Smart IoT-based water quality control for lobster aquaculture using Mamdani fuzzy logic

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Abstract. Lobster is a fishery commodity with high economic value and increasing global market demand. In Indonesia, especially in Sidoarjo Regency, there is great potential for its development. However, commonly used cultivation practices still face challenges such as unstable water quality, inefficient feeding, and the lack of an accurate data-based harvest prediction system. This research offers a solution in the form of developing an integrated Smart Aquaculture system based on the Internet of Things (IoT) and artificial intelligence (AI) to support more modern and sustainable lobster cultivation. The system is designed using an ESP32 microcontroller connected to a pH sensor (PH-4502C), a turbidity sensor, and a DS18B20 temperature sensor to monitor water quality in real time, as well as a relay module to automatically control the drain and purifier pumps using the Mamdani Fuzzy Logic method. The system is also integrated with a website, making it easier for farmers to monitor and control it remotely. A 24-hour field test demonstrated that the system accurately responded to changes in environmental parameters, maintained optimal water quality, and produced output consistent with theoretical calculations with a 0% error rate, with a 15-minute drain and purifier pump operation time. Overall, the proposed system demonstrates high reliability in maintaining optimal water quality, reducing lobster mortality risks, and improving operational efficiency. These results indicate that the system provides a solid foundation for future integration of automated feeding and data-driven harvest prediction modules.

1 Introduction

Lobster is a fishery commodity with high economic value and growing global demand. In Indonesia, particularly in Sidoarjo Regency, the potential for lobster cultivation is significant given its geographic location and favorable fishery resources. However, to compete in the international market, lobster cultivation management requires improvements in efficiency, sustainability, and the adoption of modern technology to ensure consistent quality and productivity [1].

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Lobster cultivation in the field currently faces several significant challenges. First, unstable water quality including pH, turbidity, and temperature often causes stress in lobsters and increases the risk of mortality. Second, feeding and water circulation are suboptimal due to a lack of automation. Third, an accurate, data-based harvest prediction system to support proactive cultivation decision-making remains unavailable. Consequently, cultivation practices still rely heavily on manual and reactive observations [2].

To address these issues, the application of Internet of Things (IoT)-based technology and intelligent algorithms such as fuzzy logic can be innovative solutions that support increased efficiency and sustainability of lobster cultivation [3]. By utilizing IoT sensors, water quality such as pH, temperature, and turbidity can be monitored in real time, so that potentially harmful changes in environmental conditions can be immediately detected and automatically addressed. An automated feeding system integrated with lobster growth data allows for timely and appropriate feed delivery, thereby reducing waste and supporting optimal growth. Furthermore, the application of artificial intelligence algorithms can be used to predict the ideal harvest time based on historical data and current conditions, making cultivation management more measurable and proactive, increasing productivity while maintaining lobster quality to meet global market standards.

Several previous studies have utilized IoT in aquaculture to monitor environmental parameters in real time. In [4][5], an Arduino microcontroller-based system for monitoring temperature and pH in catfish farming increased efficiency and responsiveness to environmental changes. However, similar implementations in lobsters are still limited, particularly in the integration of automated controls.

Fuzzy logic has been widely used [6], especially in the automatic control of aquaculture. In previous research, the use of fuzzy systems was used to control aeration in shrimp ponds resulting in improved dissolved oxygen quality and energy efficiency [7]. In [8] the Fuzzy logic method was used in a water quality monitoring system for vaname shrimp cultivation based on the Internet of Things (IoT). This system can automatically detect if the water quality decreases, then take corrective steps, such as turning on aeration and running a filtration process to improve water quality. In previous research, the Fuzzy logic method was also used for a water quality monitoring system to detect abnormal conditions or diseases in tilapia fish ponds based on mobile [9]. The results showed the accuracy of the system in detecting normal or abnormal conditions, as well as its ability to provide fast notifications via an Android application. However, the application of Mamdani fuzzy in the context of freshwater lobster cultivation is a relatively new approach.

