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IoT-Enabled Real-Time Monitoring and Tsukamoto Fuzzy Classification of Mandar River Water Quality via Web Integration for Sustainable Resource Management

Chairi Nur Insani*[1], Nurhikma Arifin[2]

[1, 2] Informatics, Engineering Faculty, Universitas Sulawesi Barat, Indonesia

Email: [1]chairini@unsulbar.ac.id

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Abstract

This study presents the design and implementation of a real-time water quality monitoring system that utilizes pH, Total Dissolved Solids (TDS), and turbidity sensors, integrated with an ESP32 microcontroller. Sensor data are processed using the Tsukamoto fuzzy logic method to classify river water suitability into two categories: Suitable and Not Suitable. This approach effectively addresses imprecise and uncertain data, thereby producing more reliable classifications compared to conventional threshold-based methods. System validation was conducted through field testing over seven consecutive days at four different times of the day (morning, midday, afternoon, and evening), with results demonstrating stable performance. Recorded pH values ranged from 7.02 to 9.96, TDS values from 140 to 176 ppm, and turbidity levels between 4.00 and 5.15 NTU, indicating that the Mandar River remains within safe limits for daily use. The novelty of this study lies in the direct implementation of the Tsukamoto fuzzy logic method on a resource-constrained IoT device (ESP32), enabling edge-level classification with low latency and without full reliance on cloud computing. The system is designed to maintain decision reliability even under fluctuating sensor data, thus offering a practical and integrated solution for real-time monitoring. The main contribution of this work to computer science is the demonstration of lightweight embedded intelligent algorithms capable of running on constrained devices, the reinforcement of Explainable AI through transparent linguistic rules, and the integration of IoT with edge computing to support sustainable resource management in real-time.

Keywords : *ESP32, IoT, pH sensor, real-time monitoring, TDS, Tsukamoto fuzzy logic, turbidity.*

1. INTRODUCTION

The Mandar River is located in West Sulawesi Province, originating from a spring at the base of a mountain. In Tutar District, it flows through several districts within Polewali Mandar Regency. It is one of the longest rivers in West Sulawesi. However, the Mandar River has experienced a decline in water quality due to the buildup of plastic waste and household garbage carried into the river. This river serves as a vital water source for the people of Alu in their daily lives. According to research conducted by Sukmawati et al., the biotic index of the Mandar River falls into the moderately polluted category[1]. Water is a basic necessity for human life and serves many purposes, including sanitation, hygiene, and consumption. Polluted water can have numerous adverse effects, including environmental degradation, discomfort in the surroundings, and a decline in human health and safety. The assessment of water quality is still largely carried out using conventional methods, which involve manually measuring and analyzing each piece of data obtained from testing[2]. This method is often time-consuming, error-prone, and inefficient for real-time information.

The implementation of a web-based platform for water quality monitoring enables the public to easily and directly access real-time data. Moreover, the utilization of this technology contributes to improving transparency and accountability in water resource management. This system integrates a

