Development of Smart Farming Control System based on Tsukamoto Fuzzy Algorithm

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***Abstract*—Smart farming is one of the most effective methods to increase productivity. Smart farming is changing the face of conventional agriculture methods by making them convenient, cost-effective, and energy-efficient, as well as minimizing crop waste. Smart farming reduces the physical labor produced by humans, such as irrigation, fertilization, application of pesticides, and many more. Smart farming is used for monitoring and determining the current pH level, air temperature, soil temperature, and humidity in agricultural land. With this method, the plants will have always good condition to support them. Moreover, the production of agricultural land will be increased. This paper proposes the development of smart farming monitoring system, which uses ESP32 for the microcontroller, 4 sensors for monitoring the input data, and an actuator for activating the water pump. This system is supported by Tsukamoto Fuzzy Logic based on the norms of human resources with the criteria that have been determined. The initial step is the fuzzification process which includes four input parameters (pH sensor, humidity sensor, air temperature sensor, and soil temperature sensor) used as reference values to determine defuzzification. This process is carried out through all rules. The next step is to determine the defuzzification process, which is to determine the output produced by the actuator in the water pump to release the water. The result of this paper is to produce a system that can help farmers monitor environment data from each sensor in real time and help the farmers watering the plant automatically.**

Keywords— Smart Farming; Fuzzy Logic; ESP32; Tsukamoto

I. INTRODUCTION

In the digitalization era, almost all systems and equipment utilize technology. One of the systems that can be used is Smart Farming. This system can monitor agricultural land in real-time and make agriculture more profitable for the farmers. Decreasing resource inputs will save the farmer money and labor, and increased reliability of spatially explicit data will reduce risks [1].

This system is designed to make farmers easy to use and to know parameters, namely soil moisture, temperature, pH, and automatic watering, which affect the growth of agriculture plants. This system can also increase production and is very useful for farmers in making decisions [2],[3],[4].

The current problem in Indonesia is that farmers do not have the appropriate technical assistance to manage and optimize crops efficiently with plant nutrients [5]. Therefore, we are developing a system to help Indonesian farmers solve these problems. The system is built on the idea of fuzzy logic and uses a sensor system for soil irrigation [5] and precision agriculture [6],[7].

The paper proposes the development of soil irrigation based using fuzzy logic. This paper is developing a smart farming monitoring system using four sensors, namely pH sensor, humidity sensor, air temperature sensor, and soil temperature sensor, based on the fuzzy algorithm.

II. RELATED WORK

Smart farming technology is developing with many researchers to make farming more efficient and innovative. Previous authors have declared many methods. In the IoT (Internet of Things) study, some researchers have been surveyed about smart farming based on cloud computing [8]. The advantage of this study is low-cost hardware and more reliability using cloud computing. Another method is using GSM (Global System for Mobile communication) to control the greenhouse [9]. The advantage of this study is the ability to reduce human efforts and time using GPS. Moreover, another study proposed smart farming monitoring using IoT based on mobile applications (Blynk) and serial monitoring [10]. Furthermore, the researcher describes a light spectra method for optimizing plant growth [11]. This experiment consisted of four led spectrums, red, blue, green, and white, to grow tomato plants. It found that the blue spectrum LED affected plant growth.

In the fuzzy logic model, research has been conducted to automate a sugarcane field's watering [5]. Similarly, a study in fuzzy logic combined with wireless data monitoring to control the greenhouse [12]. Other research proposed fuzzy logic processing using IoT for growing plants [13],[14],[15].

III. THE PROPOSED CONTROL SYSTEM DESIGN

This section describes the theory of control system design consisting of a diagram system and fuzzy logic system used in the proposed work.

