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A Comparative Analysis of Sugeno and Tsukamoto Fuzzy Logic for Temperature Stability in SCAMIS

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Abstract **– The digital poultry sector faces challenges in maintaining stable incubation temperatures. Comparative evaluation between Sugeno and Tsukamoto methods has not been conducted in real-world IoT systems. This research is essential to identify the most effective fuzzy logic control approach for smart incubators. This study aims to compare the effectiveness of Sugeno and Tsukamoto fuzzy logic methods through implementation in the SCAMIS platform. A comparative experimental design was employed using Sugeno and Tsukamoto models in SCAMIS. Temperature data were collected via DHT22 sensors and analyzed quantitatively. Code validation and sensor accuracy tests ensured data reliability and the credibility of fuzzy decision-making processes. The accuracy level of the DHT22 sensor when detecting temperature is 98.31%. The comparison of response time from initial temperature to target temperature (30°C - 38°C) between the Tsukamoto and Sugeno fuzzy logic methods is 1 : 3. Tsukamoto takes 1 hour 52 seconds (3,652 seconds), while Sugeno takes 3 hours 1 second (10,801 seconds). The response time required by Tsukamoto for each 1°C temperature increase is 1–7.5 minutes, while Sugeno is 1–10.3 minutes. However, in terms of temperature stability, Sugeno is more stable with an accuracy rate of 98.40% approaching the target temperature, while Tsukamoto has an accuracy rate of 96.93%. These results indicate a significant trade-off between the speed of reaching the target temperature and stability at the target temperature. Control method selection should align with specific operational priorities in smart incubation systems. These findings recommend choosing fuzzy methods based on system priorities. Future studies should evaluate energy consumption and hatching success efficiency.**

Keywords: fuzzy logic, temperature stability, smart incubator, SCAMIS, IoT.

I. INTRODUCTION

Global data indicates that the number of connected IoT devices reached approximately 16.6 billion by the end of 2023 and is projected to grow to 18.8 billion in 2024, reflecting a 13 % year of year increase, driven by advancements in smart agriculture and precision farming [1]. Within this context, maintaining controlled environmental conditions in agritech systems such as egg incubators is becoming increasingly critical. Precise temperature and humidity regulation are essential for hatching success and resource efficiency.

A pressing issue in modern poultry farming is the failure to sustain optimal incubation environments, which can lead to reduced hatchability, lower chick viability, and increased operational costs [2]. Without proper intervention, temperature fluctuations and humidity instability negatively impact embryo development, resulting in economic losses and compromised biosecurity. For instance, fuzzy logic controllers in incubators have demonstrated up to 10.68 % savings in electricity consumption along with enhanced thermal uniformity [3]. Inconsistent incubation reduces production results and increases duck mortality rates, which will have a negative impact on duck farming businesses and the communities that depend on them.

Previous research related to temperature control in egg incubators showed that the implementation of Mamdani fuzzy logic resulted in better system resilience and stability [4]. Meanwhile, another egg incubator that used Sugeno fuzzy logic was able to adjust the output in real time to temperature changes and maintain temperature stability with low error [5]. Both of these studies only used one fuzzy logic method, other methods should be applied as a comparison in controlling temperature stability.

A comparative study between fuzzy and PID controllers in a climate chamber also reported faster response and better energy efficiency [6]. In that study, temperature stability was not investigated, only the response time to the setpoint, that fuzzy logic control showing faster response time to the setpoint than PID control.

In a coffee drying system that implementing two fuzzy logic methods, Mamdani had a prediction accuracy of 95%, while Sugeno had a lower prediction accuracy of 88% [7]. This study compared Mamdani and Sugeno fuzzy logic with prediction accuracy values that need to be improved for optimal performance.

However, most previous egg incubator studies have focused on single-method implementations without direct comparative evaluation of both on identical hardware. Moreover, empirical evidence within full scale IoT integrated incubators remains sparse. Specifically, the comparative performance of Sugeno versus Tsukamoto models in a real time IoT environment has not been rigorously tested. This methodological and empirical gap is critical, as developers and practitioners lack clear guidance on the most effective fuzzy method for embedded incubator control. Therefore, this study seeks to answer: How do Sugeno and Tsukamoto fuzzy logic controllers compare in terms of responsiveness, stability, and efficiency when implemented in an IoT-based egg incubator?