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web-based interface with the Tsukamoto fuzzy logic method, specifically designed for real-time monitoring of the Mandar River's water quality, allowing users to directly access the classification results of water suitability through an interactive web interface.[3]. Employing a website as the primary platform, water quality data can be disseminated in a transparent and accessible manner to the public. In the context of utilizing information technology for water quality monitoring, several previous studies have examined and developed digital-based systems aimed at enhancing the effectiveness, efficiency, and accuracy of data management and decision-making related to water resource quality. The study conducted by Rahman et al. in the coastal region of Bangladesh demonstrated that the use of 50 sensor nodes over a 30-day period for water quality monitoring, measuring parameters such as pH, turbidity, temperature, dissolved oxygen, and salinity resulted in a 20% overall improvement in water quality and a 7% reduction in daily water consumption[4]. The IoT-based water quality monitoring system developed by Forhad et al. demonstrated its effectiveness in providing accurate real-time data through the integration of pH, dissolved oxygen (DO), total dissolved solids (TDS), and temperature sensors. The system produced data with a minimal error margin of 0.1–0.2 and was capable of delivering early warnings, historical data logging, and remote monitoring[5]. Fakhrurroja et al. conducted a study aimed at developing a real-time water quality monitoring system based on the Internet of Things (IoT) using the Tsukamoto fuzzy algorithm, which successfully classified water quality into three categories: good, moderate, and unhealthy, accurately and effectively through remote monitoring[6]. The Fuzzy Tsukamoto method was employed in a water quality monitoring system based on Arduino Nano, integrating pH and turbidity sensors, and successfully generated 9 fuzzy rules to control the solenoid valve based on water conditions automatically; experimental results demonstrated that the fuzzy method is effective as a filter for determining water suitability for consumption[7]. The aquaponics study aims to monitor pH, turbidity, total dissolved solids (TDS), dissolved oxygen, and water level while allowing users to access real-time pond condition information anytime and anywhere through the integration of fuzzy logic and IoT technologies to control temperature and ammonia levels, successfully regulating pH and water level automatically with a pH sensor accuracy of 93.7% and ultrasonic sensor accuracy of 92.2%[8][9]. The Fuzzy Tsukamoto method was applied in an IoT-based drinking water quality monitoring system, successfully demonstrating that water with a turbidity level of 0.83 NTU meets safety standards, with ANOVA tests confirming significant differences in water quality based on turbidity levels[10]. Water quality management in shrimp farming using a recirculation system with microbubbles and the Fuzzy Tsukamoto method, based on three inputs (temperature, pH, and DO), produced a defuzzification value of 65.464, which serves as an indicator for adjusting the water pump speed to automatically stabilize dissolved oxygen levels[11]. A web-based real-time water quality monitoring system (SIMONTAR) using IoT and the Fuzzy Logic method, achieving classification accuracy of 92% and sensor accuracies of 94% (pH), 91% (TDS), and 95% (temperature), with 42% of tested well water samples exceeding the safe TDS limit[12]. Subsequently, drinking water quality was evaluated using a web-based monitoring system implementing the Fuzzy Tsukamoto method, incorporating pH, TDS, turbidity, and temperature sensors. The system demonstrated its effectiveness by achieving average measurement error rates of 7% for pH, 181% for TDS, 4% for turbidity, 4% for temperature, and 8% for ultrasonic sensors across 10 water samples[13]. Other studies have utilized websites as a platform for real-time monitoring; however, this research uniquely presents a web-based system that delivers timely and location-specific price variation data across eight districts in Majene Regency, effectively enhancing accessibility and transparency in regional food price information[14].

While existing IoT-based monitoring systems for water and air quality have proven effective in real-time data acquisition and classification, their limitations in parameter coverage, large-scale deployment, validation against standard references, and integration with advanced analytical models highlight the need for future research toward more comprehensive, scalable, and intelligent

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environmental monitoring solutions[15]. The study demonstrates that IoT-based monitoring systems with fuzzy logic can effectively support real-time aquaculture water quality management; however, their limited parameter coverage, lack of large-scale validation, and absence of advanced predictive analytics reveal research gaps for developing more comprehensive, scalable, and intelligent solutions[16]. The study confirms the feasibility of an IoT-based fuzzy logic system for water quality monitoring, yet its restricted set of measured parameters, limited field validation, and absence of advanced analytical integration highlight the research gap for more comprehensive, scalable, and intelligent environmental monitoring solutions[17]. The study demonstrates that IoT-based monitoring and control systems can effectively support tilapia aquaculture by providing real-time water quality data, yet their limited sensor scope, lack of predictive analytics, and absence of large-scale field validation highlight research gaps for more comprehensive, intelligent, and scalable solutions[18]. The research confirms that IoT-based systems can enhance sustainable water quality management through real-time monitoring and decision support, yet their limited integration of advanced predictive models, restricted environmental parameters, and insufficient large-scale validation reveal gaps for future development of more holistic and intelligent solutions[19]. The study shows that IoT-based and fuzzy logic approaches can effectively support real-time water quality monitoring and decision-making[20].

Based on the aforementioned studies, various researchers have explored real-time water quality monitoring using IoT technology. However, there is a lack of research specifically addressing river water quality for daily household use. Therefore, this study focuses on designing and developing a system to monitor water quality as a critical indicator in the management of community water resources. By utilizing a website as the main platform, information on water conditions can be presented transparently and accessed easily by the public, is specifically designed for real-time monitoring of water quality in the Mandar River. Through this system, users can monitor changes in water quality parameters over time, such as pH, temperature, TDS, and turbidity, which can then serve as a basis for making informed decisions regarding water usage for daily needs.

