necessity for nutritional modification and engaged the fan. Conversely, under steady conditions observed on 2025-01-02 at 07:00:00 (temperature: 24°C, humidity: 76%, soil moisture: 41%), the system persisted in monitoring mode, demonstrating its capacity to manage non-critical situations effectively.

Defuzzification was essential in converting fuzzy values into exact control actions. On January 1, 2025, at 07:00:00, the defuzzified output advised irrigation, which was crucial for sustaining appropriate soil moisture levels. The device exhibited commendable performance during testing, demonstrating significant adaptability to diverse environmental variables. The fuzzy logic controller efficiently governed irrigation, cooling, and nutrient management utilizing real-time sensor data and inference methods. The defuzzification procedure effectively transformed fuzzy evaluations into actionable outputs with minimum inaccuracy.

The system's principal strength is the seamless integration of IoT sensors with the fuzzy logic controller, facilitating efficient real-time monitoring and automated reactions. The system demonstrated exceptional reliability and reactivity to fluctuating environmental conditions. Moreover, the utilization of fuzzy logic demonstrated benefits in managing uncertainty, thus facilitating steady and optimum growth conditions.

Notwithstanding these advantages, some restrictions were recognized. Intermittent connectivity concerns during IoT testing occasionally resulted in delays in data transmission between sensors and the cloud platform. The issues were promptly resolved by enhancing network setups and augmenting internet stability. Moreover, although the fuzzy logic controller operated efficiently, the rule base may be enhanced through additional refining. Refining the rule definitions would augment responsiveness in extreme settings, such as fast temperature variations, hence enhancing the system's overall robustness and performance.

III. CONCLUSION

This study successfully developed an IoT-based intelligent monitoring and control system for vermiculture at CV MSS, Lumajang, integrating a Sugeno fuzzy inference method with real-time environmental sensors for soil moisture, soil pH, water pH, and temperature. The system demonstrated reliable performance in maintaining optimal habitat conditions for earthworm cultivation, sustaining substrate moisture within the ideal range of 15–30% and regulating pH values between 6.0 and 7.2. Automated control actions — including irrigation activation at 40% moisture

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threshold and nutrient correction under mildly acidic conditions (pH 5.8) — were triggered accurately across all test scenarios, with negligible data transmission latency between sensors and the cloud platform. These results confirm that the integration of fuzzy logic with IoT technology provides an adaptive, scalable, and efficient solution for smart vermiculture management, reducing reliance on manual monitoring and improving overall resource efficiency. Future research may explore the incorporation of machine learning for predictive habitat control and expansion toward commercial-scale vermiculture deployment.

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