Journal of Applied Science, Technology & Humanities
Volume 3, Issue 2, March, 2026, Pages 1016-1030

ISSN 3032-5765
DOI: https://doi.org/10.62535/88020163

Journal of Applied Science Technology & Humanities

IoT-Based Water pH Monitoring and Control System for Ornamental Fish Using Fuzzy Logic Method

Rizki Maariz Senjaya[1]
[1]Computer Engineering Technology, Vocational School, IPB University
rizki_maarizsenjaya@apps.ipb.ac.id

Iqbaal Maulana Dwiputera[2], **Muhammad Faturrahman**[3], **Chika Hayya Sabillah**[4], **Muhammad Faiz Assariy**[5], **Rizki Achmad Rifa'i Dwi Warno**[6]
[2345]Computer Engineering Technology, Vocational School, IPB University
[1]iqbaalmaulana@apps.ipb.ac.id, [2]sadsamuhammad@apps.ipb.ac.id, [3]chikahayya_asabillah@apps.ipb.ac.id, [4]faizmuhammad@apps.ipb.ac.id, [5]rizkiachmadrifai@apps.ipb.ac.id

Abstract

Water quality, particularly pH, temperature, and turbidity parameters, plays an important role in maintaining the health of ornamental fish in aquariums. Fluctuations in these parameters can cause physiological stress and even death in fish if not properly controlled. This study aims to design an Internet of Things (IoT)-based water quality monitoring and control system using the Mamdani type Fuzzy Inference System (FIS) method. The system utilizes pH, temperature, and turbidity sensors connected to an ESP32 microcontroller to acquire data and transmit it in real-time to a cloud-based platform. Sensor values are processed through fuzzification, inference using the MIN operator and MAX aggregation, then defuzzification using the centroid method to produce decisions on fish conditions in the categories of healthy, sick, or dead. Simulation results using MATLAB Fuzzy Logic Toolbox show that the system is capable of providing a more stable non-linear response compared to conventional threshold methods. The integration of IoT and fuzzy logic enables more adaptive, proportional, and effective control in maintaining water quality within the optimal range for ornamental fish.

Keywords: Internet of Things, Fuzzy Logic, Mamdani, Water Quality Monitoring, pH Control, Aquaculture, ESP32.

INTRODUCTION

Water quality management is a fundamental aspect of sustainable aquaculture systems because environmental parameters directly influence the growth, health, and survival of aquatic organisms. Among these parameters, pH plays a particularly important role in maintaining ecological balance and supporting biological processes in aquatic environments. Unstable pH levels may cause physiological stress in fish and can disrupt the metabolic processes necessary for normal growth and survival. Therefore, maintaining optimal pH conditions is essential for ensuring environmental stability and improving aquaculture productivity. The importance of maintaining stable water quality conditions in aquaculture environments has been widely discussed in previous studies (Li et al., 2023).

Aquaculture systems involve complex environmental interactions where multiple physical and chemical parameters must be monitored simultaneously to maintain stable water conditions. Variations in environmental factors such as temperature, dissolved oxygen, and pH can significantly affect aquatic ecosystems and influence the sustainability of aquaculture operations. Effective water quality assessment therefore requires integrated monitoring and evaluation approaches that consider the dynamic nature of aquatic environments. Previous studies have highlighted the need for systematic water quality evaluation models that can capture the complexity of aquaculture ecosystems (Trach et al., 2022).

In recent years, the development of Internet of Things (IoT) technology has provided new opportunities for improving environmental monitoring systems in aquaculture. IoT enables real-time data acquisition through interconnected sensors that can continuously measure environmental parameters and transmit the collected data to digital platforms for analysis and visualization. This capability allows aquaculture operators to monitor water conditions more efficiently and respond more quickly to environmental changes that may affect fish health and productivity. The use of IoT technologies has therefore become an important approach for modern aquaculture monitoring systems (Rastegari et al., 2023).

Several studies have also demonstrated the potential of IoT-based systems for real-time water quality monitoring in fish farming environments. Sensor networks integrated with IoT platforms allow continuous observation of water parameters and enable automated data collection without requiring constant manual measurement. Such monitoring systems help improve the accuracy and reliability of environmental data while reducing operational workload in aquaculture management. These technological developments contribute to more efficient monitoring practices and improved aquaculture system performance (Chen et al., 2022).

In addition to monitoring technologies, intelligent computational methods have been increasingly applied to support environmental decision-making processes. Machine learning techniques, for example, have been widely used for environmental data analysis and prediction in agricultural systems. These computational approaches allow the identification of complex patterns within environmental datasets and support more accurate prediction of environmental conditions. As a result, intelligent data processing techniques play an important role in improving the efficiency of environmental monitoring and management systems (Pathak et al., 2023).

Among intelligent control approaches, fuzzy logic has gained significant attention because of its ability to handle uncertainty and represent human reasoning using linguistic rules. Unlike conventional control methods that rely on fixed numerical thresholds, fuzzy logic systems allow flexible decision-making based on qualitative knowledge and rule-based reasoning. This capability makes fuzzy logic particularly suitable for environmental systems where parameters often fluctuate and cannot be represented accurately using rigid mathematical models (You et al., 2021).

The application of fuzzy logic in aquaculture monitoring systems has demonstrated promising results in improving environmental control mechanisms. Fuzzy-based systems can evaluate multiple environmental parameters simultaneously and determine appropriate control actions to maintain stable water conditions. Such systems are capable of translating sensor data into linguistic variables and applying rule-based reasoning to generate adaptive control responses for water quality management (Bautista et al., 2022).