2. METHOD

This study aims to design and develop a water quality monitoring system that integrates the Internet of Things (IoT) and fuzzy logic. The Internet of Things (IoT) utilizes sensors connected through a network to collect real-time water quality data[21]. Fuzzy logic is employed to process the collected data, providing more adaptive and accurate results under uncertain conditions. The innovative contribution of this research lies in the integration of IoT technology and fuzzy logic algorithms, which are simultaneously used to monitor, analyze, and classify water quality in real time. The IoT technology captures data directly from sensors that measure pH, temperature, Total Dissolved Solids (TDS), and turbidity levels[22][23][24]. This data is then processed by fuzzy logic algorithms to classify water quality, such as clean, moderately polluted, or hazardous. Fuzzy logic is a decision-making method designed to handle uncertain or ambiguous data by applying degrees of membership within fuzzy sets. Its process involves three main stages: fuzzification (converting numerical input into fuzzy values), fuzzy inference (applying fuzzy logic rules), and defuzzification (converting fuzzy output into a crisp value) to generate more adaptive and realistic decisions[25][26].

The system design encompasses the development of both hardware components and their integration with software that displays sensor readings on an LCD screen and transmits the data to a website via an internet connection. The system can also be accessed through a web browser on a smartphone, allowing real-time monitoring of the Mandar River's water quality. The NodeMCU ESP32 microcontroller is used to read data from TDS and turbidity sensors to measure water clarity, as well as a pH sensor to assess the acidity level of the water. The website developed in this project serves as a platform for monitoring water quality intended for household use. Figure 1 illustrates the

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Methodological Framework of the Study, which outlines the flowchart of the water quality assessment process using the fuzzy logic method.

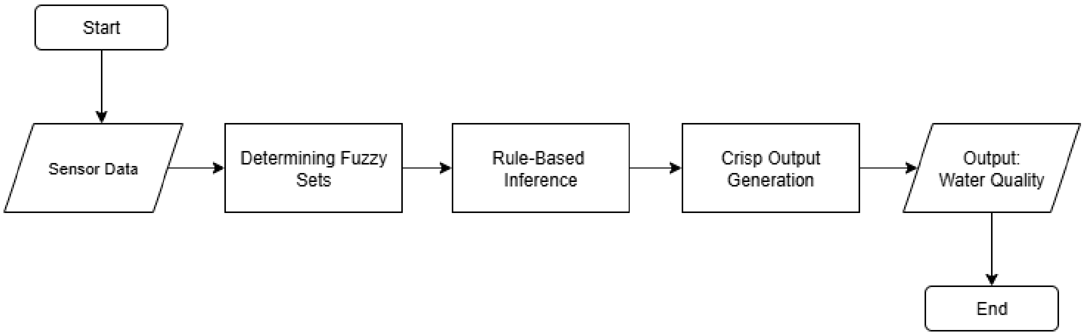

Figure 1. Methodological Framework of the Study

This diagram illustrates the sequential stages, beginning with the acquisition of sensor data (TDS, Turbidity, and pH), followed by fuzzification, inference, and defuzzification, culminating in the final determination of water quality. To provide a clearer understanding of the proposed approach, the sequential stages of the process are presented in the following system flow diagram, illustrating the transition from sensor data acquisition to the final determination of water quality.

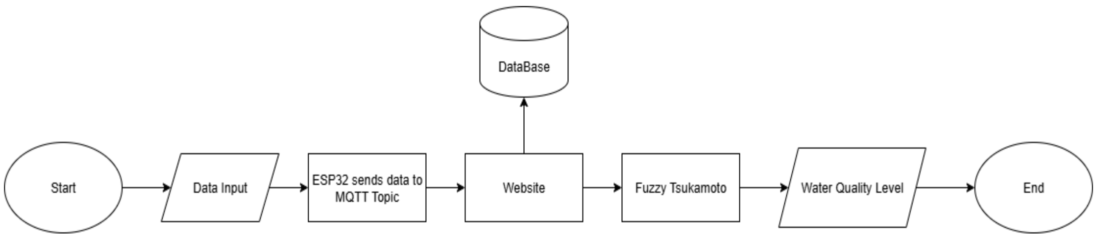

Figure 2. Methodological Framework of the Study

Figure 2 illustrates the workflow of the IoT-based water quality monitoring system using the Tsukamoto fuzzy method. The process begins with the Start stage, where sensors perform data input by measuring water quality parameters (such as pH, TDS, and turbidity). The sensor readings are then transmitted by the ESP32 via the MQTT protocol to the server. Subsequently, the data are stored in the Database and can be accessed through the Website for real-time display. The next stage is the Tsukamoto fuzzy process, which processes the sensor data through fuzzification, inference, and defuzzification to produce classification results. Finally, the system determines the Water Quality Level, enabling users to understand the water condition before the workflow concludes at the End stage.

