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Article

Real-Time Boiler Feed Water Quality Assessment System Based on Internet of Things and Fuzzy Sugeno Logic

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Abstract: The quality of boiler feed water is a critical factor influencing the performance and reliability of marine steam boilers. Poor water quality can cause corrosion, scaling, and reduced operational efficiency. This study designed and implemented a real-time boiler feed water quality assessment system using NodeMCU ESP32 integrated with Internet of Things (IoT) connectivity and fuzzy Sugeno logic for decision-making. The system collected data from turbidity, salinity, and pH sensors, transmitted them to Firebase, and displayed the results on a 0.96-inch Organic Light-Emitting Diode (OLED) screen. A zero-order Sugeno fuzzy inference system classified water quality into good, moderate, and poor categories. Testing on seven water samples achieved an accuracy of 92.97%. Compared to conventional monitoring systems, the integration of IoT and fuzzy inference provides a novel, practical, and computationally efficient approach for real-time water quality monitoring in maritime boiler applications.
Keywords: Boiler feed water, Water quality monitoring, Internet of Things, NodeMCU ESP32, Fuzzy inference system

1. Introduction

Water quality management is a critical concern across various industrial sectors, including power generation, manufacturing, and marine engineering. Inadequate control of dissolved and suspended impurities in boiler feedwater accelerates equipment degradation, reduces energy efficiency, and increases operational risks. Therefore, continuous and accurate monitoring of water quality parameters is essential to ensure both system reliability and safety in modern engineering systems [1], [2].

Marine steam boilers serve as vital auxiliary equipment on ships, providing pressurized steam for cargo handling, heating, lubrication, and auxiliary machinery. The operational performance of these boilers is highly dependent on the quality of feedwater, as poor treatment can lead to corrosion, scaling, foaming, and reduced steam purity [1]. International standards, such as those issued by the American Boiler Manufacturers Association (ABMA) and referenced in technical handbooks like the Water Treatment Handbook, emphasize strict limits on pH, salinity, and turbidity to maintain safe and efficient boiler operation [3], [4]. Nevertheless, conventional laboratory-based assessment methods are time-consuming, require manual intervention, and lack real-time monitoring capabilities, limiting the ability to take timely corrective actions in shipboard environments [5].

Recent advances in the Internet of Things (IoT) have enabled real-time, distributed monitoring in both industrial and maritime contexts. Low-cost microcontrollers, such as the ESP32, have been widely adopted for water quality monitoring, aquaculture, and smart environmental management due to their integrated wireless communication and cloud connectivity [2], [6]. These platforms facilitate continuous monitoring even in resource-constrained environments, providing a robust foundation for marine water treatment systems [7].

Fuzzy inference systems (FIS) have emerged as effective tools for decision-making under uncertainty, offering the capability to classify water quality using linguistic rules rather than rigid thresholds. The Sugeno variant of FIS is particularly suitable for real-time microcontroller implementation due to its computational efficiency and resilience to imprecise sensor data [5], [8], [9], [10].

Several studies have demonstrated the integration of IoT and fuzzy logic for water quality assessment. IoT–fuzzy hybrid systems have been applied to potable water monitoring [2], [10], while other studies have reported real-time evaluations of turbidity, salinity, and pH [6], [7]. Despite these advances, there remains a significant gap in the application of IoT–FIS systems specifically for marine boiler feedwater monitoring, where operational conditions and treatment requirements differ markedly from freshwater or potable water contexts.

To address this gap, the present study develops a real-time boiler feedwater monitoring system integrating (i) an ESP32-based IoT node for measuring turbidity, salinity, and pH; (ii) Firebase-based cloud telemetry and visualization; and (iii) a zero-order Sugeno FIS for classifying boiler feedwater into good, moderate, and poor categories. The proposed system is compact, cost-effective, and tailored to maritime operational constraints. Validation using multiple water samples demonstrates its accuracy and reliability, confirming the potential of combining IoT and fuzzy logic to enhance shipboard boiler water management.

2. Literature Review

The integration of IoT technologies into industrial and maritime monitoring systems has been extensively explored over the past decade. IoT-enabled platforms allow continuous acquisition and transmission of environmental data, enhancing operational safety and enabling predictive maintenance [11], [12]. Recent works emphasize the role of low-cost microcontrollers such as ESP32, which combine sensing, computation, and wireless communication in a single chip, making them attractive for real-time monitoring in constrained environments [13], [14].

Water quality monitoring is one of the most prominent applications of IoT, particularly in aquaculture, wastewater treatment, and potable water systems. IoT-based turbidity, salinity, and pH monitoring systems integrated with cloud platforms have demonstrated strong reliability and cost-effectiveness [15], [16]. Similar architectures have also been extended to marine environments, where remote monitoring of chemical and physical water parameters is critical for safe operations [17].