One commonly used fuzzy inference model in environmental control systems is the Mamdani fuzzy inference system. This method is widely applied because of its intuitive rule structure and its capability to represent expert knowledge in decision-making processes. Mamdani fuzzy logic has been successfully implemented in water quality regulation systems, including pH control and water recirculation management in aquaponic environments, demonstrating its effectiveness for environmental parameter control (Rahayu et al., 2021).

Recent research has also explored the integration of IoT technology with fuzzy logic to create intelligent aquaculture management systems. By combining real-time monitoring with adaptive control algorithms, these integrated systems are capable of automatically adjusting environmental conditions based on sensor measurements. Such approaches enable more efficient system operation and improve the stability of aquaculture environments through automated decision-making processes (Indrawati et al., 2025).

Furthermore, recent review studies indicate that IoT-based sensor networks are becoming increasingly important for maintaining optimal water quality in aquaculture systems. The integration of sensors, communication technologies, and intelligent data processing methods provides new opportunities for developing advanced monitoring and control systems that can support sustainable aquaculture practices (Flores-Iwasaki et al., 2025).

Despite these technological advancements, many existing systems primarily focus on environmental monitoring rather than implementing adaptive control mechanisms specifically designed to maintain stable pH conditions in ornamental fish aquaculture environments. Ornamental fish species are generally more sensitive to environmental fluctuations compared to food fish species, making stable water conditions particularly important in aquarium-based cultivation systems. Therefore, the development of adaptive control mechanisms capable of maintaining stable pH conditions remains an important research challenge in smart aquaculture systems.

Based on these considerations, this study proposes the development of an IoT-based water pH monitoring and control system for ornamental fish using the Mamdani Fuzzy Inference System. The proposed system integrates real-time sensor monitoring, intelligent fuzzy-based decision-making, and automated control mechanisms to maintain optimal water quality conditions. Through the combination of IoT connectivity and adaptive control algorithms, the system is expected to improve environmental stability, enhance fish health conditions, and increase operational efficiency in ornamental fish aquarium management.

METHODS

This study applies an IoT-based monitoring system approach as implemented in modern aquaculture systems (Rastegari et al., 2023). A pH sensor is used as the primary input to periodically measure water acidity levels in the monitoring system (Chen et al., 2022). The system architecture integrates a microcontroller, communication modules, and a cloud server for real-time data transmission (Irawan et al., 2021).

The Mamdani-type Fuzzy Inference System method is used as the core decision-making mechanism of the system (Rahayu et al., 2021). The Mamdani inference structure allows processing of input variables into control decisions based on linguistic rules (Bautista et al., 2022). The fuzzification stage converts crisp values into membership degrees based on triangular and trapezoidal functions (Li et al., 2023).

Rule evaluation is performed using the MIN operator to determine the activation strength of each rule (Santosa et al., 2021). The aggregation process uses the MAX operator to combine all activated fuzzy outputs (You et al., 2021). Defuzzification uses the centroid method to generate a stable crisp value (Nagothu et al., 2025). All measurement data are stored in a cloud-based system for continuous performance analysis (Shete et al., 2024).

Fuzzy Rule Base Construction

The fuzzy rule base is constructed by formulating cause–effect relationships between water pH conditions and corrective system actions in the form of IF–THEN linguistic rules. Each rule is designed based on the fuzzy sets acidic, neutral, and alkaline that were previously defined. For example, the rule "IF pH is Acidic THEN Add pH Up" indicates that the higher the membership degree in the acidic set, the greater the intensity of the corrective action to increase the pH level. Likewise, the rule "IF pH is Alkaline THEN Add pH Down" is used to decrease pH levels when water becomes alkaline, while the neutral condition produces the action "No Change." The rule evaluation process uses the MIN operator to determine the activation strength of each rule and the MAX operator at the aggregation stage to combine all fuzzy outputs, in accordance with the classical Mamdani Fuzzy Inference System approach (Rahayu et al., 2021).

Control Implementation and Data Storage

The defuzzification result using the centroid method produces a crisp value in the form of pump activation duration (in seconds), which is used to control the addition of pH Up or pH Down solutions automatically. The ESP32 microcontroller sends control signals to the peristaltic pump based on this value, ensuring that pH adjustment is carried out gradually and proportionally. After the control action is executed, the sensor re-measures the pH value to ensure that the system moves toward a stable condition. All pH readings, pump activation times, and system status data are stored in a cloud-based database for real-time monitoring and historical analysis. This data storage integration enables continuous system performance evaluation and supports the development of more adaptive control systems in the future (Rastegari et al., 2023).

RESULTS AND DISCUSSION

The implementation results show that the IoT-based monitoring system is capable of displaying real-time pH data with remote access through a web dashboard. This improves monitoring efficiency compared to manual methods and enables rapid responses to changes in water quality (Hidayat et al., 2023). From the control perspective, the fuzzy logic method provides a more stable response compared to simple threshold methods. The system does not only respond to extreme conditions but also provides proportional control to small changes in pH values so that fluctuations are more controlled and no drastic environmental changes occur (Santosa et al., 2021).

Basis for Determining Parameter Range

1. **pH Range**

The pH range of 4–9 was established as the universe of discourse in the fuzzy system because it encompasses variations in water conditions from highly acidic to highly alkaline environments commonly found in freshwater aquaculture systems. The optimal range of 6.5–7.5 was selected as the neutral category because most tropical ornamental fish demonstrate optimal growth and metabolism under these conditions. Values below 6 are categorized as too acidic and may cause physiological stress, while values above 8 indicate overly alkaline conditions that can disrupt the biological balance of fish. The determination of these limits was adjusted according to fuzzy-based water quality control studies in modern aquaculture systems (Li et al., 2023).