Sensors such as the DS18B20 for temperature, turbidity sensor modules (e.g., SEN0189), and pH sensor PH-4502C have been widely adopted for aquatic environmental monitoring purposes. Several previous studies have shown that a voltage divider is needed to safely access the analog signals of these sensors to the microcontroller ADC, in order to keep the voltage below the tolerable limit ($\leq$3.3 V) [10][11]. However, the implementation of the combination of these three sensors in one integrated system together with a fuzzy logic-controlled opto-isolation relay module has not been widely carried out, so this study provides an important technical contribution.

The integration of mobile applications or websites is currently very important for monitoring pond conditions remotely [5][6][9]. IoT technology allows the integration of sensors that can monitor various water quality parameters in real-time through applications or online platforms [12]. This system allows continuous and accurate monitoring of water conditions via mobile devices or computers, thereby increasing the productivity and sustainability of fish farming [13].

Artificial Intelligence technology can be utilized to predict cultivation results in the field of aquaculture [14]. In [15] a prediction system for the quantity of cultivated fish consumption results was created using the application of data regression methods, in [16] a prediction system for the harvest of vaname shrimp using the Least Square method was created, as well as predicting the selling price of dried seaweed at the farmer level with data mining [17]. Although many AI applications are used to predict cultivation results in marine aquaculture [18], harvest prediction systems for lobsters that utilize water quality data, pump operations, and historical trends are still minimal [19]. This research paves the way for the integration of data-based harvest prediction modules as the next stage of development.

Therefore, this research aims to design and implement an integrated Smart Aquaculture system that combines IoT-based real-time monitoring, Mamdani fuzzy logic control, and cloud-based remote supervision to improve the stability of lobster cultivation environments. The main contributions of this work are threefold: (1) developing a multi-sensor water quality monitoring system specifically optimized for freshwater lobster cultivation, (2) integrating Mamdani fuzzy logic to control drain and purifier pump operations based on pH, turbidity, and temperature conditions, and (3) providing a unified web-based platform for remote control and data visualization. This combination has not been widely explored in existing lobster aquaculture studies and therefore represents a novel technical and practical contribution.

2 Materials and Methods

2.1 System Prototype Development

This system prototype uses an ESP32 microcontroller with DS18B20 (temperature), PH-4502C (pH), and salinity sensors to monitor lobster cultivation water quality in real-time. Servo motor actuators control feed and nutrient dispensing, while relay modules automatically regulate drain and purifier pumps based on Mamdani Fuzzy Logic decisions. Sensor data is sent via Wi-Fi/MQTT to the IoT Cloud Platform to be recorded, processed, and displayed on a web monitoring platform that also provides manual control. Control signals from the system and the user are forwarded to the actuators via servo motors and relays, enabling the prototype to support integrated water quality monitoring and control. Figure 1 shows the prototype design of the system to be built.

Fig. 1. Prototype design of the tool

2.2 Design Sistem

Figure 2 shows a block diagram of the system created in this study. This diagram shows the connections between the ESP32, pH sensor (PH-4502C), turbidity sensor (analog), DS18B20 temperature sensor (waterproof), 2-channel relay module (5V), and power source. The main components used in this system include the ESP32 development board as the main microcontroller, a PH-4502C type pH sensor to measure water acidity, an analog turbidity sensor such as SEN0189 to detect clarity, and a waterproof DS18B20 temperature sensor to monitor pool temperature. A 2-channel 5V relay module is used to control external devices such as pumps, aeration or filtration systems, with support for a 5V power supply for the relay and sensor module, as well as a 5 V or 3.3V supply for the ESP32 via USB or regulator, considering that the ESP32 requires 3.3V logic.

Fig. 2. Design System

2.3 Mamdani Fuzzy Logic Method

This study uses the Mamdani Fuzzy Logic method to support automated decision-making in lobster cultivation. Parameters such as pH, temperature, and turbidity are processed through fuzzy membership with the membership function shown in Figure 3. A rule base is designed to determine actions such as turning on filtration and automatically providing nutrients and feed when the pump is active. The fuzzification, rule evaluation, and defuzzification processes produce control decisions that are appropriate to pond conditions in real time.