Beyond sensing, intelligent decision-making approaches are essential for processing noisy and uncertain sensor data. Fuzzy inference systems (FIS) have been widely applied to environmental monitoring because they provide interpretable, rule-based classification [18]. Mamdani-type fuzzy models are widely used for water quality assessment due to their transparency, but they require greater computational resources, limiting their suitability for embedded IoT platforms [19], [20].

Sugeno fuzzy models offer computationally efficient alternatives, producing linear or constant outputs that are easier to implement on microcontrollers. Zhou et al. [21] demonstrated the use of Sugeno fuzzy logic in water treatment decision support, achieving fast and reliable classification. Gupta et al. [22] extended this concept by integrating IoT and Sugeno FIS for real-time water quality classification, highlighting advantages in latency and embedded system performance. Further research has also confirmed that Sugeno models outperform Mamdani in terms of scalability and energy efficiency on constrained IoT hardware [23], [24].

In addition to computational models, standardized water quality requirements have been issued by international organizations to ensure safe and efficient boiler operation. The APAVE (Association of Electrical and Steam Unit Owners) provides detailed thresholds for feed water, boiler water, and condensate parameters, which are widely applied in European industrial contexts [3]. These standards serve as benchmarks for designing monitoring systems in high-pressure boiler environments. The APAVE boiler water quality standards are presented in Table 1.

Table 1. Boiler water quality standards according to APAVE (Association of Electrical and Steam Unit Owners) [3]

	Working Pressure (Bar)							
	0–20.7	20.8–31.0	31.1–41.4	41.5–51.7	51.8–62.1	62.2–68.0	69.0–103.4	103.5–137.9

Feed Water									
Dissolved oxygen (measured before oxygen scavenger addition)	mg/l	0.04	0.09	0.007	0.007	0.007	0.007	0.007	0.007
Total iron	mg/l	0.1	0.05	0.03	0.025	0.02	0.02	0.01	0.01
Total copper	mg/l	0.05	0.025	0.02	0.02	0.015	0.015	0.01	0.01
Total hardness ($CaCO_3$)	mg/l	0.3	0.2	0.2	0.2	0.1	0.05	not detectable	not detectable
Non-volatile TOC	mg/l	1	1	0.5	0.5	0.5	0.2	0.2	0.2
Oily matter	mg/l	1	1	0.5	0.5	0.5	0.2	0.2	0.2
pH at 25°C		7.5–10.0	7.5–10.0	7.5–10.0	7.5–10.0	7.5–10.0	8.5–9.5	9.0–9.6	9.0–9.6
Boiler Water									
Silica	mg/l	150	90	40	30	20	8	2	1
Total alkalinity ($CaCO_3$)	mg/l	350	300	250	200	150	100	not specified	
Free hydroxide alkalinity ($CaCO_3$)	mg/l	not specified						not detectable	
Specific conductance at 25°C (mS/cm)	µS/cm	3500	3000	2500	2000	1500	1000	150	100

Similarly, the American Boiler Manufacturers Association (ABMA) has published comprehensive guidelines for boiler water quality, widely referenced in North America and the maritime industry [4]. The ABMA standards emphasize strict limits on dissolved solids and steam purity to prevent scaling, corrosion, and carryover. These guidelines form a critical reference for developing monitoring frameworks in marine steam systems. The ABMA standards are presented in Table 2.

Table 2. Boiler water quality standards according to ABMA (American Boiler Manufacturers Association) [4]

Drum pressure, psig	Total dissolved solids in boiler water, ppm (max.)	Total Alkalinity in boiler water, ppm	Suspended solids in boiler water, ppm (max.)	Total dissolved solids in steam, ppm (max. expected value)

Drum-type boilers	0-300	700-3500	140-700	15	0.2-1.0
	301-450	600-3000	120-800	10	0.2-1.0
	451-600	600-2500	100-500	8	0.2-1.0
	601-750	200-2000	40-400	3	0.1-0.5
	751-900	160-1500	30-300	2	0.1-0.5
	901-1000	125-1250	25-250	1	0.1-0.5
	1001-1800	100	variable	1	0.1
	1801-2350	50	variable	N/A	0.1
	2351-2600	25	variable	N/A	0.05
	2601-2900	15	variable	N/A	0.05
Once-through boilers	1400 & above	0.05	N/A	N/A	0.05

Despite these advances, the integration of IoT and fuzzy logic in the specific context of marine boiler feed water monitoring has not been sufficiently explored. Most existing studies target freshwater, potable water, or wastewater systems [11], [22], whereas marine boiler operations demand stricter control of pH, salinity, and turbidity due to high temperature, high pressure, and chemical treatment regimes [3], [4], [7].