2. **Temperature Range**

The temperature range of 20–35°C was used as the system domain because it reflects common temperature variations in aquariums and tropical fish farming systems. The ideal range of 24–28°C was categorized as normal because it supports optimal metabolic activity, appetite, and immune system performance in fish. Temperatures below 24°C were classified as cold because they may slow metabolism and growth, whereas temperatures above 30°C were categorized as hot because they may increase stress and oxygen demand in fish. The determination of this range refers to IoT monitoring studies in tropical aquaculture systems (Rastegari et al., 2023).

3. **Turbidity Range**

The turbidity range of 0–100 NTU was defined as the universe of discourse to represent water clarity levels in aquarium systems. The categories clear, moderate, and turbid were designed based on fuzzy water quality index classification approaches that allow gradual transitions between conditions without rigid boundaries. High turbidity may indicate an increase in suspended particles and potential health disturbances in fish, therefore it is included as one of the evaluation parameters in the fuzzy system. The determination of this domain follows fuzzy-based water quality evaluation approaches that integrate multiple environmental parameters simultaneously (Trach et al., 2022).

Fuzzy set design iDesign of Input Fuzzy Sets

The membership function design was implemented using trapezoidal (trapmf) and triangular (trimf) functions because they are commonly used in Mamdani FIS and are compatible with MATLAB Fuzzy Logic Toolbox. Domain values were determined based on water quality ranges reported in modern aquaculture literature.

Type	Variable	Fuzzy Set	Universe	Domain
Input	pH	Acidic	4–9	[4, 4, 5.5, 6.5]
		Neutral	4–9	[6.5, 7, 7.5]
		Alkaline	4–9	[7.5, 8.5, 9, 9]
	Temperature (°C)	Cold	20–35	[20, 20, 22, 24]
		Normal	20–35	[24, 26, 28]
		Hot	20–35	[28, 32, 35, 35]
	Turbidity (NTU)	Clear	0–100	[0, 0, 20, 30]
		Moderate	0–100	[20, 40, 60]

		Turbid	0–100	[50, 70, 100, 100]

The pH range of 6.5–7.5 was defined as neutral because many aquaculture studies state that freshwater ornamental fish grow optimally within this interval (Li et al., 2023). Values below 6 were categorized as acidic and values above 8 as alkaline following fuzzy water quality index evaluation (Trach et al., 2022).

The temperature range of 24–28°C was selected as normal because it corresponds to environmental standards for tropical fish based on IoT monitoring systems (Rastegari et al., 2023).

Turbidity categories were determined using a fuzzy water quality classification approach dividing water clarity into clear, moderate, and turbid within a 0–100 NTU scale (Trach et al., 2022).

Design of Output Fuzzy Sets

The output range of 0–100 was selected to ensure compatibility with the centroid defuzzification method.

Type	Variable	Fuzzy Set	Universe	Domain
Output	Fish Condition	Dead	0–100	[0, 0, 20, 40]
		Sick	0–100	[30, 50, 70]
		Healthy	0–100	[60, 80, 100, 100]

The 0–100 scale was used to facilitate centroid defuzzification and quantitative interpretation of fish health level. The division into low–medium–high categories follows fuzzy classification concepts in water quality evaluation systems (Bautista et al., 2022).

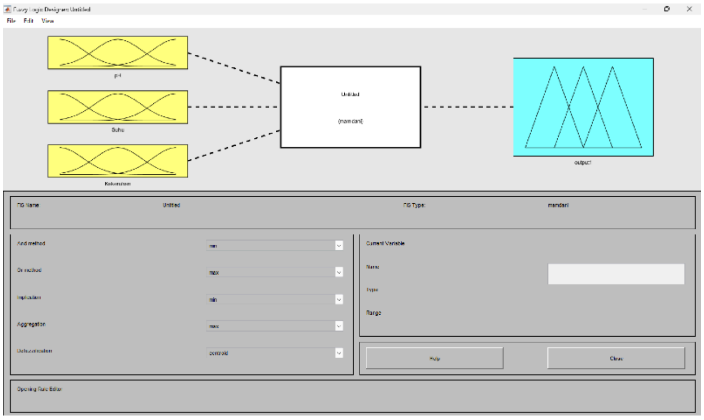
Penyusunan Rule Base

The rule base was constructed based on the combination of three input variables (3 × 3 × 3 = 27 rules).

No	pH	Temperature	Turbidity	Condition
1	Neutral	Normal	Clear	Healthy
2	Neutral	Normal	Moderate	Healthy
3	Neutral	Normal	Turbid	Sick
4	Neutral	Cold	Clear	Healthy
5	Neutral	Cold	Moderate	Sick
6	Neutral	Cold	Turbid	Sick
7	Neutral	Hot	Clear	Sick
8	Neutral	Hot	Moderate	Sick
9	Neutral	Hot	Turbid	Dead
10	Acidic	Normal	Clear	Sick
11	Acidic	Normal	Moderate	Sick
12	Acidic	Normal	Turbid	Dead
13	Acidic	Cold	Clear	Sick
14	Acidic	Cold	Moderate	Sick
15	Acidic	Cold	Turbid	Dead
16	Acidic	Hot	Clear	Sick
17	Acidic	Hot	Moderate	Dead
18	Acidic	Hot	Turbid	Dead
19	Alkaline	Normal	Clear	Sick
20	Alkaline	Normal	Moderate	Sick
21	Alkaline	Normal	Turbid	Dead
22	Alkaline	Cold	Clear	Sick
23	Alkaline	Cold	Moderate	Sick
24	Alkaline	Cold	Turbid	Dead
25	Alkaline	Hot	Clear	Dead
26	Alkaline	Hot	Moderate	Dead
27	Alkaline	Hot	Turbid	Dead