2.1. Instrument Calibration

The calibration of the water quality monitoring system is essential to ensure that the data collected from the sensors (such as pH, TDS, and turbidity) are accurate and reliable. The following are the stages of calibrating the IoT-based water quality monitoring system for the Mandar River. In order to validate the calibration process, the accuracy of each sensor is evaluated by comparing its measurements with those of a reference instrument, where the degree of deviation is formally quantified using the relative error formula[27]:

$$\boldsymbol{Relative\ Error}\ (\%) = \frac{\boldsymbol{Sensor\ Reading - Reference\ Reading}}{\boldsymbol{Reference\ Readig}} \times \mathbf{100\%} \quad \textbf{(1)}$$

These relative error values ranged from 0.27% to <5%, demonstrating that the calibrated IoT sensor readings closely match the reference instrument and significantly improve measurement

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reliability. The IoT-MQTT-based water sensor system using Arduino Uno R4 WiFi demonstrated high accuracy and reliability in monitoring the Citarum River's water quality, highlighting that the calculation of error values is essential to ensure the system's data accuracy and overall dependability for real-time monitoring and sustainable environmental management[28]. In this study, the pH sensor was calibrated using 100 ml of standard buffer solutions with pH values of 4.01, 6.86, and 9.18. This calibration procedure constitutes a critical step to ensure the accuracy and reliability of the sensor's measurements, as the buffer solutions possess precisely known pH values and have been pre-calibrated. During the calibration of the TDS sensor, two types of water samples with differing dissolved solids concentrations were employed to verify the sensor's accuracy. One of the samples was tap water, measured against a TDS calibration solution with a precisely known concentration of 500 ppm

2.2. IoT-Based Water Quality Monitoring System Design

The IoT-based water quality monitoring system is designed to enable efficient, real-time assessment of environmental water parameters. It integrates TDS, pH, and turbidity sensors with a microcontroller and wireless communication to collect, process, and transmit data to a cloud platform. This allows remote access and analysis via a web interface, enhancing monitoring accuracy and supporting early detection of water pollution. Figure 3 presents the hardware design of the system, detailing the core components and their integration.