This study aims to design and implement dual fuzzy logic controllers (Sugeno and Tsukamoto) in SCAMIS, and to compare their performance quantitatively in terms of response time and temperature stability.

II. BASIC THEORY

The literature on fuzzy logic-based temperature control systems in automated incubators has expanded significantly in the past decade, driven by advancements in Internet of Things (IoT) technologies and low power microcontroller platforms. Maintaining a stable temperature is crucial in enclosed systems such as egg incubators, where precise environmental regulation directly impacts biological outcomes. Prior research has demonstrated the effectiveness of fuzzy logic Sugeno and Tsukamoto methods in delivering adaptive and precise temperature control. This review encompasses studies published primarily in the last five years, focusing on the integration of fuzzy control methods with IoT and Android Apps. The literature is organized thematically to examine the effectiveness of different control approaches, methodological comparisons, and the application of smart technologies in incubator systems. The review aims to identify critical research gaps addressed by the current experimental study.

Fuzzy logic has emerged as a prominent approach in temperature control systems due to its ability to handle uncertainty and generate decisions using linguistically defined rules. In smart Insulated greenhouses, fuzzy logic is able to control temperature with a very low error rate of only 0.69% and an efficiency rate of up to 99.35% [8]. Fuzzy logic systems also can maintain room temperatures, industrial equipment, and even electronic devices within a target range with high precision and fast response times [9].

The Sugeno and Tsukamoto fuzzy methods are two popular approaches to fuzzy logic-based temperature control. Both are effective in maintaining temperature stability, but they have different characteristics and advantages depending on the application requirements. Sugeno fuzzy method is highly effective for complex temperature control systems, such as those in power plants and industrial areas, because it can handle load variations and disturbances with high precision and maintain system stability mathematically [10], [11]. Meanwhile, Tsukamoto fuzzy method is effective for simple applications such as mini greenhouses, maintaining a stable temperature within the target range with a sensor error of around 5.39% [12]. Both methods are effective in maintaining temperature stability, but Sugeno is more suitable for complex, high-precision systems, while Tsukamoto is ideal for simple applications with basic stability requirements. The choice of method should be tailored to the system complexity and accuracy targets.

The integration of fuzzy logic with IoT and Android applications is increasingly being used to create intelligent, responsive, and accessible automation systems. This approach enables real-time sensor data-driven decision-making, as well as remote control and monitoring via mobile devices. There are three advantages of integrating fuzzy logic with Internet of Things (IoT) technology and Android applications. First, Intelligent Decision Making means Fuzzy logic is able to handle uncertain sensor data, so that automated decisions are more optimal [13] - [14]. Second, Real-Time & Remote Monitoring means IoT connects devices to the internet, while Android applications facilitate control and monitoring from anywhere [15] - [16]. And third, Efficiency and Low Cost: This system improves operational efficiency and can be implemented at a relatively low cost [14], [16].

The literature collectively supports the effectiveness of fuzzy logic, particularly Sugeno and Tsukamoto methods, in stabilizing temperature in incubator systems. A recurring pattern is the preference for Sugeno in low-resource real-time systems and for Tsukamoto in applications requiring finer control. However, a critical research gap lies in the lack of experimental comparative studies involving both inference methods implemented in the same IoT-based incubator system. Most existing works treat the methods in isolation or rely on simulations rather than real-world validation. This study addresses that gap by experimentally comparing both fuzzy methods on integrated IoT and mobile application to providing real-time performance insights under operational conditions.

III. METHOD

This research uses a quantitative experimental approach with a comparative design to compare the performance of Sugeno and Tsukamoto fuzzy logic methods in controlling temperature at SCAMIS. The selection of this design is based on the objective to test the difference in effectiveness between two control algorithms under uniform experimental conditions. The research was conducted in one observation cycle for each method, with a systematic sequence from system design to temperature control performance analysis.

Smart Control and Monitoring Incubator System (SCAMIS) is a smart system that includes an egg incubator integrated with a mobile application so that it can be monitored and controlled remotely in real-time. The system is called smart because the incubator has been embedded with a microcontroller with fuzzy algorithms that can control temperature stability automatically. SCAMIS design activities are divided into four stages, including designing the communication architecture between devices, designing hardware, designing software, and determining criteria and fuzzy logic rules.