2.3.1 Fuzzyfication

1) pH

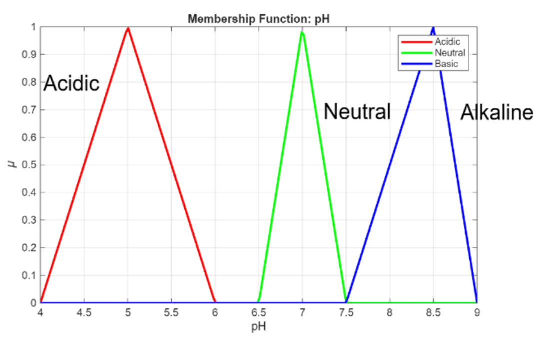

Fig. 3. pH Membership Function

$$\mu_{Acidic}(x) = \begin{cases} 0 & if\ x \leq 4\ or\ x \geq 6 \\ \frac{x-4}{5-4} & if\ 4 < x < 5 \\ \frac{6-x}{6-5} & if\ 5 < x < 6 \end{cases} \quad (1)$$

$$\mu_{Neutral}(x) = \begin{cases} 0 & if\ x \leq 6{,}5\ or\ x \geq 7{,}5 \\ \frac{x-6{,}5}{7-6{,}5} & if\ 6{,}5 < x < 7 \\ \frac{7{,}5-x}{7{,}5-7} & if\ 7 < x < 7{,}5 \end{cases} \quad (2)$$

$$\mu_{Alkaline}(x) = \begin{cases} 0 & if\ x \leq 7{,}5\ or\ x \geq 9 \\ \frac{x-7{,}5}{8{,}5-7{,}5} & if\ 7{,}5 < x < 8{,}5 \\ \frac{9-x}{9-8{,}5} & if\ 8{,}5 < x < 9 \end{cases} \quad (3)$$

2) Turbidity

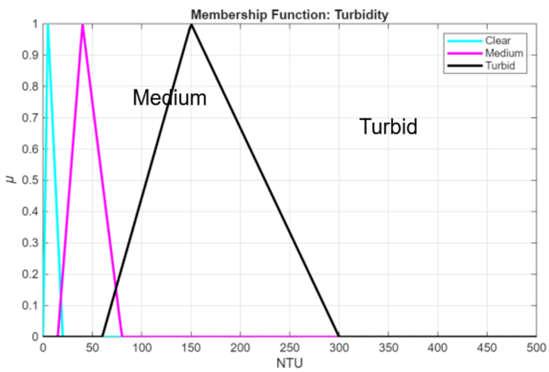

Fig. 4. Turbidity Membership Function

$$\mu_{Clear}(x) = \begin{cases} 0 & if\ x \leq 0\ or\ x \geq 20 \\ \frac{x-0}{5-0} & if\ 0 < x < 5 \\ \frac{20-x}{20-5} & if\ 5 < x < 20 \end{cases} \quad (4)$$

$$\mu_{Moderate}(x) = \begin{cases} 0 & if\ x \leq 15\ or\ x \geq 80 \\ \frac{x-15}{40-15} & if\ 15 < x < 40 \\ \frac{80-x}{80-40} & if\ 40 < x < 80 \end{cases} \quad (5)$$

$$\mu_{Turbid}(x) = \begin{cases} 0 & if\ x \leq 60\ or\ x \geq 300 \\ \frac{x-60}{150-60} & if\ 60 < x < 150 \\ \frac{300-x}{300-150} & if\ 150 < x < 300 \end{cases} \quad (6)$$

3) Temperature

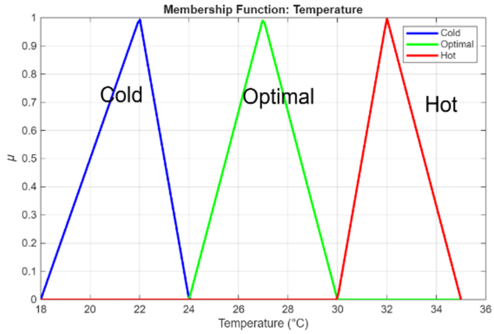

Fig. 5. Temperature Membership Function

$$\mu_{Cold}\ (x) = \begin{cases} 0 & if\ x \leq 18\ or\ x \geq 24 \\ \frac{x-18}{22-18} & if\ 18 < x < 22 \\ \frac{24-x}{24-22} & if\ 22 < x < 24 \end{cases} \tag{7}$$