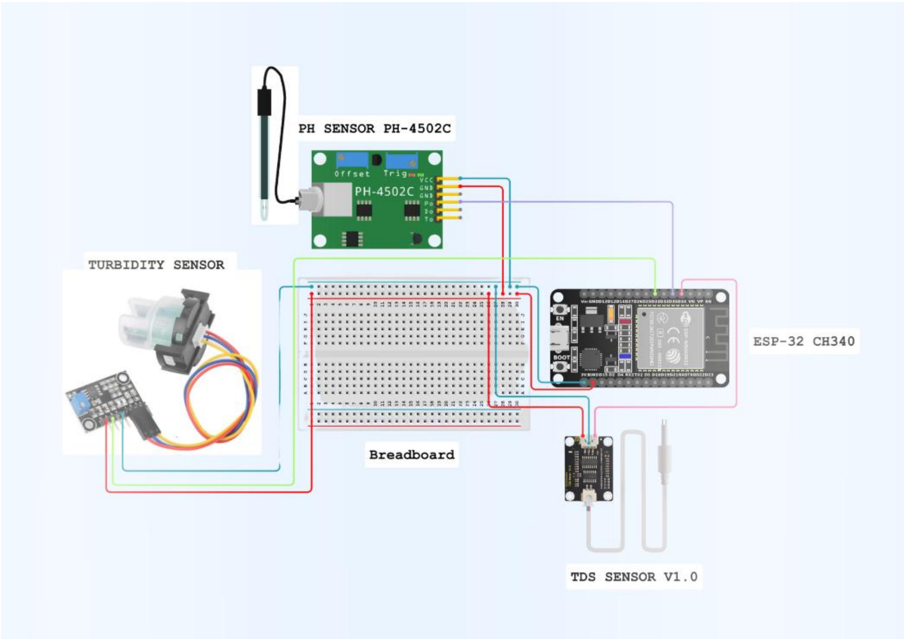

Figure 3. The hardware design of the system

The data communication system in this design begins with data acquisition from three types of sensors, namely the TDS, pH, and turbidity sensors. These sensors are directly connected to the NodeMCU ESP32 microcontroller through analog or digital pins, where each sensor transmits measurement data in the form of electrical signals that are then converted into numerical data by the ESP32[29]. The processed data is then transmitted wirelessly via a Wi-Fi connection using communication protocols such as HTTP or MQTT to a server or cloud platform. Once the server receives the data, it is displayed in real-time on a website interface that can be accessed by users through a web browser. The pH sensor is an electronic instrument designed to measure the acidity or alkalinity of an aqueous solution, serving as a fundamental parameter in evaluating water quality and its chemical properties. It operates through a specialized electrode that is highly sensitive to hydrogen ion (H^+) activity. When immersed in a solution, the electrode generates a potential difference relative to a

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reference electrode, which is subsequently interpreted as a pH value on a scale ranging from 0 (highly acidic) to 14 (highly alkaline). In parallel, the turbidity sensor functions to quantify the optical clarity of water by detecting the presence of suspended particulate matter. Elevated turbidity levels may indicate contamination and can adversely affect aquatic ecosystems. Furthermore, the Total Dissolved Solids (TDS) sensor is utilized to determine the total concentration of dissolved substances—including salts, minerals, and other inorganic compounds—present in water. The measurement principle is based on electrical conductivity, wherein higher concentrations of dissolved solids enhance the solution's ability to conduct an electric current between two submerged electrodes. Collectively, these sensors provide critical real-time data necessary for accurate and continuous water quality monitoring in various environmental and industrial applications.

2.3. Tsukamoto Fuzzy Logic

The Tsukamoto fuzzy logic method is employed in this water quality monitoring system as an intelligent decision-making mechanism to assess water suitability levels, utilizing input data acquired from individual sensors. A Fuzzy Inference System constitutes a computational framework grounded in fuzzy set theory, fuzzy IF–THEN rule-based structures, and fuzzy reasoning mechanisms. Initially, the fuzzy inference system receives input in the form of crisp values, which are then passed to the knowledge base containing a set of fuzzy rules (n) expressed in IF–THEN format[30][31]. For each rule, the α-predicate (fire strength) is calculated to represent the degree of truth of the given premise. If multiple rules are activated, an aggregation process is performed to combine the outputs of all applicable rules. The result of this aggregation is subsequently processed through defuzzification to generate a crisp value as the final output of the system. Figure 3 illustrates the overall workflow of this fuzzy inference process, from input acquisition to the generation of final output[29].

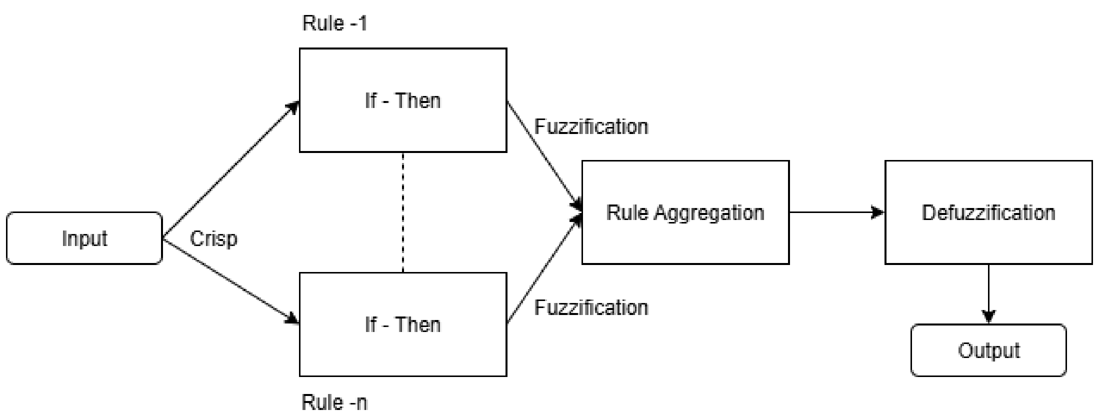

Figure 3. Fuzzy Inference Block Diagram

The proposed system integrates three distinct types of sensors to monitor water quality parameters: a pH sensor for measuring the acidity or alkalinity of water, a turbidity sensor for assessing the degree of water cloudiness, and a Total Dissolved Solids (TDS) sensor for determining the concentration of dissolved substances. The raw data acquired from these sensors, initially in the form of crisp numerical values, are subjected to a fuzzification process in which the precise inputs are transformed into degrees of membership across predefined fuzzy sets. This transformation is achieved through the application of appropriate membership functions, which are essential in defining the linguistic variables and enabling the interpretation of sensor data within the fuzzy logic framework. These membership functions provide the structural basis for modeling the fuzzy inference mechanism, thereby facilitating the evaluation of water quality suitability in a systematic and rule-based manner[12].