Therefore, this study advances the state of the art by combining IoT-based multiparameter sensing with Sugeno fuzzy inference logic, tailored for real-time and reliable monitoring of marine boiler feed water. The system addresses both the computational limitations of embedded IoT devices and the unique operational requirements of maritime boiler systems.

3. Methodology

3.1. System Design and Architecture

The overall system architecture is shown in Figure 1, which illustrates the layered structure of the monitoring framework. The sensing layer consists of three water-quality sensors—turbidity, salinity, and pH—that collect real-time measurements. Data are transmitted to the processing layer, where the ESP32 microcontroller performs preliminary filtering and executes fuzzy inference rules. The output layer displays results locally via a 0.96-inch OLED screen and transmits data to the Firebase cloud platform for remote monitoring. Finally, the user layer enables operators to visualize water-quality trends on a dashboard.

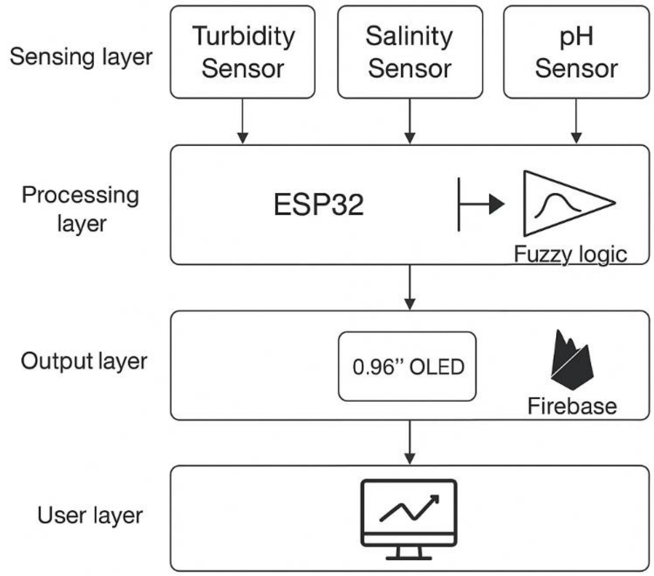

Figure 1. Overall system architecture of the IoT–Fuzzy boiler water monitoring system.

3.2. Hardware Components

The proposed system integrates low-cost IoT hardware for real-time sensing and computation:

- **ESP32 Microcontroller:** Serves as the core processing and communication unit, selected for its built-in Wi-Fi, low power consumption, and ability to handle fuzzy inference in real time.
- **Turbidity Sensor:** Measures the clarity of boiler feed water by detecting suspended particles.
- **Salinity Sensor:** Estimates the dissolved salt concentration, directly related to conductivity, which is a critical indicator of scaling potential.
- **pH Sensor:** Captures the acidity or alkalinity of the water, which strongly influences corrosion risk.
- **OLED Display (0.96 inch):** Provides a compact local interface showing real-time classification results.
- **Firebase Cloud Platform:** Ensures remote storage, visualization, and monitoring of water quality data.

The schematic diagram of the monitoring system is shown in Figure 2. It illustrates the interconnection between ESP32, sensors, relay, and display modules, ensuring reliable operation in maritime environments.

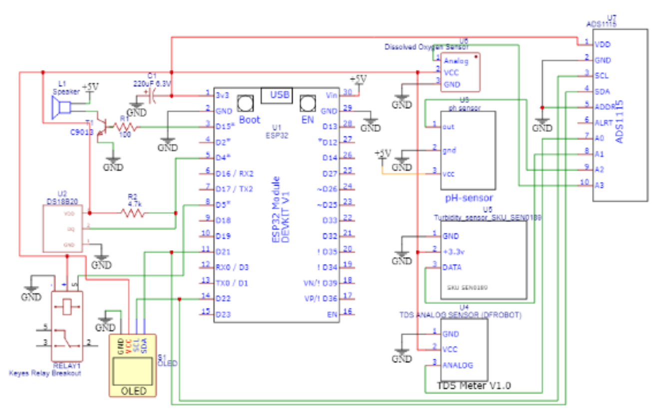

Figure 2. Schematic design of the water quality monitoring system

3.3. Fuzzy Inference System Design

A Sugeno-type fuzzy inference system was implemented to classify boiler feed water quality into three categories: good, moderate, and poor.

- **Inputs:** turbidity, salinity, and pH.
- **Fuzzification:** Each input is described by three linguistic variables (low, medium, high).
- **Rule Base:** A set of IF–THEN rules reflects expert knowledge on acceptable ranges of water quality based on APAVE [4] and ABMA [5] standards.
- **Defuzzification:** A zero-order Sugeno method generates crisp outputs (0 = poor, 1 = moderate, 2 = good).