$$\mu_{Optimal}\ (x) = \begin{cases} 0 & if\ x \leq 24\ or\ x \geq 30 \\ \frac{x-24}{27-24} & if\ 24 < x < 27 \\ \frac{30-x}{30-27} & if\ 27 < x < 30 \end{cases} \tag{8}$$

$$\mu_{Hot}\ (x) = \begin{cases} 0 & if\ x \leq 30\ or\ x \geq 35 \\ \frac{x-30}{32-30} & if\ 30 < x < 32 \\ \frac{35-x}{35-32} & if\ 32 < x < 35 \end{cases} \tag{9}$$

4) Output Action (domain 0 - 100)

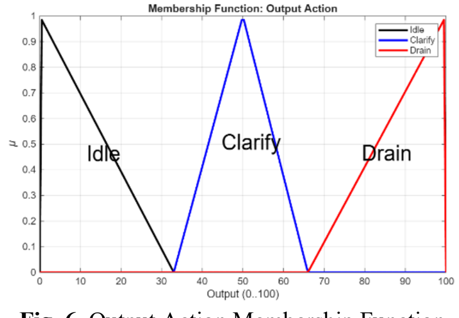

Fig. 6. Output Action Membership Function

$$\mu_{Iddle}\ (x) = \begin{cases} 1 & if\ x = 0 \\ \frac{33-x}{33-0} & if\ 0 < x < 33 \\ 0 & if\ x \geq 33 \end{cases} \tag{10}$$

$$\mu_{Clarify}\ (x) = \begin{cases} 0 & if\ x \leq 33\ or\ x \geq 66 \\ \frac{x-33}{50-33} & if\ 33 < x < 50 \\ \frac{66-x}{66-50} & if\ 50 < x < 66 \end{cases} \tag{11}$$

$$\mu_{Drain}(x) = \begin{cases} 0 & if\ x \leq 66 \\ \frac{x-66}{100-66} & if\ 66 < x < 100 \\ 1 & if\ x \geq 100 \end{cases} \tag{12}$$

2.3.2 Inference Engine

The inference process uses predefined rules to map fuzzy inputs to fuzzy outputs. These rules form the knowledge base of the system.

Table 1. Rule base fuzzy

No	pH	Turbidity	Temperature	Output
1	Acidic	Clarify	Cold	Clarify
2	Acidic	Clarify	Optimal	Clarify
3	Acidic	Clarify	Hot	Drain
4	Acidic	Moderate	Cold	Clarify
5	Acidic	Moderate	Optimal	Clarify
6	Acidic	Moderate	Hot	Drain
7	Acidic	Turbid	Cold	Clarify
8	Acidic	Turbid	Optimal	Drain
9	Acidic	Turbid	Hot	Drain
10	Neutral	Clear	Cold	Idle
11	Neutral	Clear	Optimal	Idle
12	Neutral	Clear	Hot	Clarify
13	Neutral	Moderate	Cold	Clarify
14	Neutral	Moderate	Optimal	Clarify
15	Neutral	Moderate	Hot	Clarify
16	Neutral	Turbid	Cold	Clarify
17	Neutral	Turbid	Optimal	Clarify
18	Neutral	Turbid	Hot	Drain
19	Alkaline	Clear	Cold	Clarify
20	Alkaline	Clear	Optimal	Clarify
21	Alkaline	Clear	Hot	Drain
22	Alkaline	Moderate	Cold	Clarify
23	Alkaline	Moderate	Optimal	Clarify
24	Alkaline	Moderate	Hot	Drain
25	Alkaline	Turbid	Cold	Clarify
26	Alkaline	Turbid	Optimal	Drain
27	Alkaline	Turbid	Hot	Drain

Rule Base

[R1] IF pH is Acidic AND Turbidity is Clear AND Temperature is Cold THEN Output is Clarify