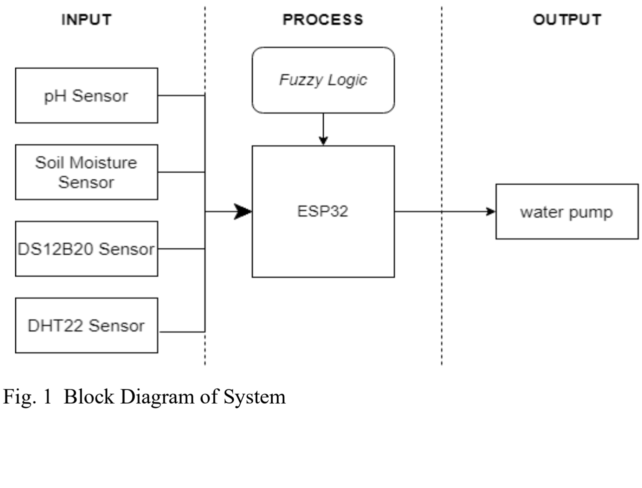


Fig. 1 Block Diagram of System

A. Diagram System

This system explains the diagram of smart farming system, which consists of block diagram, flowchart diagram, and hardware diagram.

The block diagram in Fig. 1 shows the input from a pH soil sensor, soil moisture sensor, soil temperature sensor (DS18B20), and air temperature and humidity sensor (DHT22). All sensors data are processed in microcontroller ESP32. The Fuzzy logic model is implemented to process data from those sensors. The output in this system is to control the water pump.

The flowchart diagram in Fig. 2 shows the sensors started reading data. The data reading results will be categorized based on the function of each sensor. The selected data from the categorized data above fulfills the criteria needed to decide the water pump activation and displays the real-time data to the user.

B. Fuzzy Logic

Fuzzy logic is an algorithm working with fuzzy numbers with uncertainty conditions [12]. Fuzzy logic is used to imitate human reasoning and cognition [16]. The Tsukamoto fuzzy method is used to assist in providing recommendations quickly, precisely, and accurately. Each consequence of the IF-THEN rule must be represented in a fuzzy set with a monotonous membership function. This method has three steps: fuzzification, fuzzy rule inference, and defuzzification [17]. The fuzzy logic diagram is shown in Fig. 3.

Fuzzification is the first step for converting a crisp input value to a fuzzy value that is performed by using the information in the knowledge base [18],[19]. The Fuzzification step includes the expert's knowledge to define the area of the condition of each parameter [20]. In fuzzification, a fuzzy set will determine the membership value between 0 and 1. Suppose there is a set A, and x is an element of it. If x has a value of 0 means x is not a member of set A. Likewise, if x has a value of 1, it means that x becomes a full member of set A.