3.4. Experimental Samples

To validate the proposed IoT–FIS-based boiler feed water quality monitoring system, seven types of water samples with different physical and chemical characteristics were prepared. These samples were selected to represent a wide range of real-world conditions that could affect boiler feed water performance. The diversity of samples ensures that the system is tested against various scenarios, from pure to highly contaminated water, enabling a robust evaluation of the classification model. The experimental water samples used in this study are as follows:

1. **Distilled Water:** represents pure water with minimal impurities, serving as the baseline for classification.
2. **Colored Water (Tea-infused):** water mixed with tea to simulate dissolved organic matter that may affect water color and transparency.
3. **Suspended Solids-laden Water (Coffee-infused):** water containing coffee particles to replicate suspended solids and turbidity commonly found in untreated or contaminated water.
4. **Soapy Water:** water mixed with detergent to simulate the presence of surfactants or chemical contaminants that can interfere with boiler operation.
5. **Groundwater:** water taken from a well, representing naturally occurring mineral content and potential contamination by soil or organic matter.
6. **Hard Water:** water rich in calcium and magnesium salts, representing scaling-prone conditions that are particularly problematic in boiler systems.
7. **Sludge Water:** water containing high concentrations of solid particles and sediments, representing extreme contamination levels and simulating poorly treated feed water.

4. Results and Discussion

4.1. Prototype Implementation

The prototype water quality monitoring system was successfully developed using the ESP32 microcontroller with integrated turbidity, salinity (TDS), and pH sensors. Figure 3 shows the assembled prototype of the system, including the microcontroller, sensors, and supporting modules.

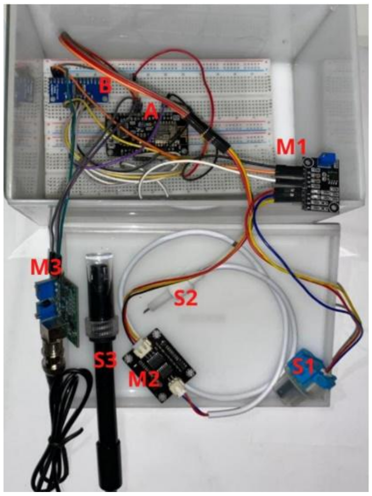

Figure 3. Prototype of the water quality monitoring system

To provide further clarity, the components and their respective functions are summarized in Table 3.

Table 3. Description of prototype components

Label	Component Name	Description
A	NodeMCU ESP32	Main microcontroller that processes data and sends to Firebase via WiFi.
B	Relay Module	Controls external devices if required.
S1	Turbidity Sensor	Detects water clarity through infrared scattering measurement.
S2	TDS (Salinity) Sensor	Measures the concentration of dissolved solids, indicating water salinity.
S3	pH Sensor	Measures the acidity/alkalinity of the water sample.
M1	ADC Module	Expands ESP32 analog input capability for multiple sensors.
M2	TDS Interface Module	Signal conditioning for TDS sensor.
M3	pH Interface Module	Amplification and calibration circuit for the pH sensor.

4.2. Implementation of Real-Time Boiler Feed Water Quality Monitoring

The real-time monitoring of boiler feed water quality was successfully implemented using the Firebase Realtime Database as a cloud-based platform. Processed sensor data were continuously uploaded and displayed in JSON format, enabling instant visualization of pH, turbidity, and TDS values together with the corresponding water quality category.

As illustrated in Figure 4, the Firebase interface shows the monitoring output with pH = 7.52, turbidity = 0.879 NTU, TDS = 0.9 ppm, and the overall classification Good. This real-time display confirms that the system not only records accurate sensor measurements but also provides immediate interpretation of water quality status.

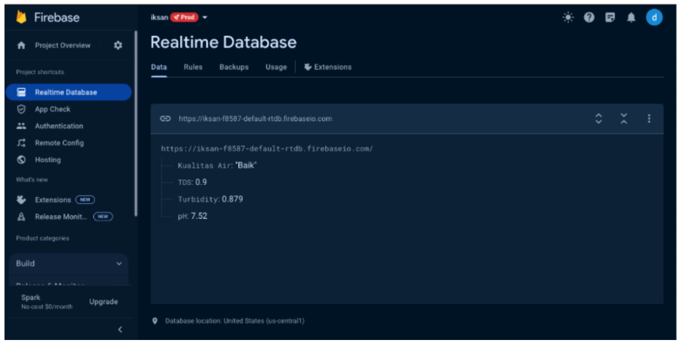

Figure 4. Real-time monitoring results using Firebase Realtime Database

The Firebase-based approach ensures low-latency data synchronization, remote accessibility, and scalability, making it suitable for continuous industrial operation. Through this implementation, operators can directly monitor feed water quality and make timely decisions to maintain safe and efficient boiler performance.