A. Architecture Design

The design of data communication architecture in this system uses three platforms connected by the internet that describe in Figure 1 below. The three platforms are incubators, smartphones and firebase.

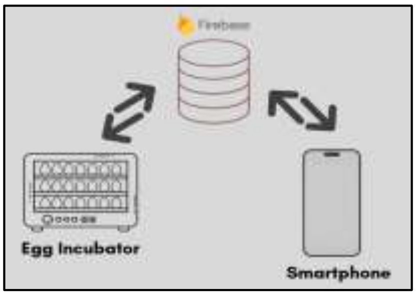

Figure 1. SCAMIS Architecture.

The incubator acts as egg hatching hardware that can receive and send data to firebase via the internet. Then firebase acts as a real time database storage medium and also functions as a link between the incubator and smartphone. While the smartphone through an integrated application functions to receive, display and send data to firebase.

B. Hardware Design

The initial step in the SCAMIS hardware design stage begins with determining the components needed to form the incubator. These components include the ESP8266 microcontroller as the control brain and Wi-Fi module, DHT22 as a temperature and humidity sensor, servo and dimmer as a regulator of the amount of electrical power that can affect the brightness of the lamp as a heat source, as well as other supporting components such as fans, relays, LCD, humidifier and dynamo. The wiring schematic of incubator describes in Figure 2 below.

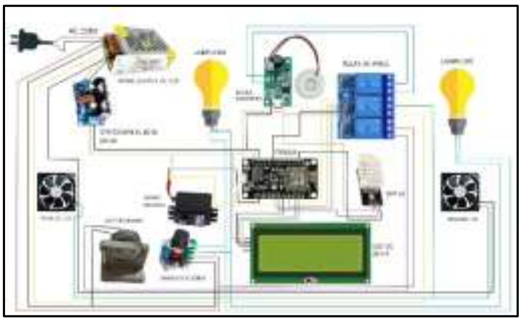

Figure 2. Incubator circuit scheme.

The temperature control system in the incubator works by reading the room temperature using a DHT22 sensor, then processed by the ESP8266 microcontroller. The temperature data read will be used by the Sugeno or Tsukamoto fuzzy logic system to determine the amount of power needed. The output signal from the fuzzy system is sent to the relay module or AC dimmer which regulates the amount of electrical power that affects the brightness of the lamp as the main heating element. A stable temperature inside the incubator will be signaled through a temperature indicator and can be monitored through an android application connected to Firebase, so that users can know the real-time status of the system and operate it more safely and efficiently.

C. Software Design

The design of software on SCAMIS is more emphasized on the business process or how the incubator works in controlling the temperature to be stable. how the temperature control system works in the incubator begins with the initialization of the required variables and connecting all devices to be connected via the internet, the system will start reading the sensor and produce a temperature value. The temperature value becomes input in the Tsukamoto or Sugeno fuzzy logic process. The fuzzy logic process includes fuzzification, evaluation of rules (inference) and Defuzzification will produce a PWM (Pulse Width Modulation) value output. This PWM value will be an input that can determine the brightness level of the lamp as an incubator heat conductor.

For more details, the incubator work system in controlling the temperature to remain stable using the Tsukamoto or Sugeno fuzzy logic method is described through Figure 3 below.

Figure 3. Flowchart of Temperature Control System Using Fuzzy Logic.

D. Fuzzy Logic Rules Design

In the flowchart picture above, it can be seen that the temperature value is an input that will be processed in the fuzzy logic process which will then produce an output in the form of a PWM Value. In the fuzzy logic process, there are three processes that are carried out sequentially, namely fuzzification, Evaluation rules, and Defuzzification.

1. Fuzzification

Fuzzification is the process of converting crisp input data into fuzzy sets through membership functions as explained in table 1 below.