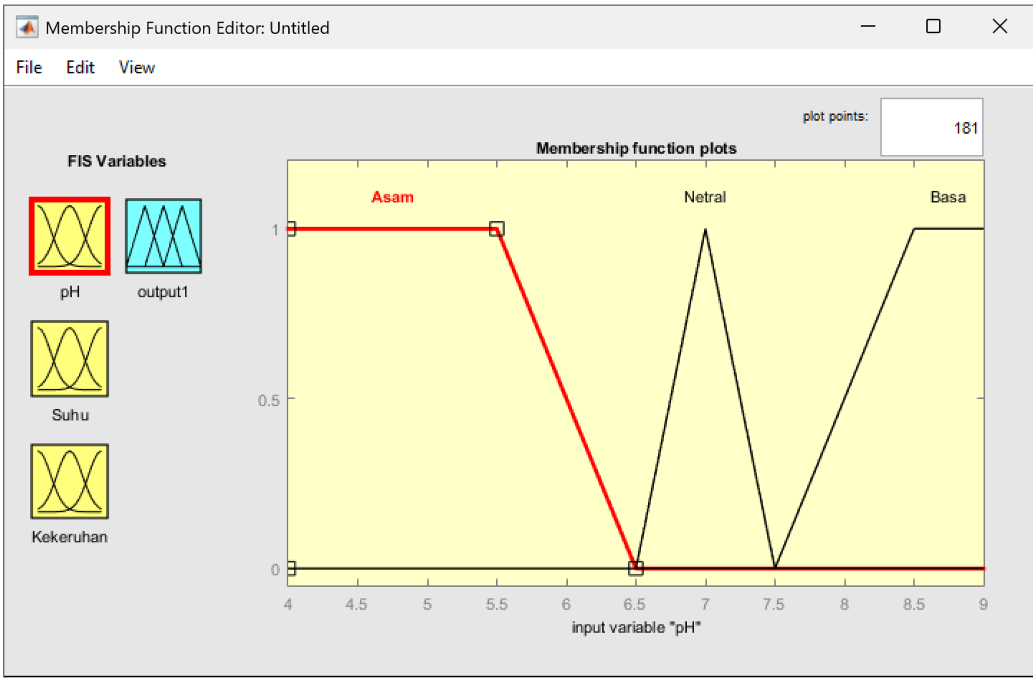
The rule base was constructed based on the principle that optimal conditions occur when all parameters are in ideal categories, whereas extreme combinations such as acidic pH and high temperature with turbid water increase the risk of fish mortality. The inference structure uses the MIN operator for implication and the MAX operator for aggregation according to the classical Mamdani method.

Fuzzifikasi Variable Input



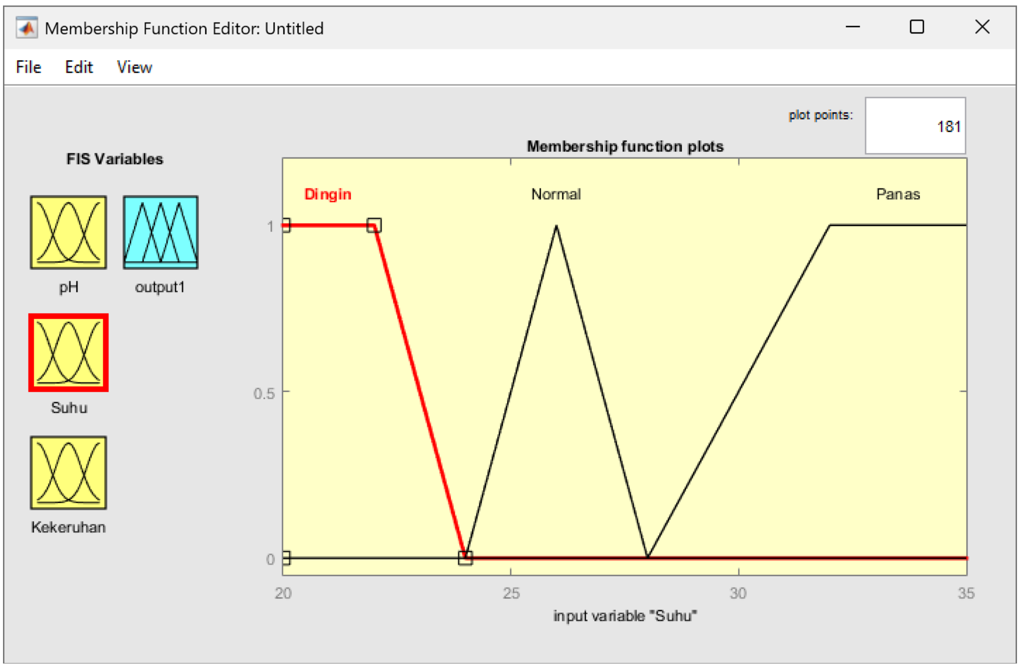
The figure shows the MATLAB Fuzzy Logic Designer interface representing a Mamdani-type Fuzzy Inference System (FIS) structure. Three input variables are displayed: pH, Temperature, and Turbidity, each defined with triangular and trapezoidal membership functions. These inputs are connected to the Mamdani inference engine block located in the center, which processes the fuzzy rules. On the right side, the output variable represents the fish condition. At the bottom of the interface, the inference configuration is shown: the AND operator uses the min method, the OR operator uses max, implication uses min, aggregation uses max, and defuzzification applies the centroid method. This configuration confirms that the system follows the classical Mamdani approach to convert crisp sensor inputs into adaptive and non-linear decision outputs.