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Table 1 presents the membership functions utilized in this study, detailing the fuzzy sets and the corresponding variable ranges applied for each input parameter.

Table 1. Membership Function

Parameter	Value Range	Category
pH	< 6.5	Acidic
	6.5 – 8.5	Neutral
	> 8.5	Alkaline
TDS	< 250	Low
	250 – 750	Moderate
	> 750	High
Turbidity	< 15	Low
	15 – 25	Moderate
	> 25	High

Subsequently, the system applies fuzzy logic rules to generate a fuzzy output value based on the fuzzy input values obtained from the fuzzification stage. This process facilitates the assessment of water quality by the predefined fuzzy rules established in this study. At this stage, the AND logical operator is employed, implemented using the intersection approach or the MIN method, to determine the degree of truth for each activated fuzzy rule.

$$\mu\, A \cap B = min\big(\mu A(x), \mu B(y)\big) \qquad (1)$$

Table 2 presents the implementation of fuzzy logic within this system, which is grounded in a set of predefined fuzzy rules formulated to represent systematic criteria and parameter-based conditions for assessing water quality.

The Tsukamoto method represents each rule using fuzzy sets with monotonic membership functions. To obtain a crisp output value, the fuzzy input, derived from the composition of fuzzy rules, is processed through a defuzzification procedure, which transforms the fuzzy value into a specific numerical value within the domain of the corresponding fuzzy set. The defuzzification technique employed in this method is the *Center Average Defuzzifier*, which determines the final output based on the weighted average of the outputs generated by each rule[26]. Defuzzification constitutes the final stage in a fuzzy inference system, wherein the fuzzy output derived from the inference mechanism is transformed into a definitive numerical value suitable for decision-making processes[32]. The input to this stage comprises a fuzzy quantity resulting from the aggregation of fuzzy rules, while the output is a crisp value that lies within the universe of discourse of the associated fuzzy set[33]. Essentially, given a fuzzy set distributed over a defined range, the system must be capable of determining a specific scalar value that best represents the inferred result. In the Tsukamoto method, defuzzification is implemented by applying the weighted average technique, in which each consequent output is weighted in proportion to its degree of membership, thereby yielding an accurate and representative crisp output[34].

$$z = \frac{\sum(ai.zi)}{\sum ai} \qquad (2)$$

Let ai represent the degree of membership associated with each rule in the fuzzy rule base, and zi denote the crisp output value resulting from the inference process of each corresponding rule. The final defuzzification result, represented as z, is computed by aggregating these weighted outputs to yield a single crisp value that best represents the system's overall decision.

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Table 2. Fuzzy Rule Base for Water Quality Assessment