[R2] IF pH is Acidic AND Turbidity is Clear AND Temperature is Optimal THEN Output is Clarify

[R3] IF pH is Acidic AND Turbidity is Clear AND Temperature is Hot THEN Output is Drain

[R4] IF pH is Acidic AND Turbidity is Medium AND Temperature is Cold THEN Output is Clarify

[R5] IF pH is Acidic AND Turbidity is Medium AND Temperature is Optimal THEN Output is Clarify

[R6] IF pH is Acidic AND Turbidity is Medium AND Temperature is Hot THEN Output is Drain

[R7] IF pH is Acidic AND Turbidity is Turbid AND Temperature is Cold THEN Output is Clarify

[R8] IF pH is Acidic AND Turbidity is Turbid AND Temperature is Optimal THEN Output is Drain

[R9] IF pH is Acidic AND Turbidity is Turbid AND Temperature is Hot THEN Output is Drain

[R10] IF pH is Neutral AND Turbidity is Clear AND Temperature is Cold THEN Output is Idle

[R11] IF pH is Neutral AND Turbidity is Clear AND Temperature is Optimal THEN Output is Idle

[R12] IF pH is Neutral AND Turbidity is Clear AND Temperature is Hot THEN Output is Clarify

[R13] IF pH is Neutral AND Turbidity is Medium AND Temperature is Cold THEN Output is Clarify

[R14] IF pH is Neutral AND Turbidity is Medium AND Temperature is Optimal THEN Output is Clarify

[R15] IF pH is Neutral AND Turbidity is Medium AND Temperature is Hot THEN Output is Clarify

[R16] IF pH is Neutral AND Turbidity is Turbid AND Temperature is Cold THEN Output is Clarify

[R17] IF pH is Neutral AND Turbidity is Turbid AND Temperature is Optimal THEN Output is Clarify

[R18] IF pH is Neutral AND Turbidity is Turbid AND Temperature is Hot THEN Output is Drain

[R19] IF pH is Basic AND Turbidity is Clear AND Temperature is Cold THEN Output is Clarify

[R20] IF pH is Basic AND Turbidity is Clear AND Temperature is Optimal THEN Output is Clarify

[R21] IF pH is Basic AND Turbidity is Clear AND Temperature is Hot THEN Output is Drain

[R22] IF pH is Basic AND Turbidity is Medium AND Temperature is Cold THEN Output is Clarify

[R23] IF pH is Basic AND Turbidity is Medium AND Temperature is Optimal THEN Output is Clarify

[R24] IF pH is Basic AND Turbidity is Medium AND Temperature is Hot THEN Output is Drain

[R25] IF pH is Basic AND Turbidity is Turbid AND Temperature is Cold THEN Output is Clarify

[R26] IF pH is Basic AND Turbidity is Turbid AND Temperature is Optimal THEN Output is Drain

[R27] IF pH is Basic AND Turbidity is Turbid AND Temperature is Hot THEN Output is Drain

2.3.3 Defuzzification

Defuzzification is the process of converting the fuzzy output obtained from the inference stage into a crisp value. The input of this process is a fuzzy set resulting from rule composition, and the output is a single number. In this case, the method used is the Centroid method. This method calculates the center of gravity of the fuzzy region. For discrete variables, the formula is:

$$Z^* = \frac{\sum_{i=1}^{N} \alpha_i . z_i}{\sum_{i=1}^{N} \alpha_i} \qquad (13)$$

Where:

$Z*$ = Crisp output value
α_i = The power of the i-th rule
z_i = The crisp output value of the i-th rule

2.4 System Accuracy Testing

At this stage, system accuracy is tested by comparing the results of direct field testing with theoretical calculations. This comparison aims to ensure that the Mamdani fuzzy method is implemented correctly in the monitoring system and produces accurate decisions. The test results determine whether the system output aligns with the theoretical calculations, thus ensuring the system's validity and reliability.