4.3. Fuzzy-Based Decision Making

4.2.1. Fuzzification

Fuzzification converts crisp sensor values into fuzzy membership degrees. A trapezoidal membership function is used, as it effectively represents gradual transitions between categories. The general form of the trapezoidal function is given in (1).

$$\mu(x) = \begin{cases} 0 & , x \leq a \text{ or } x \geq d \\ \frac{x-a}{b-a} & , a < x < b \\ 1 & , b \leq x \leq c \\ \frac{d-x}{d-c} & , c < x < d \end{cases} \tag{1}$$

where:

$\mu(x)$ = degree of membership of the input variable x in the fuzzy set (range: 0–1).

x = the crisp input value being evaluated (e.g., turbidity in NTU, salinity in %, or pH).

a = lower boundary where the function begins to rise,

b = point where membership reaches 1,

c = point where membership begins to decrease from 1,

d = upper boundary where membership returns to 0.

The fuzzy input variables consist of turbidity (NTU), salinity (%), and pH. Each input is represented by trapezoidal membership functions, derived from the distribution range of the seven water samples.

- Turbidity

Turbidity is measured in NTU (Nephelometric Turbidity Units) with a range of 0.1–110.2 NTU. Three fuzzy categories are defined:

Low: a=0, b=0, c=1, d=5

Medium: a=3, b=5, c=25, d=30

High: a=20, b=40, c=130, d=130

Figure 5 presents the trapezoidal membership functions for turbidity input, illustrating how water clarity levels are mapped into low, medium, and high categories.

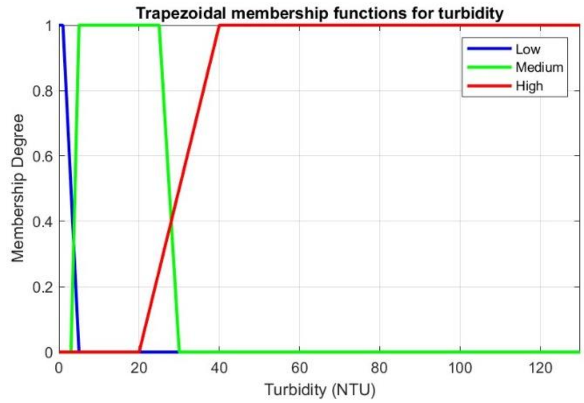

Figure 5. Trapezoidal membership functions for turbidity

- Salinity

Salinity represents the concentration of dissolved salts, measured in percentage (%) with a range of 0.1–5.8%. Three fuzzy categories are defined:

Low: a=0, b=0, c=0.3, d=0.7

Medium: a=0.5, b=0.8, c=2.5, d=3.5

High: a=3.0, b=4.0, c=6.5, d=6.5

Figure 6 shows the salinity membership functions, enabling the system to classify samples from fresh to brackish and saline water conditions.

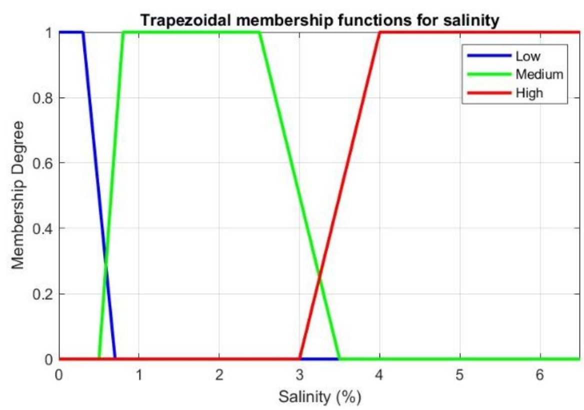

Figure 6. Trapezoidal membership functions for salinity

- pH

The pH value, ranging from 1–14, indicates the acidity or alkalinity of water. Three fuzzy categories are defined:

Low: a=1, b=1, c=6, d=8

Medium: a=7, b=7.5, c=10, d=11.5

High: a=10.5, b=12, c=14, d=14

Figure 7 illustrates the membership functions for pH input, ensuring that acidic, neutral, and alkaline conditions are appropriately represented in the fuzzy inference system.