Table 1. Fuzzy Logic Criteria of Temperature

No	Fuzzy Set	Value	Membership Function
1	Low	≤ 36	Semi Trapezoidal Infimum
2	Medium	38	Triangular
3	Hot	≥ 40	Semi Trapezoidal Supremum

Temperature value as crisp input will be converted into a fuzzy set according to the range criteria and described through a membership function graph. The membership function graph according to the Table 1 above can be described in Figure 4 below:

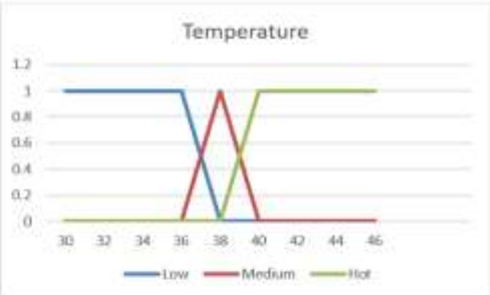

Figure 4. Membership Function Graph of Temperature

PWM Value as output must also be categorized as a fuzzy set according to the range criteria and described through a membership function graph.

Table 2. Fuzzy Logic Criteria for PWM Value

No	Fuzzy set	Range	Membership Function
1	Off	0	Triangular
2	Dim	50	Triangular
3	Bright	100	Triangular

The membership function graph of the PWM Value output variable based on the table 2 above can be described in Figure 5 below.

Figure 5. Membership Function Graph of PWM

2. Evaluation Rules

Evaluation rules are fuzzy logic rules that used to process fuzzy inputs and produce fuzzy outputs based on logical inference. In the evaluation rules process, both input and output values are still in the form of fuzzy sets.

Table 3. Tsukamoto Fuzzy logic Rules

Rules No.	Input (Temperature)	Output (PWM Value)
1	Low	Brigth
2	Medium	Dim
3	Hot	Off

The Table 3 above explain that The first rule states that if the temperature value is a Low fuzzy set, then PWM Value is a bright fuzzy set. The second rule states that if the temperature value is a Medium fuzzy set, then PWM Value is a Dim fuzzy set. The third rule states that if the temperature value is a Hot fuzzy set, then PWM Value is an Off fuzzy set.

3. Defuzzification

Defuzzification is the process of converting fuzzy set outputs into crisp (numeric) values that can be used by real systems. Therefore, the results of the evaluation rules process which are still in the form of fuzzy sets need to be converted into crisp values by calculating the degree of membership through the membership graph function.

IV. Results and Discussion

A. Design Result

SCAMIS is a smart system that includes an egg incubator that integrated with a mobile application. The incubator (Figure 6) has two lamps as heat enhancer, DHT22 sensors to detect temperature and humidity values, fans as heat reducers, humidifiers as humidity enhancers, and dynamo as egg movers.

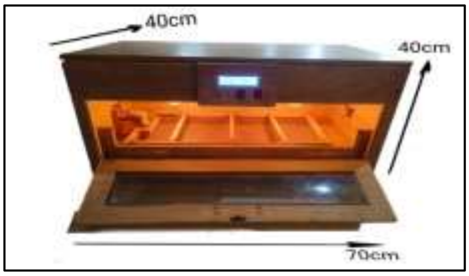

Figure 6. Egg Incubator

SCAMIS mobile app displays information of temperature, humidity, and light brightness. With SCAMIS mobile app we can turn on/off the fan, dynamo, and adjust the brightness of the lights. Through SCAMIS, the Incubator can be controlled with automatic and manual modes.

Figure 7. SCAMIS Data Synchronization

B. Testing Result

1. Sensor Accuracy

The DHT22 sensor detects the temperature value as the input required by the fuzzy logic process. The temperature value produced by the DHT22 sensor needs to be tested for accuracy and error. Testing the accuracy of the DHT22 sensor is done by comparing with the temperature and humidity values of thermometer digital that are commonly used every day.

Table 4. DHT22 Sensor Accuracy Level Test Results

No.	Temperature in Incubator (Celsius)	Temperature on a digital thermometer (Celsius)	Error (%)	Accuracy (%)
1	30.20	30.10	0.33	99.67
2	32.20	31.60	1.90	98.10
3	34.10	34.20	0.29	99.71
4	34.90	34.50	1.16	98.84
5	35.90	35.10	2.28	97.72
6	37.30	36.30	2.75	97.25
7	38.10	37.40	1.87	98.13
8	38.60	37.90	1.85	98.15
9	38.80	38.00	2.11	97.89
10	38.90	38.00	2.37	97.63
	Average		1.69	98.31

Based on Table 4 above, it can be concluded that the DHT22 sensor used can accurately detect the temperature value of the incubator. The accuracy level of the temperature sensor reading is 98.31% with an error rate of 1.69%.