1. **ph**



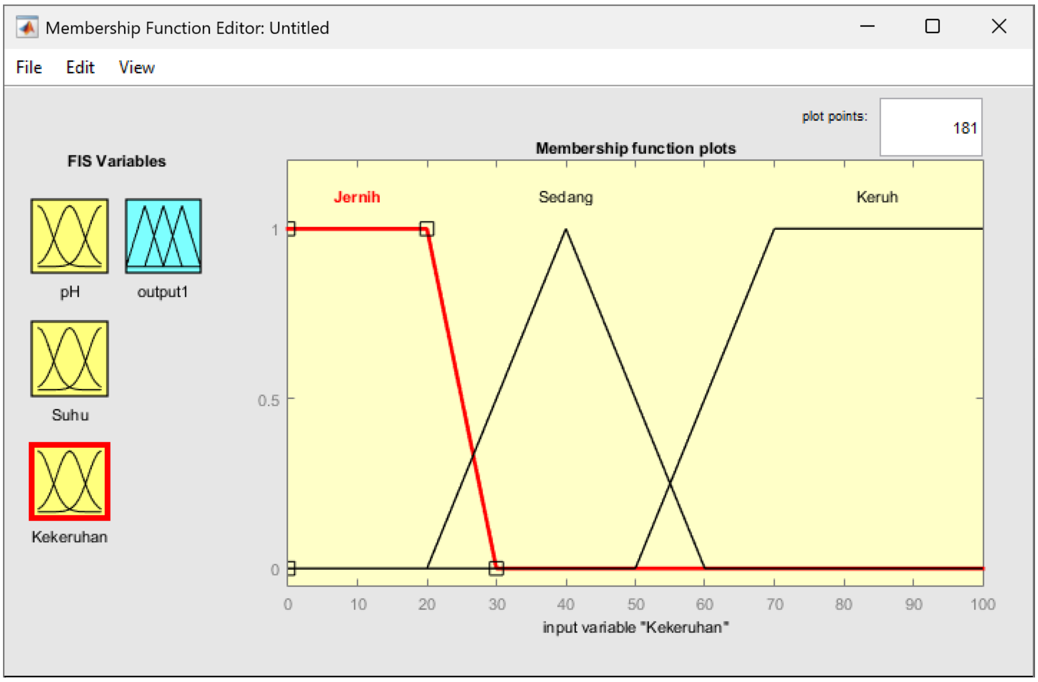
The system utilizes three fuzzy sets for the pH variable: Acidic (trapmf), Neutral (trimf), and Alkaline (trapmf) within the range of 4–9. The trapezoidal membership function is applied to the extreme categories (Acidic and Alkaline) to provide a plateau region where the membership degree (μ) equals 1. Meanwhile, the triangular membership function is used for the Neutral category to represent the ideal condition with a single peak at pH 7. This design enables smooth transitions between categories so that small changes in pH values do not immediately result in drastic changes in control decisions. Therefore, the system can respond proportionally to gradual environmental variations..

2. **Temperature**



The temperature variable consists of three fuzzy categories: Cold (trapmf), Normal (trimf), and Hot (trapmf) within the range of 20–35°C. The Normal category has a peak around 26°C, representing the optimal environmental condition for tropical ornamental fish. The trapezoidal membership functions for Cold and Hot are used to stabilize system responses under extreme thermal conditions. This approach allows the fuzzy system to gradually distinguish between optimal conditions and thermal stress conditions without producing abrupt control outputs.