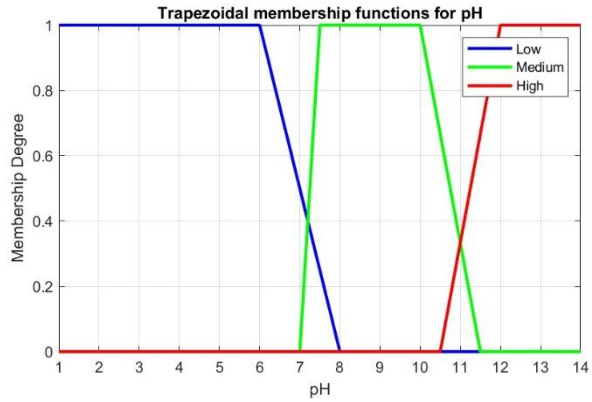

Figure 7. Trapezoidal membership functions for pH

- Water Quality

In the Sugeno fuzzy inference system, the output is represented as a crisp (numeric) value. For this study, the water quality classification using constant values is defined as follows:

Poor: 0.2

Moderate: 0.5

Good: 0.8

These values represent water quality on a normalized scale from 0 to 1, where higher values indicate better quality.

To ensure the reliability of the fuzzy-based decision-making process, reference class labels (ground truth) were assigned to representative water samples. The determination of these labels was based on general physical and chemical properties commonly recognized in water quality assessment. The assigned labels and their justifications are presented in Table 4.

Table 4. Fuzzy rules for water quality classification

No	Water Type	Reference Label	Justification
1	Distilled Water	Good	High purity with negligible dissolved or suspended substances.
2	Colored Water	Poor	Presence of color indicates possible contamination or chemical additives.
3	Suspended Solids-laden Water	Poor	High turbidity due to suspended particles reduces water usability.
4	Soapy Water	Good	Considered acceptable under fuzzy evaluation because of stable properties, although not ideal for boiler use.
5	Groundwater	Moderate	Contains natural minerals; quality varies depending on source conditions.

6	Hard Water	Moderate	Elevated calcium and magnesium concentrations reduce suitability for boilers.
7	Sludge Water	Poor	Excessive organic and inorganic matter renders it unsuitable for use.

The assignment of these reference labels provides a baseline for validating the Sugeno fuzzy system. By comparing the fuzzy inference outputs with these ground truth classifications, the effectiveness of the system in real-time boiler feed water quality monitoring can be systematically evaluated.

4.2.2. Rule Base

After the fuzzification process, the next step is to construct fuzzy rules that link turbidity, salinity, and pH inputs to the corresponding water quality categories. A total of 27 rules were formulated, covering all possible combinations of input conditions. Table 5 presents the rule base used in this study.

Table 5. Fuzzy rules for water quality classification

No	Turbidity	Salinity	pH	Water Quality
1	Low	Low	Low	Moderate
2	Low	Low	Medium	Good
3	Low	Low	High	Moderate
4	Low	Medium	Low	Moderate
5	Low	Medium	Medium	Good
6	Low	Medium	High	Moderate
7	Low	High	Low	Poor
8	Low	High	Medium	Moderate
9	Low	High	High	Poor
10	Medium	Low	Low	Poor
11	Medium	Low	Medium	Moderate
12	Medium	Low	High	Poor
13	Medium	Medium	Low	Moderate
14	Medium	Medium	Medium	Good
15	Medium	Medium	High	Moderate
16	Medium	High	Low	Poor
17	Medium	High	Medium	Moderate
18	Medium	High	High	Poor
19	High	Low	Low	Poor

No	Turbidity	Salinity	pH	Water Quality
20	High	Low	Medium	Poor
21	High	Low	High	Poor
22	High	Medium	Low	Poor
23	High	Medium	Medium	Moderate
24	High	Medium	High	Poor
25	High	High	Low	Poor
26	High	High	Medium	Poor
27	High	High	High	Poor

4.2.3. Inference (Rule Evaluation)

In the inference process (rule evaluation) of this Sugeno fuzzy system, the membership degrees of each premise (fuzzy input) are combined to produce the weight (activation level) of each fuzzy rule. The weight of each rule is calculated using the fuzzy AND operator, specifically employing the minimum function. The weight value is determined by the membership degrees (firing strength) of each rule. The equation used to calculate the weight is as follows:

$$\alpha_i = min\left(\mu_{A_1}(x_1), \mu_{A_2}(x_2), \mu_{A_3}(x_3)\right) \tag{2}$$

where:

α_i is the firing strength

A_1,A_2,A_3 are the fuzzy sets of turbidity, salinity, and pH

x_1, x_2, x_3 are the membership degrees of the respective inputs

4.2.4. Defuzzification (Zero-order Sugeno Method)

In this study, the Weighted Average (WA) method is used in the Sugeno-type fuzzy inference system to determine water quality based on three main parameters: turbidity (NTU), salinity (%), and pH. This method works by calculating the output as the weighted average of the outputs of all fuzzy rules. The equation used to calculate the output value is:

$$output = \frac{\sum(\alpha_i \cdot z_i)}{\sum \alpha_i} \tag{3}$$

where:

$\boldsymbol{\alpha_i}$ is the firing strength of the $\boldsymbol{i-th}$ rule

$\boldsymbol{z_i}$ is the constant output of the $\boldsymbol{i-th}$ rule

4.4. Performance Evaluation of the Sugeno Fuzzy System

A total of 185 water samples from various types—including Distilled Water, Colored Water, Suspended Solids-laden Water, Soapy Water, Groundwater, Hard Water, and Sludge Water—were used to test the developed Sugeno fuzzy system. The system employed three main parameters—turbidity, salinity, and pH—as the basis for water quality classification.