2. Fuzzy Logic Rules

The Tsukamoto and Sugeno fuzzy logic have been converted into source code and embedded to ESP8266 microcontroller need to be tested for validation of all the rules. This is done to ensure that the entire fuzzy logic process runs correctly.

Table 5. Testing Results of Tsukamoto Fuzzy Logic Rules

No	Input Variable		Output Variable		Description
	Temperature (°Celsius)	Criteria	PWM Value	Criteria	
1	33.20	Low	100	Bright	Fulfill Rule 1
2	34.60	Low	100	Bright	Fulfill Rule 1
3	35.80	Low	100	Bright	Fulfill Rule 1
4	36.50	Medium	80	Dim	Fulfill Rule 2
5	37.90	Medium	52	Dim	Fulfill Rule 2
6	38.00	Medium	50	Dim	Fulfill Rule 2
7	38.50	Hot	42	Off	Fulfill Rule 3
8	38.80	Hot	38	Off	Fulfill Rule 3
9	39.40	Hot	22	Off	Fulfill Rule 3
10	40.40	Hot	23	Off	Fulfill Rule 3

Table 6. Testing Results of Sugeno Fuzzy Logic Rules

No	Input Variable		Output Variable		Description
	Temperature (°Celsius)	Criteria	PWM Value	Criteria	
1	31.30	Low	100	Bright	Fulfill Rule 1
2	33.60	Low	100	Bright	Fulfill Rule 1
3	36.00	Low	100	Bright	Fulfill Rule 1
4	36.90	Medium	77	Dim	Fulfill Rule 2
5	37.80	Medium	55	Dim	Fulfill Rule 2
6	38.00	Medium	50	Dim	Fulfill Rule 2
7	38.50	Hot	35	Off	Fulfill Rule 3
8	39.00	Hot	25	Off	Fulfill Rule 3
9	39.10	Hot	23	Off	Fulfill Rule 3
10	40.30	Hot	0	Off	Fulfill Rule 3

Based on Tables 5 and Table 6, it can be concluded that the program code embedded in ESP8266 is in accordance with the rules of Tsukamoto and Sugeno fuzzy logic.

3. Fuzzy Logic Time Response

In order to know the ability of each fuzzy logic method, it is necessary to test the length of time required from the initial temperature to the set point temperature with the same data collection time.

Table 7. Tsukamoto Fuzzy Logic Time Response

No	Time Taking the initial temperature (hh: mm: ss)	Initial Temperature (Celsius)	Set Point Temperature (Celsius)	Time required to set point (hh : mm : ss)
1	03:15:05	30	38	01:00:52
2	03:16:07	31	38	00:59:50
3	03:17:12	32	38	00:58:45
4	03:19:22	33	38	00:56:35
5	03:21:26	34	38	00:54:31
6	03:24:37	35	38	00:51:20
7	03:26:40	36	38	00:49:17
8	03:34:14	37	38	00:41:43
9	04:15:57	38	38	00:00:00

Table 8. Time Response Fuzzy Logic Sugeno

No	Time Taking the initial temperature (hh: mm: ss)	Initial Temperature (Celsius)	Set Point Temperature (Celsius)	Time required to set point (hh : mm : ss)
1	03:16:39	30	38	03:00:01
2	03:17:44	31	38	02:58:56
3	03:18:46	32	38	02:57:54
4	03:19:54	33	38	02:56:46
5	03:20:55	34	38	02:55:45
6	03:24:03	35	38	02:52:37
7	03:28:11	36	38	02:48:29
8	03:38:34	37	38	02:38:06
9	06:16:40	38	38	00:00:00

Based on Table 7 and Table 8 above, it can be concluded that the Tsukamoto fuzzy logic method takes 1 hour 52 seconds to process from an initial temperature of 30^0 C to 38^0 C. While the Sugeno fuzzy logic method takes 3 hours 1 second to process from an initial temperature of 30^0 C to 38^0 C.