3. Results and Discussion

3.1 Prototype Development and Design System

Figure 3 shows a prototype of the developed water quality monitoring system. This system uses ESP32 as the main controller connected to sensor nodes, namely the DS18B20 temperature sensor, pH sensor, and salinity sensor. Sensor measurement data is sent via Wi-Fi to the IoT server to be processed using the Mamdani Fuzzy Logic method to assess water quality conditions to decide on the active water pump, air pump, and cooling fan. Monitoring results are displayed on a web dashboard so users can monitor water conditions in real-time.

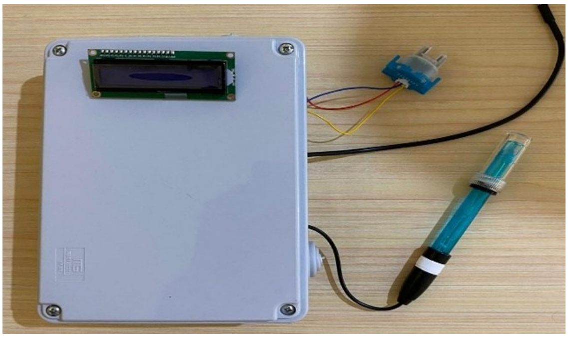

Fig. 7. System Prototype

3.2 Application of Mamdani Fuzzy Method

Based on table 2, the results of the system testing indicate that the control decisions generated by the Mamdani fuzzy logic algorithm are able to respond dynamically to variations in the lobster pond's environmental conditions. Under conditions of pH, turbidity, and temperature that are within the normal range, the system does not activate the pump (Normal status), as seen at 00:00, 04:00, 07:00, 10:00, 14:00, 16:00, 19:00, and 22:00. Conversely, when the pH parameter deviates from the ideal range or the turbidity and temperature levels increase, the system automatically activates the pump, both the purification pump and the drain pump. When the pump is active, nutrients and feed will also be automatically provided, with an average operating duration of 15 minutes. For example, when the pH drops to 6.1–6.4 or increases to 8.2–8.4, the system activates the drain pump to maintain optimal water quality. Similarly, when turbidity reaches high levels (≥ 260 NTU) or temperatures approach 30°C, the purification pump is activated to improve environmental conditions. This pattern demonstrates the system's ability to detect critical conditions and provide timely responses according to established rules. This is expected to reduce the risk of lobster stress and mortality and maintain pond environmental stability more efficiently than manual controls.

Table 2. System test results

Time	pH	Turbidity (NTU)	Temperature (°C)	Pump Duration	System Decision (minutes)
00:00	7.2	180	27.5	Normal	0
01:00	6.3	210	28.1	Drain Pump ON	15
02:00	7.8	260	29.0	Pompa Penjernih ON	15
03:00	6.9	230	23.5	Pompa Penjernih ON	15
04:00	7.4	190	26.8	Normal	0
05:00	8.2	220	28.3	Drain Pump ON	15
06:00	7.0	270	25.9	Pompa Penjernih ON	15
07:00	7.3	180	24.2	Normal	0
08:00	6.1	240	29.4	Drain Pump ON	15
09:00	7.6	280	30.5	Purifier Pump ON	15
10:00	7.0	200	27.1	Normal	0
11:00	8.3	210	25.6	Drain Pump ON	15
12:00	7.5	260	28.7	Purifier Pump ON	15
13:00	6.8	190	22.9	Purifier Pump ON	15
14:00	7.1	230	26.5	Normal	0
15:00	8.0	270	29.9	Purifier Pump ON	15
16:00	7.2	180	27.8	Normal	0
17:00	6.4	220	28.4	Drain Pump ON	15
18:00	7.7	260	30.2	Purifier Pump ON	15
19:00	7.0	240	24.7	Normal	0
20:00	6.2	280	29.1	Drain Pump ON	15
21:00	7.9	300	31.0	Purifier Pump ON	15
22:00	7.1	210	27.3	Normal	0
23:00	8.4	200	26.9	Drain Pump ON	15

Despite its practicality, the Mamdani Fuzzy Logic method has several limitations. First, its performance depends heavily on expert-designed membership functions and rule bases, making the system potentially subjective and less scalable for different pond conditions. Second, Mamdani systems require manual tuning when environmental behavior changes significantly, which may reduce adaptability in large-scale or long-term deployments. Third, compared to machine learning approaches, Mamdani fuzzy logic does not automatically learn patterns from historical data. However, its interpretability, computational simplicity, and suitability for embedded systems justify its use in this study. Future work may incorporate adaptive neuro-fuzzy or reinforcement learning to improve system adaptability.