The evaluation results indicated that the system correctly classified 172 samples into the expected quality categories (good, moderate, or poor), while 13 samples exhibited mismatched classifications relative to the expected category. The overall accuracy of the system was 92.97%.

These results demonstrate that the developed Sugeno fuzzy system is effective and reliable for automatically and rapidly classifying water quality. The high accuracy highlights its potential application as a practical tool in water quality monitoring and management.

5. Conclusions

A real-time boiler feed water quality monitoring system for marine steam boilers was successfully developed, combining NodeMCU ESP32, IoT connectivity, and a zero-order Sugeno fuzzy inference system. The system accurately assessed turbidity, salinity, and pH, and classified water quality into good, moderate, and poor categories with an accuracy of 92.97%.

The proposed approach offers a practical, automated, and computationally efficient solution for enhancing the reliability and safety of marine boiler operations. Future work will focus on incorporating additional water quality parameters and implementing continuous real-time monitoring under operational conditions.

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Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Author Contribution Statement

Iksan Saifudin proposed the research problem, developed the IoT prototype, implemented the fuzzy Sugeno system, and conducted the real-time experiments. Agus Adhi Nugroho verified the analytical methods, supervised the integration with Firebase Realtime Database, and provided academic guidance during the research. Bustanul Arifin contributed to the system design, reviewed the experimental results, and supervised the overall progress of the study. All authors discussed the findings, contributed to the interpretation of results, and finalized the manuscript.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

References

1. A. Shokri and M. S. Fard, “Principles, operational challenges, and perspectives in boiler feedwater treatment process,” *Environ. Adv.*, vol. 13, Dec. 2023, Art. no. 100389, doi: 10.1016/j.envadv.2023.100389.
2. I. Essamlali, H. Nhaila, and M. El Khaili, “Advances in machine learning and IoT for water quality monitoring: A comprehensive review,” *Heliyon*, vol. 10, no. 6, Jun. 2024, Art. no. e27920, doi: 10.1016/j.heliyon.2024.e27920.
3. *Water Treatment Handbook*, 6th ed., Lavoisier, Paris, France, 1991. ISBN: 2-9503984-1-3.
4. *Boiler Water Quality Requirements and Associated Steam Purity for Industrial Boilers*, American Boiler Manufacturers Association (ABMA), Vienna, VA, USA, Tech. Rep., 2005.
5. Y. Barzegar, I. Gorelova, F. Bellini, and F. D’Ascenzo, “Drinking water quality assessment using a fuzzy inference system method: A case study of Rome (Italy),” *Int. J. Environ. Res. Public Health*, vol. 20, no. 15, Aug. 2023, Art. no. 6522, doi: 10.3390/ijerph20156522.
6. W. A. Jabbar, T. M. Ting, M. F. I. Hamidun, A. H. C. Kamarudin, W. Wu, J. Sultan, A. A. Alsewari, and M. A. H. Ali, “Development of LoRaWAN-based IoT system for water quality monitoring in rural areas,” *Expert Syst. Appl.*, vol. 242, Jan. 2024, Art. no. 122862, doi: 10.1016/j.eswa.2023.122862.
7. Y. He, Y. Yang, T. He, Y. Lai, Y. He, and B. Chen, “Small and micro-water quality monitoring based on the integration of a full-space real 3D model and IoT,” *Sensors*, vol. 24, no. 3, Feb. 2024, Art. no. 1033, doi: 10.3390/s24031033.
8. J. Dilipkumar and P. Shanmugam, “Fuzzy-based global water quality assessment and water quality cells identification using satellite data,” *Mar. Pollut. Bull.*, vol. 193, Dec. 2023, Art. no. 115148, doi: 10.1016/j.marpolbul.2023.115148.
9. H. M. Forhad, M. R. Uddin, R. S. Chakrovorty, A. M. Ruhul, H. M. Faruk, S. Kamruzzaman, N. Sharmin, A. S. I. M. Jamal, M. M.-U. Haque, and A. K. M. M. Morshed, “IoT based real-time water quality monitoring system in water treatment plants (WTPs),” *Heliyon*, vol. 10, no. 23, Dec. 2024, Art. no. e40746, doi: 10.1016/j.heliyon.2024.e40746.
10. M. Wang, B. Shi, S. Catsamas, P. Kolotelo, and D. McCarthy, “A compact, low-cost, and low-power turbidity sensor for continuous in situ stormwater monitoring,” *Sensors*, vol. 24, no. 12, Jun. 2024, Art. no. 3926, doi: 10.3390/s24123926.