4. Temperature Stability Level

After testing the ability of the process to the set point, it is also necessary to test the level of temperature stability at a predetermined set point.

Table 9. Tsukamoto Fuzzy Logic Temperature Stability.

No	Time	I	II	III	IV	Average	Error (%)	Accuracy (%)
1	6.15 - 7.00	38.80	38.80	38.70	38.80	38.78	2.04	97.96
2	7.15 - 8.00	38.90	38.80	38.80	38.80	38.83	2.17	97.83
3	8.15 - 9.00	38.80	38.70	38.80	38.90	38.80	2.11	97.89
4	9.15 - 10.00	39.00	38.90	38.90	39.00	38.95	2.50	97.50
5	10.15 - 11.00	39.10	39.10	39.20	39.20	39.15	3.03	96.97
6	11.15 - 12.00	39.20	39.30	39.30	39.30	39.28	3.36	96.64
7	12.15 - 13.00	39.30	39.40	39.50	39.40	39.40	3.68	96.32
8	13.15 - 14.00	39.40	39.30	39.40	39.40	39.38	3.62	96.38
9	14.15 - 15.00	39.40	39.40	39.40	39.40	39.40	3.68	96.32
10	15.15 - 16.00	39.40	39.30	39.30	39.40	39.35	3.55	96.45
11	16.15 - 17.00	39.30	39.40	39.40	39.40	39.38	3.62	96.38
12	17.15 - 18.00	39.30	39.40	39.30	39.30	39.33	3.49	96.51
			Average				3.07	96.93

Table 10. Sugeno Fuzzy Logic Temperature Stability

No	Time	I	II	III	IV	Average	Error (%)	Accuracy (%)
1	6.15 - 7.00	38.00	38.00	37.90	38.00	37.98	0.07	99.93
2	7.15 - 8.00	37.90	37.90	38.10	38.00	37.98	0.07	99.93
3	8.15 - 9.00	38.00	38.10	38.20	38.20	38.13	0.33	99.67
4	9.15 - 10.00	38.30	38.40	38.40	38.40	38.38	0.99	99.01
5	10.15 - 11.00	38.40	38.50	38.60	38.60	38.53	1.38	98.62
6	11.15 - 12.00	38.60	38.70	38.70	38.90	38.73	1.91	98.09
7	12.15 - 13.00	38.90	38.90	38.80	38.90	38.88	2.30	97.70
8	13.15 - 14.00	38.80	38.90	38.90	38.90	38.88	2.30	97.70
9	14.15 - 15.00	38.90	38.90	38.90	38.90	38.90	2.37	97.63
10	15.15 - 16.00	38.90	38.90	38.90	39.00	38.93	2.43	97.57
11	16.15 - 17.00	39.00	39.00	39.00	39.00	39.00	2.63	97.37
12	17.15 - 18.00	39.00	39.00	38.80	38.80	38.90	2.37	97.63
			Average				1.60	98.40

Based on Table 9 and Table 10 above, it can be concluded that the Tsukamoto fuzzy logic method has a temperature stability level with an accuracy value of 96.93%, while the Sugeno fuzzy logic method has a temperature stability level with an accuracy value of 98.40%.

C. Analysis Result

1. Comparative analysis of time response

The first analysis is to identify the difference or gap in the time required from a certain temperature to the set point temperature. The following graph as describe in Figure 8 explains the amount of time difference in seconds.