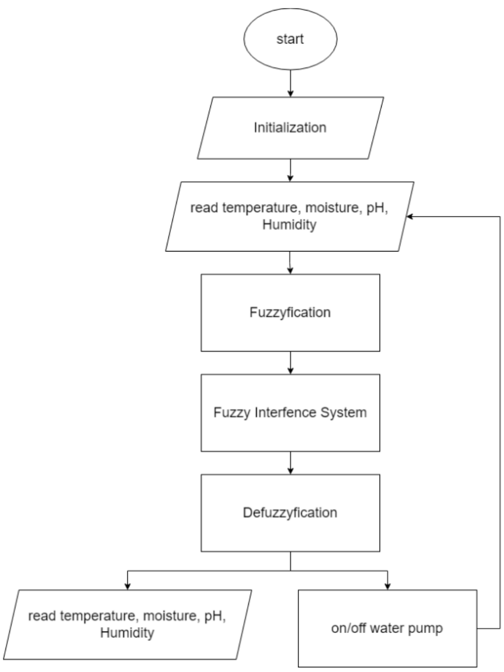


Fig. 2 Flowchart Diagram System

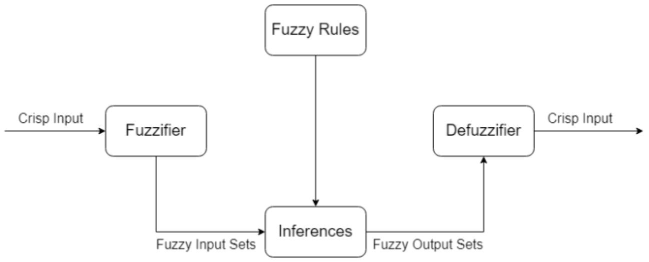


Fig. 3 The Workflow of Fuzzy Logic

This paper proposes five sensor variables and one actuator variable to determine each range and membership function in a smart farming system. The pH soil variable consists of 3 membership sets, namely acid, normal, and base. Fig. 4 represents the pH sensor's membership function. The value is categorized into three criteria, acid with a range of 0 - 6, normal in a range of 7, and wet in a range of 8 – 14.

The air temperature variable consists of 3 membership sets, namely cold, normal, and warm. Fig. 5 represents the membership function of air temperature sensor. The value is categorized into three criteria: cold in the range of 0 – 15 degrees Celsius, normal in a range of 16 – 40 degrees Celsius, and warm in a range of 41 – 60 degrees Celsius.

The soil temperature variable consists of 3 membership sets, namely cold, normal, and warm. Fig. 6 represents the membership function of the soil temperature sensor. The value is categorized into three criteria: cold in the range of 0 – 15 degrees Celsius, normal in a range of 16 – 40 degrees Celsius, and warm in a range of 41 – 60 degrees Celsius.

The humidity variable consists of 3 membership sets, namely dry, normal, and wet. Fig. 7 represents the membership function of the humidity sensor. The measurement unit of humidity is Relative Humidity (RH). The value is categorized into three criteria: dry with a range of 0% – 40 % RH, normal with 41% – 70% RH, and wet with 71% – 100% RH.