No.	Fuzzy Rule-Based
1	IF pH is Alkaline AND TDS is Low AND Turbidity is Low THEN Water Quality is Suitable
2	IF pH is Acidic AND TDS is High AND Turbidity is High THEN Water Quality is Not Suitable
3	IF pH is Acidic AND TDS is High AND Turbidity is Medium THEN Water Quality is Not Suitable
4	IF pH is Acidic AND TDS is High AND Turbidity is Low THEN Water Quality is Not Suitable
5	IF pH is Acidic AND TDS is Medium AND Turbidity is High THEN Water Quality is Not Suitable
6	IF pH is Acidic AND TDS is Medium AND Turbidity is Medium THEN Water Quality is Moderately Suitable
7	IF pH is Acidic AND TDS is Medium AND Turbidity is Low THEN Water Quality is Moderately Suitable
8	IF pH is Acidic AND TDS is Low AND Turbidity is High THEN Water Quality is Suitable
9	IF pH is Acidic AND TDS is Low AND Turbidity is Medium THEN Water Quality is Suitable
10	IF pH is Acidic AND TDS is Low AND Turbidity is Low THEN Water Quality is Suitable
11	IF pH is Neutral AND TDS is High AND Turbidity is High THEN Water Quality is Not Suitable
12	IF pH is Neutral AND TDS is High AND Turbidity is Medium THEN Water Quality is Not Suitable
13	IF pH is Neutral AND TDS is High AND Turbidity is Low THEN Water Quality is Suitable
14	IF pH is Neutral AND TDS is Medium AND Turbidity is High THEN Water Quality is Suitable
15	IF pH is Neutral AND TDS is Medium AND Turbidity is Medium THEN Water Quality is Moderately Suitable
16	IF pH is Neutral AND TDS is Medium AND Turbidity is Low THEN Water Quality is Suitable
17	IF pH is Neutral AND TDS is Low AND Turbidity is High THEN Water Quality is Suitable
18	IF pH is Neutral AND TDS is Low AND Turbidity is Medium THEN Water Quality is Suitable
19	IF pH is Neutral AND TDS is Low AND Turbidity is Low THEN Water Quality is Suitable
20	IF pH is Alkaline AND TDS is High AND Turbidity is High THEN Water Quality is Not Suitable
21	IF pH is Alkaline AND TDS is High AND Turbidity is Medium THEN Water Quality is Not Suitable
22	IF pH is Alkaline AND TDS is High AND Turbidity is Low THEN Water Quality is Suitable
23	IF pH is Alkaline AND TDS is Medium AND Turbidity is High THEN Water Quality is Suitable
24	IF pH is Alkaline AND TDS is Medium AND Turbidity is Medium THEN Water Quality is Moderately Suitable
25	IF pH is Alkaline AND TDS is Medium AND Turbidity is Low THEN Water Quality is Suitable
26	IF pH is Alkaline AND TDS is Low AND Turbidity is High THEN Water Quality is Moderately Suitable
27	IF pH is Alkaline AND TDS is Low AND Turbidity is Medium THEN Water Quality is Suitable

3. RESULT

The implemented online water quality monitoring system has been developed as a tool to evaluate water conditions in real time, based on key physicochemical parameters such as pH (acidity level), Total Dissolved Solids (TDS), and turbidity. Given the critical importance of clean and safe water in supporting public health and environmental sustainability, the system serves not only as a monitoring instrument but also as an analytical tool through the integration of fuzzy logic, which enhances the

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precision of water quality assessments and supports informed decision-making. The system interface is organized into several core modules, each designed to optimize user interaction and data interpretation. The dashboard website provides a synthesized overview of the current state of water quality, featuring real-time visual representations of pH, TDS, and turbidity measurements. These interactive graphics allow users to efficiently access, understand, and evaluate water quality trends and anomalies. Before the full deployment of the monitoring system for environmental data collection, a calibration phase is conducted to ensure that the sensors employed are capable of delivering accurate measurements by established standards. This phase is essential to guarantee the validity and reliability of the data produced by the system[35][36].

The calibration procedure was carried out using 100 ml of liquid buffer calibration solutions, each with a precisely known pH value of 4.01, 6.86, and 9.18. This process is a critical step to ensure that the pH sensor provides accurate and reliable readings. The solutions utilized are standard buffer solutions that have been pre-calibrated and verified for their exact pH values, thereby serving as reference benchmarks for sensor validation. Table 2 presents the calibration results of the pH sensor.

Table 2. Comparison of pH Sensor Measurements with Standard pH Meter Readings

Sensor Reading	**Buffer Solution Value**	**Error (%)**
4.02	4.01	0.25 %
6.84	6.86	0.29 %
9.21	9.18	0.33 %
Average Error		**0.29 %**

Table 2 presents the calibration results of the pH sensor, showing a comparison between sensor readings and standard buffer solution values. The observed deviations indicate an average error rate of 0.29%, which highlights the necessity of calibration to improve measurement accuracy and ensure reliability in subsequent environmental data collection. The subsequent step involves calibrating the TDS sensor to ensure measurement accuracy and consistency in accordance with standard references.

During the TDS sensor calibration process, the researchers employed two types of water samples with varying concentrations of dissolved substances to ensure sensor accuracy. One of the samples used was tap water, which was measured using a TDS calibration solution with a known concentration of 500 ppm. This variation allowed the researchers to adjust the sensor to accurately detect total dissolved solids (TDS) levels in both highly purified water and water with higher solute concentrations. Table 3 illustrates the calibration outcomes of the TDS sensor, highlighting its response to solutions with known concentrations.