3.2 System Accuracy Test Results

Figure 8 shows the test results integrated directly into the website dashboard. In this test, the monitoring system displays sensor measurements of 28°C water temperature, 5.5 pH, and 70 NTU turbidity. The temperature was detected within normal conditions for cultivation, while the pH indicated acidic conditions, below the ideal standard (6.5–8.5). The turbidity value of 70 NTU is considered moderate, so it is still tolerable, although it has the potential to affect water quality.

The dashboard also displays the results of the analysis using Mamdani Fuzzy Logic, which concluded that a water clarification process was necessary (a crisp value of 65.38). In the actuator control section, only the air pump was active, while the water pump and cooling fan were inactive. This indicates that the system has automatically responded to the detected water quality conditions.

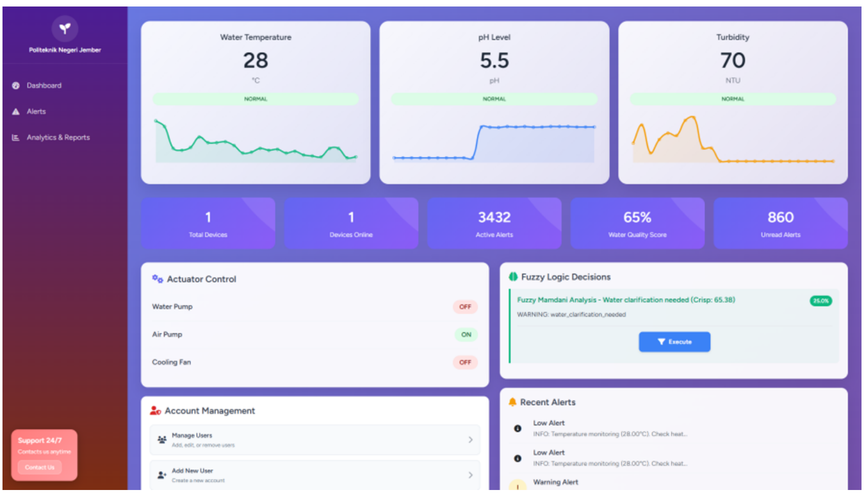

Fig. 8. Monitoring results on the website dashboard

To ensure the accuracy of data collection, a comparison was made between the results of field testing and theoretical calculations, with the following test samples: pH = 5.5, Turbidity = 70 NTU, Temperature = 28°C.

1) Fuzzyfication

pH = 5,5

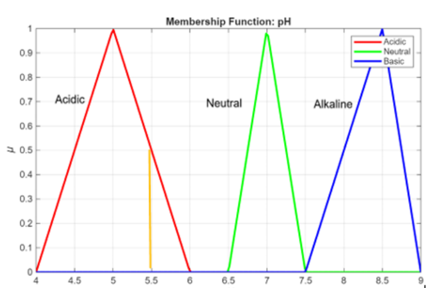

Fig. 9. pH Membership Function

$$\mu\ (5{,}50)_{Acid} = \frac{6 - x}{6 - 5} = \frac{5 - 5{,}50}{6 - 5} = \frac{0{,}50}{1} = 0{,}50$$

Turbidity = 70

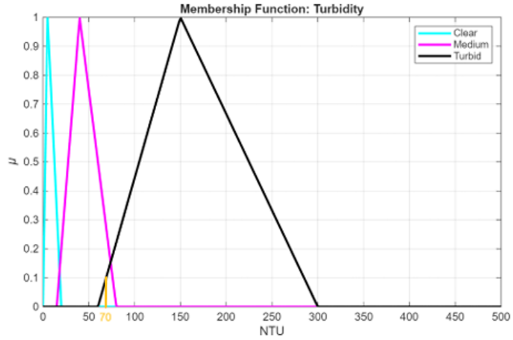

Fig. 10. Turbidity Membership Function

$$\mu\ (70)_{Moderate} = \frac{80 - x}{80 - 40} = \frac{80 - 70}{80 - 40} = \frac{10}{40} = 0{,}25$$

$$\mu\ (70)_{Turbid} = \frac{x - 60}{150 - 60} = \frac{70 - 60}{150 - 60} = \frac{10}{90} \approx 0{,}1111$$

.