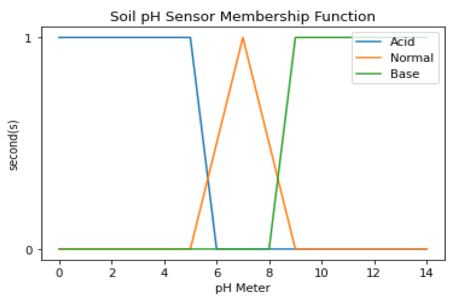


Fig. 4 Membership Function of Soil pH Sensor

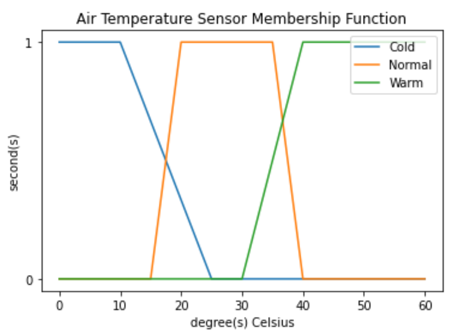


Fig. 5 Membership Function of Air Temperature Sensor

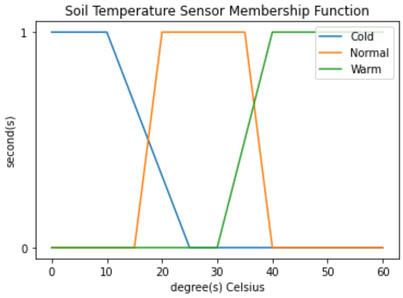


Fig. 6 Membership Function of Soil Temperature Sensor

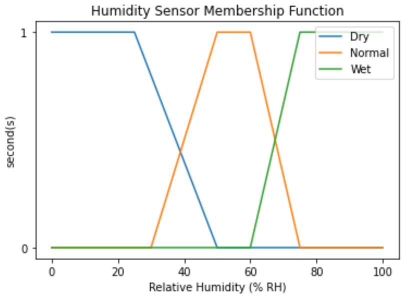


Fig. 7 Membership Function of Humidity Sensor

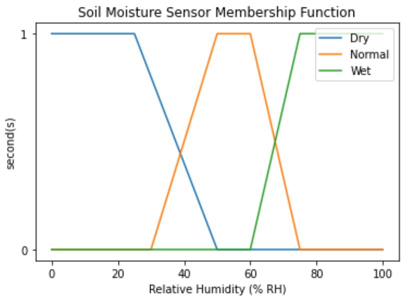


Fig. 8 Membership Function of Soil Moisture Sensor

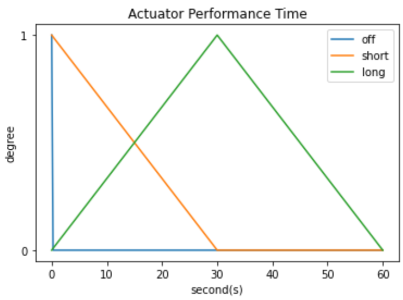


Fig. 9 Actuator Performance Time

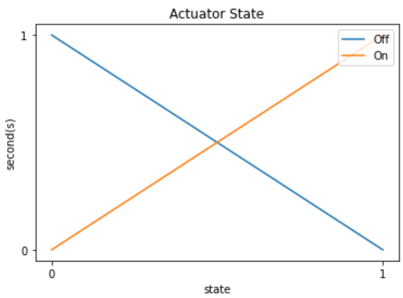


Fig. 10 Actuator State

The humidity variable consists of 3 membership sets, namely dry, normal, and wet. Fig. 8 shows the membership function of the soil moisture sensor. The measurement unit of moisture is Relative Humidity (RH). The value is classified into three groups: dry with a range of 0% – 40 %, normal with 41% – 70%, and wet in the range of 71% – 100% range.

The actuator in the proposed smart farming system uses a water pump connected to a relay. The variable of this actuator is symbolized by A, consisting of 3 membership sets, namely off, short, and long in units of seconds. Fig. 9 represents the actuator performance time of the actuator. If the condition is off, the line diagram will not move up. The chart will move up for 30 seconds in short-time condition. Likewise, for a long-time, the graph will move for 60 seconds. Fig. 10 represents the membership function of the water pump state. The value is categorized into two criteria: on-state, which has a value of 1, and off-state, which has a value of 0.

Inference is a process by using a function MIN application to get the value of each α-predicate rule (α1, α2, α3, α4,…, αn. Then each value of α-predicate is used to calculate output results (crisp). The rule of this process is shown in (1).

$$\begin{gathered} if\ a_1\ is\ A_{i1}\ and\ a_2\ is\ A_{i2}\ \ldots \\ and\ a_n\ is\ A_{in}\ then\ B_i \end{gathered} \tag{1}$$

Where a is a variable. A is membership of variable a. k is the index of membership of a. B is membership of the output membership function. From (1) above, the sample results of the inference rule obtained from calculating the fuzzy membership values in the fuzzification step are shown in (2).

[R1] if Soil Moisture is dry and Humidity is dry and Soil pH is acid and Air Temperature is cold and Soil Temperature is cold then long-time watering
[R2] if Soil Moisture is dry and Humidity is normal and Soil pH is acid and Air Temperature is cold and Soil Temperature is cold then short-time watering
[R3] if Soil Moisture is dry and Humidity is normal and Soil pH is acid and Air Temperature is normal and Soil Temperature is normal then short-time watering (2)
[R4] if Soil Moisture is normal and Humidity is normal and Soil pH is acid and Air Temperature is normal and Soil Temperature is warm then actuator is off

Equation (2) can be explained that R1 - R5 is a condition variable. Dry, acid, normal, cold, and warm are membership of soil moisture, humidity, pH, air temperature, and soil temperature. TABLE I shows the samples of fuzzy rules.

Defuzzification converts inference engine output from fuzzy to crisp [19]. This step turns the fuzzy number back into a crisp number to obtain the decision. In the Tsukamoto method, to determine the output crisp, the defuzzification-centered average is shown in (3).