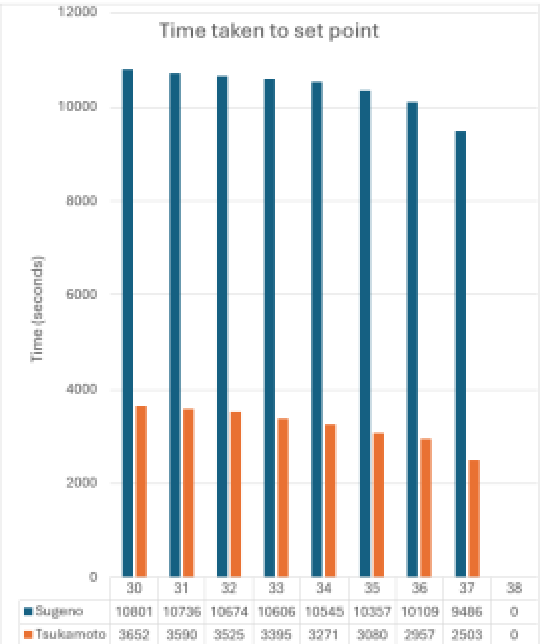

Figure 8. Comparison Chart of Time required to set point

Fuzzy logic Tsukamoto tends to take a faster time than Fuzzy Logic Sugeno. When looking at data with an initial temperature of 30^0 C to 38^0 C, the Tsukamoto method only takes 3,652 seconds, while the Sugeno method takes 10,801 seconds. The total difference between the two methods reaches 7,149 seconds or around 1 hour 59 minutes 9 seconds.

Further analysis is done by identifying the time required for every 1^0 C increase in temperature. The graph below has described the comparison of the time required for each 1^0 C temperature increase starting from 30^0 C - 31^0 C, 31^0 C - 32^0 C and so on.

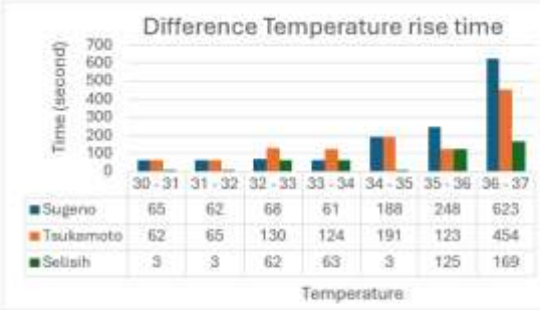

Figure 9. Comparison Chart of Time required to set point

Based on the information from the comparison graph as describe in Figure 9 above, the Sugeno method takes a variable time of 1 to 10,3 minutes for an increase per 1^0 C. While the Tsukamoto method takes a variable time of 1 to 7,5 minutes for an increase per 1^0 C. Both methods require the fastest time at the beginning of the change in temperature increase, while the longest time is at the end of the change in temperature increase. Comparison of the difference in time required between the two methods varies from 3 seconds to 3 minutes for each temperature increase per degree.

2. Comparative Analysis of Temperature Stability Level

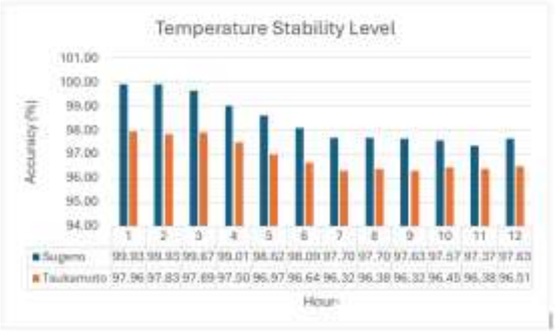

Figure 10. Comparison Chart of Temperature Stability Accuracy Level

The second analysis is to identify the level of temperature stability of the Tsukamoto and Sugeno methods. It is clearly seen in the comparison graph above, the Sugeno method has a temperature stability level with better accuracy than the Tsukamoto method. Tests conducted from the 1st hour to the 12th hour Sugeno method is always superior to the accuracy of temperature stability compared to Tsukamoto method.

V. Conclusion

This study successfully evaluated and compared the effectiveness of two fuzzy logic methods (Sugeno and Tsukamoto) for temperature control within an IoT-based incubator system (SCAMIS). The results of testing and analysis in this study concluded that Tsukamoto excels in response time (1 hour 52 seconds), while Sugeno offers higher temperature stability (accuracy of 98.40%). These results indicate that selecting a fuzzy logic method should align with system priorities: speed or stability. The core contribution lies in presenting empirical comparative evidence of both fuzzy models under identical hardware and real-time IoT conditions that previously underexplored. Practically, this study provides concrete guidance for developers and poultry farmers to select the appropriate control method through the SCAMIS platform. The findings also highlight opportunities for improving energy efficiency and hatch success rates at an operational level. Overall, the research underscores the strategic value of implementing intelligent control systems to enhance productivity and efficiency in modern poultry farming.

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