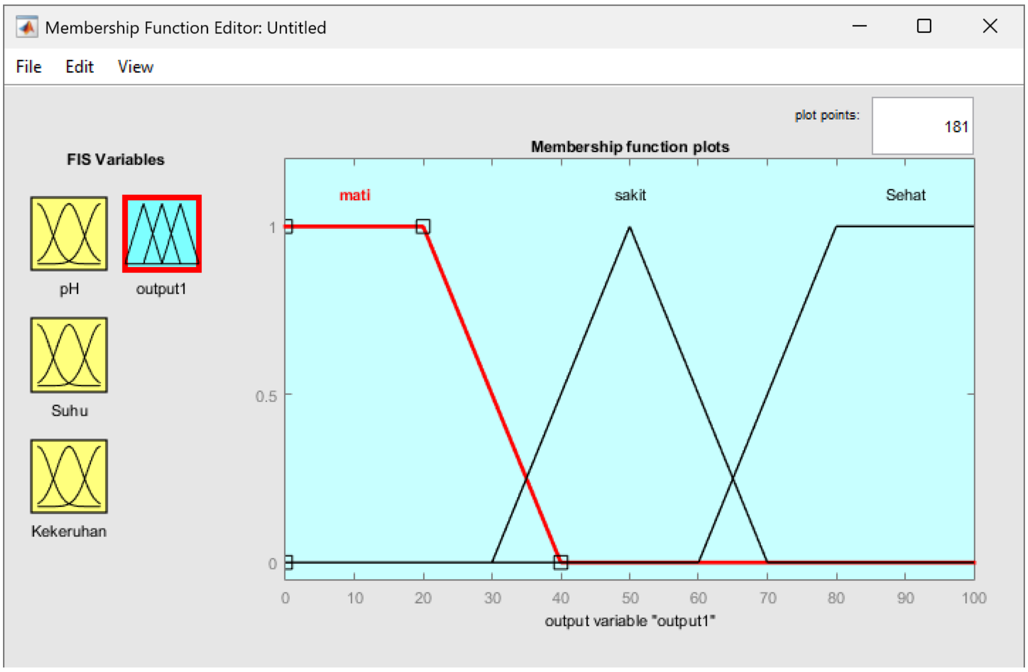
3. Turbidity



For the turbidity variable, three fuzzy sets are defined: Clear (trapmf), Moderate (trimf), and Turbid (trapmf) within the range of 0–100 NTU. The triangular function used in the Moderate category allows the system to detect water quality changes sensitively within transition ranges. Meanwhile, the trapezoidal functions applied to Clear and Turbid provide stability when the water is completely clear or highly turbid. This structure enables the system to realistically integrate the effect of suspended particles on fish health conditions and produce smooth, adaptive decision outputs.

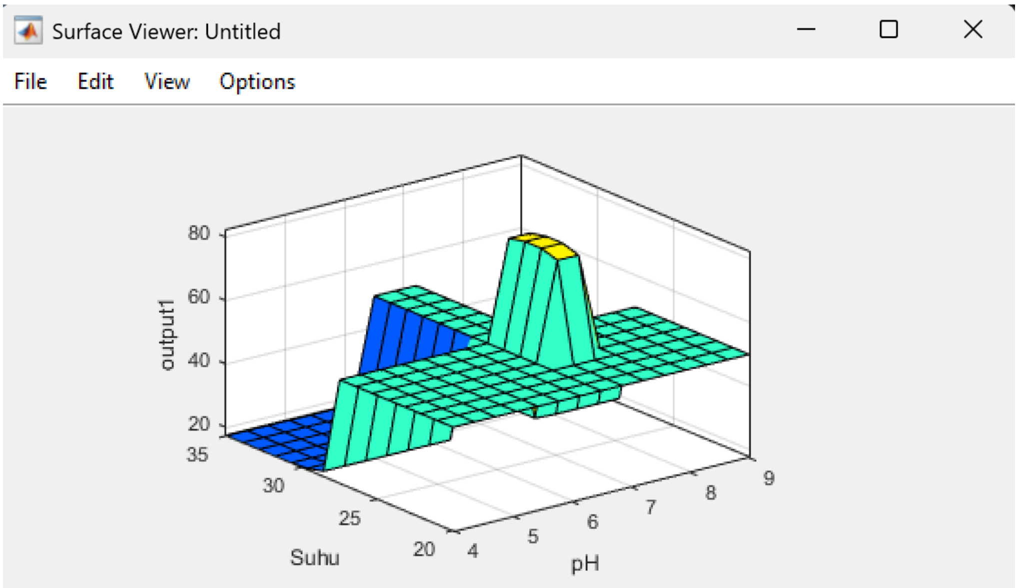
Output Aggregation

1. Condition



Three output categories are defined: Dead, Sick, and Healthy, within the range of 0–100. The aggregation process is performed using the MAX operator to combine the results of each rule implication. The resulting fuzzy output is a combination of areas that are clipped based on the α value (obtained from the MIN operator during rule evaluation). This method ensures that the final decision considers all activated rules rather than relying on a single rule only..

2. Surface



The surface view illustrates the relationship between two input variables (pH and Temperature) and the output variable (fish condition). The three-dimensional surface shows that the highest output value (Healthy) occurs when pH is neutral and temperature is normal. In contrast, extreme combinations result in lower output values (Dead). This visualization demonstrates that the fuzzy system produces a non-linear response that is more flexible and realistic compared to conventional threshold-based methods..

Calculation

Fuzzifikasi

1. **Ph**

   Acidic Domain:
   [4, 4, 5.5, 6.5]

   Since 6.2 lies on the descending side:

$$\mu_{Acidic}(6.2) = \frac{6.5-6.2}{6.5-5.5} = \frac{0.3}{1} = 0.3$$

   Neutral = 0
   Alkaline = 0

2. **Temperature**

   Hot Domain:
   [28, 32, 35, 35]

   Since it lies on the ascending side:

$$\mu_{Hot}(29) = \frac{29-28}{32-28} = \frac{1}{4} = 0.25$$

   Normal = 0
   Cold = 0

3. **Turbidity**

   Moderate Domain:
   [20, 40, 60]

   Since it lies on the descending side:

$$\mu_{Moderate}(55) = \frac{60-55}{60-40} = \frac{5}{20} = 0.25$$

   Turbid Domain:
   [50, 70, 100, 100]

   Since it lies on the ascending side:

$$\mu_{Turbid}(55) = \frac{55-50}{70-50} = \frac{5}{20} = 0.25$$

Inference (MIN Operator)

1. Active Rule:
   IF pH is Acidic AND Temperature is Hot AND Turbidity is Moderate
   THEN Sick

$$\alpha_1 = min(0.3, 0.25, 0.25) = 0.25$$

2. Second Rule:
   IF pH is Acidic AND Temperature is Hot AND Turbidity is Turbid
   THEN Dead

$$\alpha_2 = min(0.3, 0.25, 0.25) = 0.25$$

Determination of Output Area

1. **Sick Output**

   Domain:
   [30, 50, 70]

   Affected by α = 0.25

   Since it is triangular, it is clipped at height 0.25.