TABLE II. SAMPLE OF FUZZY RULES

Soil Moisture	Humidity	pH	Air Temperature	Soil Temperature	water pump
dry	dry	acid	cold	cold	long
dry	dry	acid	cold	normal	long
dry	dry	acid	cold	warm	long
dry	normal	acid	normal	cold	short
dry	normal	acid	normal	normal	short
dry	normal	acid	normal	warm	short
dry	wet	normal	warm	cold	short
dry	wet	normal	warm	normal	short
dry	wet	normal	warm	warm	short
normal	dry	normal	cold	cold	short
normal	dry	normal	cold	normal	short
normal	dry	normal	cold	warm	short
normal	normal	base	normal	cold	off
normal	normal	base	normal	normal	off
normal	normal	base	normal	warm	off
normal	wet	base	warm	cold	off
normal	wet	base	warm	normal	off
normal	wet	base	warm	warm	off
wet	dry	base	cold	cold	off
wet	dry	acid	cold	normal	off
wet	dry	acid	cold	warm	off
wet	normal	acid	normal	cold	off
wet	normal	acid	normal	normal	off
wet	normal	acid	normal	warm	off
wet	wet	acid	warm	cold	off
wet	wet	acid	warm	normal	off
wet	wet	acid	warm	warm	off

$$Z = \frac{\propto 1 * z1 + \propto 2 * z2 \ldots + \propto_n * z_n}{\propto 1 + \propto 2 \ldots + \propto_n} \qquad (3)$$

Where Z is the defuzzification value of the actuator parameter, $\propto$ is the value of minimal predicate inference rules, and z is membership value of the actuator performance time.

IV. IMPLEMENTATION

This paper is based on a greenhouse system's Internet of Things (IoT) concept. This experiment uses three components. There are ESP32, sensors (pH sensor, air temperature - humidity sensor, soil moisture sensor, soil temperature sensor), and a water pump.

A. *Experiment Setup*

The microcontroller, sensors, and water pump are combined into a handmade tool. The tool consists of a grey box containing the ESP32 microcontroller, the actuator, and the associated cables. Besides that, a pipe rod is used to stick it into the soil, water pump, and sensors. This tool is shown in Fig. 11.

This experiment was carried out in potted plants 43 centimeters in diameter and 32 centimeters in height. Then smart farming tool was plugged into the soil from the potted plant. This tool reads the data value from the plant. The bottle of water was used to water the plants through the water pump when in dry condition. This method is shown in Fig. 12.

B. *Experiment Result*

This system was tested five times on the same day, in the morning, afternoon, evening, and night. There was no rain at all on this day. Therefore, the data resulting from the soil moisture sensor, humidity sensor, air temperature, and soil temperature was dry in every test. TABLE III shows the data result of sensors and the water pump action based on fuzzy logic in Fig. 4 - 10 and the fuzzy rule base system.

This is a comparison graph between the experimental time and the reading results for each sensor based on the data result in TABLE IV, as shown in Fig. 11.

V. CONCLUSION

This paper applies a system of farming technology to control and monitor agricultural land using the fuzzy algorithm method. The membership function on the fuzzy logic is designed from each data sensor. This system effectively increases agricultural land quality using pH sensors, humidity sensor, air temperature sensor, soil temperature sensor, and water pump.

This study needs some improvement in analyzing and handling this system with damage that may appear by adding a database system for monitoring the history of this system. It also requires an approach to improve the performance by adding image detection and protection system from pests or insects.