Temperature = 28°C

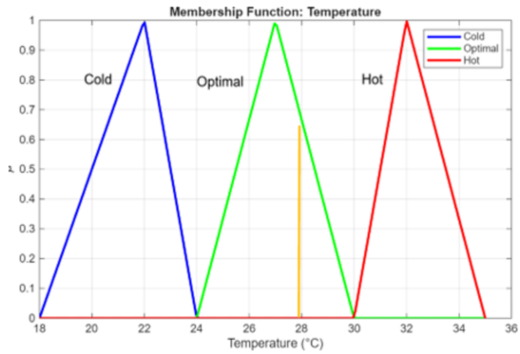

Fig. 11. Temperature Membership Function

$$\mu\ (28)_{Optimal} = \frac{30 - x}{30 - 27} = \frac{30 - 28}{30 - 27} = \frac{2}{3} \approx 0{,}6667$$

2) Inference Rule

Based on the membership value, the active rule is the one that has all antecedents with a value > 0.

- **Rule 5:** IF pH is Acidic (0.50) AND Turbdity is Moderate (0.25) AND Temperature is Optimal (0.6667) THEN Output is **Clarify**.
  $\alpha 5 = \min(0.50, 0.25, 0.6667)$
  $= 0.25$
- **Rule 8:** IF pH is Acidic (0.50) AND Turbidity is Turbid (0.111) AND Temperature is Optimal (0.6667) THEN Output is **Drain**.
  $\alpha 8 = \min(0.50, 0.111, 0.6667)$
  $= 0.111$

3) Defuzzification

Using the Centroid formula with the midpoint value for the output: Clarify (z_5) = 50 and Drain (z_8) = 100.

$$Z^* = \frac{(\alpha_5 \cdot z_5)+(\alpha_8 \cdot z_8)}{\alpha_5+\alpha_8} Z^* = \frac{(0.25 \cdot 50)+(0.1111 \cdot 100)}{0.25+0.1111} = \frac{12.5+11.11}{0.3611} = \frac{23.61}{0.3611} \approx 65.38$$

The crisp output value obtained is 65.38. This value is on the border between Clarify (33-66) so the system decides to activate the Clarify pump because it is between (33-66).

Based on the results of a comparative analysis between theoretical fuzzy calculations and field testing implementation through the created monitoring system, it was concluded that both showed the same results. With the same test input values, both theoretical and field practice produced the same output or decision. In the field test, the system gave a decision that the air clarification process was required with a crisp value of 65.38, so that the actuator in the form of an air pump was active so that nutrients and feed were also automatically provided. This result is in line with the theoretical test which also produced a crisp output value of 65.38. This value is on the border of the Clarify category (33–66), so the system's decision was to activate the water pump. This proves that the developed monitoring system is able to accurately represent the results of fuzzy calculations.

4 Conclusion

This study successfully developed an integrated Smart Aquaculture system for lobster cultivation that combines IoT-based monitoring, Mamdani fuzzy logic control, and cloud-based supervision. The system demonstrated accurate real-time responses to fluctuations in pH, turbidity, and temperature, and its control decisions produced a 0% operational error during testing. Compared to traditional manual cultivation, the proposed system provides three key advantages: (1) continuous and precise water quality regulation, (2) reduced mortality risk due to faster corrective actions, and (3) improved operational efficiency through automated pump control. The novelty of this work lies in the integration of a multi-sensor monitoring module with a fuzzy-driven pump control system specifically tailored for lobster cultivation, supported by a remote web-based interface. These findings indicate strong potential for the system to serve as a foundation for future enhancements, including automated feeding, predictive analytics, and AI-based harvest forecasting.

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