   Intersection point on ascending side:

$$0.25 = \frac{z-30}{50-30} 0.25 = \frac{z-30}{20} z - 30 = 5z = 35$$

   Intersection point on descending side:

$$0.25 = \frac{70-z}{20} 70 - z = 5z = 65$$

   Active region:
   $35 \leq z \leq 65$

2. **Dead Output**

   Domain:
   [0, 0, 20, 40]

   Affected by α = 0.25

   Intersection point on ascending side:

$$0.25 = \frac{z-0}{20-0} z = 5$$

   Active region:
   $5 \leq z \leq 40$

Centroid Calculation

Since there are two areas (Sick and Dead), MAX aggregation is applied.

Weighted average approach:

Area of Sick≈ 0.25 × 30 = 7.5

Mid Point ≈ 50

Area Of Dead ≈ 0.25 × 35 = 8.75

Midpoint ≈ 20

$$Z^* = \frac{(7.5\times50)+(8.75\times20)}{7.5+8.75} = \frac{375+175}{16.25} = \frac{550}{16.25} \approx 33.8$$

CONCLUSION

Based on the design and simulation results using the MATLAB Fuzzy Logic Toolbox, the IoT-based water quality monitoring and control system employing the Mamdani-type Fuzzy Inference System has been successfully implemented effectively. The design of membership functions using a combination of trapezoidal and triangular shapes allows the system to proportionally represent extreme conditions as well as ideal conditions.

The inference process using the MIN operator and MAX aggregation produces smoother responses compared to conventional threshold methods. The simulation results and manual calculations demonstrate that the system is capable of integrating pH, temperature, and turbidity parameters simultaneously to determine fish health conditions in the categories of healthy, sick, or dead.

The Surface Viewer visualization confirms that the system exhibits non-linear characteristics that correspond to the dynamics of aquatic environments. Therefore, the Mamdani fuzzy approach provides an adaptive, stable, and realistic solution for maintaining aquarium water quality and improving the efficiency of ornamental fish maintenance..

REFERENCES

Scientific Journal Articles

Abdi F, Cichalewski W, Jałmużna W, Butkowski Ł, Branlard J, Bellandi A, Jabłoński G. 2023. FPGA-Based Implementation of an Adaptive Noise Controller for Continuous Wave Superconducting Cavity. *Electronics (Basel)*. 13(1):155. doi:10.3390/electronics13010155.

Asadulagi M-AM, Pershin IM, Tsapleva V V. 2024. Research on Hydrolithospheric Processes Using the Results of Groundwater Inflow Testing. *Water (Basel)*. 16(3):487. doi:10.3390/w16030487.

Bautista MGAC, Palconit MGB, Rosales MA, II RSC, Bandala AA, Dadios EP, Duarte B. 2022. Fuzzy Logic-Based Adaptive Aquaculture Water Monitoring System Based on Instantaneous Limnological Parameters. *Journal of Advanced Computational Intelligence and Intelligent Informatics*. 26(6):937–943. doi:10.20965/jaciii.2022.p0937.

Cabane H, Farias K. 2024. On the impact of event-driven architecture on performance: An exploratory study. *Future Generation Computer Systems*. 153:52–69. doi:10.1016/j.future.2023.10.021.

Chen C-H, Wu Y-C, Zhang J-X, Chen Y-H. 2022. IoT-Based Fish Farm Water Quality Monitoring System. *Sensors*. 22(17):6700. doi:10.3390/s22176700.

Flores-Iwasaki M, Guadalupe GA, Pachas-Caycho M, Chapa-Gonza S, Mori-Zabarburú RC, Guerrero-Abad JC. 2025. Internet of Things (IoT) Sensors for Water Quality Monitoring in Aquaculture Systems: A Systematic Review and Bibliometric Analysis. *AgriEngineering*. 7(3):78. doi:10.3390/agriengineering7030078.

Hidayat AP, Santosa SH, Dardanella D. 2023. Implementasi Green Supply Chain Management untuk Pasokan Telur Ayam Menggunakan Metode Fuzzy AHP. *JATI UNIK : Jurnal Ilmiah Teknik dan Manajemen Industri*. 6(2):52–60. doi:10.30737/jatiunik.v6i2.3113.

Indrawati EM, Suprianto B, Kartini UT. 2025. Development of Fuzzy Logic Automatic Fish Feeding System and Iot-based Water Quality Control. *Journal of Engineering Research and Reports*. 27(3):56–69. doi:10.9734/jerr/2025/v27i31417.

Irawan Y, Chrismondari, Yolnasdi, Linarta A, Muhardi, Febriani A. 2021. Smart Home Light Based Service Oriented Architecture and IoT. *J Phys Conf Ser*. 1845(1):012070. doi:10.1088/1742-6596/1845/1/012070.

Joniwarta, Priatna W, Hamdani AR, Alexander AD. 2023. Implementasi Fuzzy Logic Pada Sistem Kontrol pH Air Mineral Berbasis IOT. *The Indonesian Journal of Computer Science*. 12(4). doi:10.33022/ijcs.v12i4.3356.

Li H-C, Yu K-W, Lien C-H, Lin C, Yu C-R, Vaidyanathan S. 2023. Improving Aquaculture Water Quality Using Dual-Input Fuzzy Logic Control for Ammonia Nitrogen Management. *J Mar Sci Eng*. 11(6):1109. doi:10.3390/jmse11061109.

Li M, Li C. 2022. Comparison of Flows through a Tidal Inlet in Late Spring and after the Passage of an Atmospheric Cold Front in Winter Using Acoustic Doppler Profilers and Vessel-Based Observations. *Sensors*. 22(9):3478. doi:10.3390/s22093478.

Marín-San Román S, Pérez-Álvarez EP, Sáenz de Urturi I, Parra-Torrejón B, Ramírez-Rodríguez GB, Delgado-López JM, Garde-Cerdán T. 2023. Changes on Grape Aroma Composition as a Consequence of Foliar Application of Methyl Jasmonate and Nano-Sized Particles Doped with Methyl Jasmonate. *Applied Sciences*. 13(4):2487. doi:10.3390/app13042487.