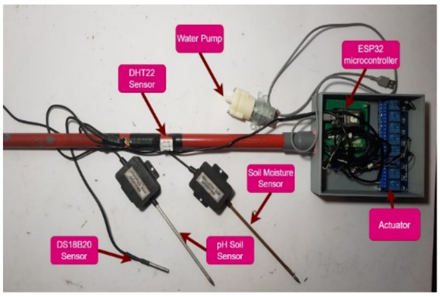
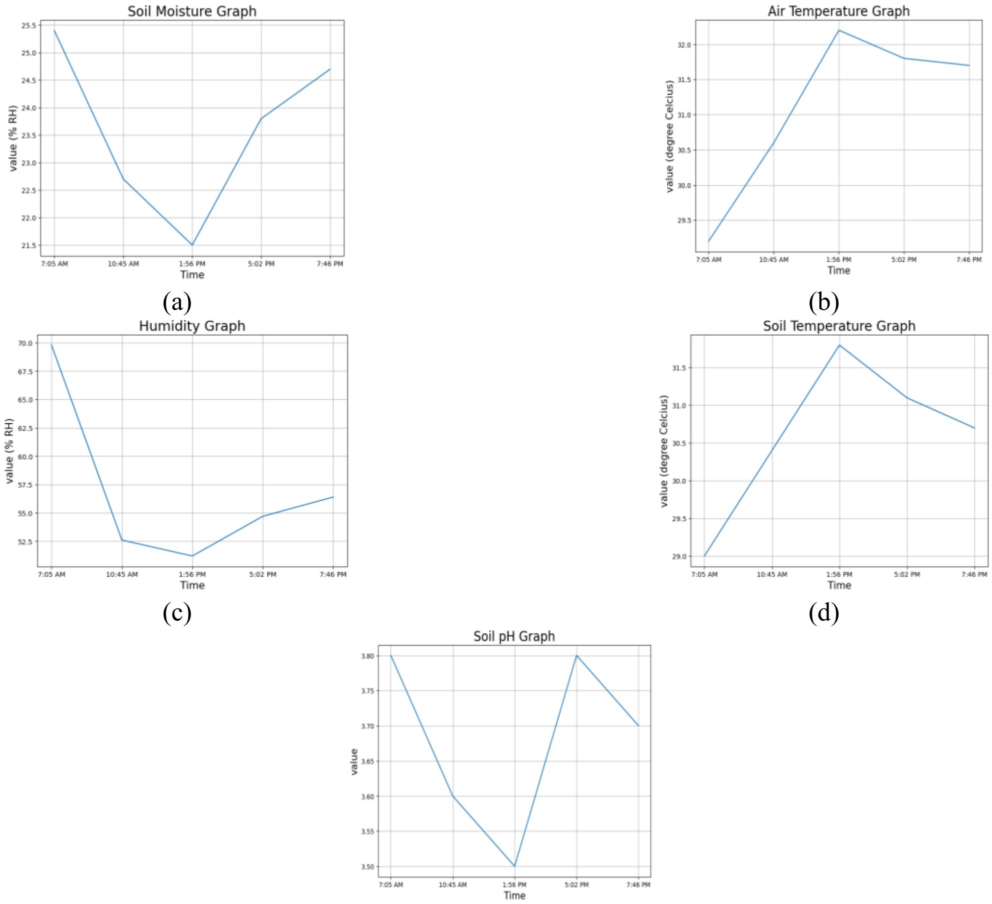


Fig. 11 Smart Farming Tool

Fig. 12 Experiment Setup of Smart Farming Tool

TABLE V. EXPERIMENTAL RESULT

No	Date	Time	Data					Time (second(s))
			Soil Moisture (% RH)	*Humidity (% RH)*	*Soil pH*	*Air Temperature (degree Celsius)*	*Soil Temperature (degree Celsius)*	*Water Pump*
1	02/12/2022	7:05 AM	25.4	69.8	3.8	29.2	29.0	30
2	02/12/2022	10:45 AM	22.7	52.6	3.6	30.6	30.4	30
3	02/12/2022	1:56 PM	21.5	51.2	3.5	32.2	31.8	30
4	02/12/2022	5:02 PM	23.8	54.7	3.8	31.8	31.1	30
5	02/12/2022	7:46 PM	24.7	56.4	3.7	31.7	30.7	30



(a) (b) (c) (d) (e)

Fig. 13 Graphic of Data Sensor

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