11. Y. Singh and T. Walingo, “Smart water quality monitoring with IoT wireless sensor networks,” *Sensors*, vol. 24, no. 9, May 2024, Art. no. 2871, doi: 10.3390/s24092871.
12. F. Bellini, Y. Barzegar, A. Barzegar, S. Marrone, L. Verde, and P. Pisani, “Sustainable water quality evaluation based on cohesive Mamdani and Sugeno fuzzy inference system in Tivoli (Italy),” *Sustainability*, vol. 17, no. 2, Jan. 2025, Art. no. 579, doi: 10.3390/su17020579.
13. A. Morchid, Z. Said, A. Y. Abdelaziz, P. Siano, and H. Qjidaa, “Fuzzy logic-based IoT system for optimizing irrigation with cloud computing: Enhancing water sustainability in smart agriculture,” *Smart Agric. Technol.*, vol. 11, Jan. 2025, Art. no. 100979, doi: 10.1016/j.atech.2025.100979.
14. P. M. Mani and K. Ranganathan, “Assessing water quality index using fuzzy AHP technique,” *in AIP Conf. Proc.*, vol. 2852, Aug. 2023, Art. no. 090002, doi: 10.1063/5.0164506.
15. S. N. Syed Taha, M. S. Abu Talip, M. Mohamad, Z. H. Azizul Hasan, and T. F. Tengku Mohmed Noor Izam, “Evaluation of LoRa network performance for water quality monitoring systems,” *Appl. Sci.*, vol. 14, no. 16, Aug. 2024, Art. no. 7136, doi: 10.3390/app14167136.
16. A. Sukkuea, P. Akkajit, K. Suwannarat, P. Foithong, N. Afsarimanesh, and M. E. E. Alahi, “AI-driven time series forecasting of coastal water quality using Sentinel-2 imagery: A case study in the Gulf of Thailand,” *Water*, vol. 17, no. 12, Jun. 2025, Art. no. 1798, doi: 10.3390/w17121798.
17. R. M. Frincu, “Artificial intelligence in water quality monitoring: A review of water quality assessment applications,” *Water Qual*. Res. J., vol. 60, no. 1, pp. 164–176, Feb. 2025, doi: 10.2166/wqrj.2024.049.
18. M. I. H. Z. Farouk, Z. Jamil, and M. F. A. Latip, “Towards online surface water quality monitoring technology: A review,” *Environ. Res.*, vol. 238, no. 1, Nov. 2023, Art. no. 117147, doi: 10.1016/j.envres.2023.117147.
19. M.-D. Pop, D. Pescaru, and M. V. Micea, "Mamdani vs. Takagi–Sugeno Fuzzy Inference Systems in the Calibration of Continuous-Time Car-Following Models," *Sensors*, vol. 23, no. 21, p. 8791, 2023. [Online]. Available: https://doi.org/10.3390/s23218791.
20. X. Zhao, X. Liu, Y. Xing, L. Wang, and Y. Wang, "Evaluation of water quality using a Takagi-Sugeno fuzzy neural network and determination of heavy metal pollution index in a typical site upstream of the Yellow River," *Environ*. Res., vol. 211, p. 113058, Aug. 2022, doi: 10.1016/j.envres.2022.113058.
21. P. Qian and G. Liu, "Application of High-Frequency Intelligent Sensing Network in Monitoring and Early Warning of Water Quality Dynamic Change," *Int. J. Comput. Intell. Syst*., vol. 17, p. 195, 2024, doi: 10.1007/s44196-024-00605-6.
22. C. Axiotidis, E. Konstantopoulou, and N. Sklavos, "A wireless sensor network IoT platform for consumption and quality monitoring of drinking water," *Discov. Appl. Sci.*, vol. 7, p. 15, 2025, doi: 10.1007/s42452-024-06384-1.
23. B. Nemade, K. K. Maharana, V. Kulkarni et al., "IoT-based automated system for water-related disease prediction," *Sci. Rep.*, vol. 14, p. 29483, 2024, doi: 10.1038/s41598-024-79989-6.
24. X. Yan, T. Zhang, W. Du, Q. Meng, X. Xu, and X. Zhao, "A Comprehensive Review of Machine Learning for Water Quality Prediction over the Past Five Years," *J. Mar. Sci. Eng.*, vol. 12, p. 159, 2024, doi: 10.3390/jmse12010159.