McGregor D, Frodsham S, Deller C. 2023. Participatory Inquiries That Promote Consideration of Socio-Scientific Issues Related to Sustainability within Three Different Contexts: Agriculture, Botany and Palaeontology. *Sustainability*. 15(8):6895. doi:10.3390/su15086895.

Mohd Jais NA, Abdullah AF, Mohd Kassim MS, Abd Karim MM, M A, Muhadi N 'Atirah. 2024. Improved accuracy in IoT-Based water quality monitoring for aquaculture tanks using low-cost sensors: Asian seabass fish farming. *Heliyon*. 10(8):e29022. doi:10.1016/j.heliyon.2024.e29022.

Nagothu SK, Bindu Sri P, Anitha G, Vincent S, Kumar OP. 2025. Advancing aquaculture: fuzzy logic-based water quality monitoring and maintenance system for precision aquaculture. *Aquaculture International*. 33(1):32. doi:10.1007/s10499-024-01701-2.

Nakai K, Yamada K, Nagata T, Saito Y, Nonomura T. 2021. Effect of Objective Function on Data-Driven Greedy Sparse Sensor Optimization. *IEEE Access*. 9:46731–46743. doi:10.1109/ACCESS.2021.3067712.

Pathak H, Igathinathane C, Howatt K, Zhang Z. 2023. Machine learning and handcrafted image processing methods for classifying common weeds in corn field. *Smart Agricultural Technology*. 5:100249. doi:10.1016/j.atech.2023.100249.

Rahayu LP, Kindhi B Al, Pradika CD, Adhim FI, Priananda CW, Musthofa A, Indasyah E, Istiqomah F. 2021. Design of pH Control System and Water Recirculation in Aquaponic Cultivation Using Mamdani Fuzzy Logic Control. Di dalam: *2021 International Conference on Advanced Mechatronics, Intelligent Manufacture and Industrial Automation (ICAMIMIA)*. IEEE. hlm 287–292.

Rastegari H, Nadi F, Lam SS, Ikhwanuddin M, Kasan NA, Rahmat RF, Mahari WAW. 2023. Internet of Things in aquaculture: A review of the challenges and potential solutions based on current and future trends. *Smart Agricultural Technology*. 4:100187. doi:10.1016/j.atech.2023.100187.

Santosa SH, Hidayat AP, Siskandar R. 2021. SAFEA application design on determining the optimal order quantity of chicken eggs based on fuzzy logic. *IAES International Journal of Artificial Intelligence (IJ-AI)*. 10(4):858. doi:10.11591/ijai.v10.i4.pp858-871.

Sarker MdJ, Sarker PK, Islam MdA, Rima NN, Joydas TV, Sultana N, Islam MdM, Hossain MdY, Hossain MB. 2024. Biometry, Growth, and Recruitment Pattern of a Commercially Important Nereid polychaete, Namalycastis fauveli, from the East Coast of Bangladesh. *J Mar Sci Eng*. 12(2):312. doi:10.3390/jmse12020312.

Shete RP, Bongale AM, Dharrao D. 2024. IoT-enabled effective real-time water quality monitoring method for aquaculture. *MethodsX*. 13:102906. doi:10.1016/j.mex.2024.102906.

Sundararajan SCM, Shankar YB, Selvam SP, Manogaran N, Seerangan K, Natesan D, Selvarajan S. 2025. IoT-based prediction model for aquaponic fish pond water quality using multiscale feature fusion with convolutional autoencoder and GRU networks. *Sci Rep*. 15(1):1925. doi:10.1038/s41598-024-84943-7.

Tay A, Lafont F, Balmat J-F, Hadjali A. 2023. An intelligent fuzzy system to manage western flower thrips population under biological treatment in roses yield. *Comput Electron Agric*. 212:108066. doi:10.1016/j.compag.2023.108066.

Trach R, Trach Y, Kiersnowska A, Markiewicz A, Lendo-Siwicka M, Rusakov K. 2022. A Study of Assessment and Prediction of Water Quality Index Using Fuzzy Logic and ANN Models. *Sustainability*. 14(9):5656. doi:10.3390/su14095656.

Xu J, Li H, Zhang X, Wang T, Huang Y, Yuan D. 2021. Development of an anti-chloride interference and high sensitivity on-line analyzer for analysis of total phosphorus in industrial circulating cooling water. *Measurement*. 178:109351. doi:10.1016/j.measurement.2021.109351.

Yang C-H, Lu P-P, Cao Y-M, Xu M, Yu Z-Y, Cheng P-F. 2022. Study on the Plugging Limit and Combination of CO2 Displacement Flow Control System Based on Nuclear Magnetic Resonance (NMR). *Processes*. 10(7):1342. doi:10.3390/pr10071342.

You G, Xu B, Su H, Zhang S, Pan J, Hou X, Li J, Ding R. 2021. Evaluation of Aquaculture Water Quality Based on Improved Fuzzy Comprehensive Evaluation Method. *Water (Basel)*. 13(8):1019. doi:10.3390/w13081019.

Zhu Y, Yang G, Yang H, Guo L, Xu B, Li Zhenhai, Han S, Zhu X, Li Zhenhong, Jones G. 2022. Forecasting regional apple first flowering using the sequential model and gridded meteorological data with spatially optimized calibration. *Comput Electron Agric*. 196:106869. doi:10.1016/j.compag.2022.106869.