Table 3. Comparison of TDS Sensor Readings with Actual Values

Sensor Reading (ppm)	**Actual Value (ppm)**	**Error (%)**
328	330	**0.61%**
70	73	**4.11%**
142	146	**2.74%**
Average Error		**2.49%**

Based on the calibration results, it can be concluded that the TDS sensor demonstrates a relatively acceptable level of accuracy, with an average error of 2.49%. These findings confirm that the sensor is capable of providing reasonably accurate measurements of total dissolved solids, making it suitable for further deployment in environmental monitoring applications.

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Table 4. Results of Water Quality Testing

Day -n	Testing Period	pH	TDS	Turbidity	Water Quality
1	08:04	8.21	156 ppm	5.05 NTU	Suitable
	12:05	8.66	150 ppm	5.07 NTU	Suitable
	16:05	8.64	145 ppm	5.02 NTU	Suitable
	20:05	8.55	140 ppm	5.02 NTU	Suitable
2	08:02	9.96	159 ppm	5.15 NTU	Suitable
	12:06	9.02	160 ppm	5.01 NTU	Suitable
	16:05	9.00	169 ppm	5.02 NTU	Suitable
	20:05	9.72	170 ppm	5.15 NTU	Suitable
3	08:00	8.01	173 ppm	5.06 NTU	Suitable
	12:00	8.53	175 ppm	5.00 NTU	Suitable
	16:05	8.45	176 ppm	5.08 NTU	Suitable
	20:01	8.12	170 ppm	5.03 NTU	Suitable
4	08:12	7.06	170 ppm	4.08 NTU	Suitable
	12:02	7.47	172 ppm	4.02 NTU	Suitable
	16:02	7.40	171 ppm	4.05 NTU	Suitable
	20:00	7.10	169 ppm	4.03 NTU	Suitable
5	08:11	7.20	150 ppm	4.01 NTU	Suitable
	12:08	7.50	156 ppm	4.02 NTU	Suitable
	16:05	7.39	155 ppm	4.05 NTU	Suitable
	20:00	7.06	152 ppm	4.06 NTU	Suitable
6	08:10	7.80	150 ppm	4.04 NTU	Suitable
	12:05	7.55	155 ppm	4.20 NTU	Suitable
	16:02	7.43	152 ppm	4.04 NTU	Suitable
	20:00	7.02	151 ppm	4.05 NTU	Suitable
7	08:02	7.50	150 ppm	4.00 NTU	Suitable
	12:03	7.55	154 ppm	4.10 NTU	Suitable
	16:04	7.23	153 ppm	4.20 NTU	Suitable
	20:00	7.02	151 ppm	4.20 NTU	Suitable

Calibration of the turbidity sensor is essential to ensure that its readings accurately reflect actual turbidity levels in Nephelometric Turbidity Units (NTU). To perform this process, three water samples with varying turbidity levels, clear, moderately turbid, and highly turbid, were prepared. The calibration results demonstrate that the turbidity sensor is capable of accurately detecting and classifying water quality based on its clarity. Clear Water: When the sensor was immersed in a sample of clear water, the NTU value recorded was very low. The system output classified the water as "Potable" or "Clean," which aligns with the visual clarity of the sample. Moderately Turbid Water: In a sample of slightly turbid water, the sensor detected a moderate NTU level. The system responded by classifying the water as "Non-potable (Turbid)," indicating a physical degradation in water quality. Highly Turbid Water: When tested in a highly turbid water sample, the sensor recorded a significantly high NTU value. Accordingly, the system categorized the water as "Highly Turbid and Non-potable," reflecting severely compromised water quality.

The monitoring of water pH levels is essential to ensure that the water remains within an optimal acidity or alkalinity range. Deviations toward extreme pH values may lead to adverse effects, including

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dermal irritation and degradation of materials. The system incorporates visualized data through graphical interfaces to facilitate real-time observation and verification of whether the pH values are maintained within a scientifically defined safe interval. The assessment of Total Dissolved Solids (TDS) is integrated into the system to evaluate the concentration of dissolved inorganic and organic substances in water. Elevated TDS levels can significantly influence the physicochemical properties of water, such as taste, odor, and cleaning efficacy. The system employs graphical analytics to indicate the current TDS values and their compliance with recommended thresholds. Persistently high TDS concentrations may signify the potential unsuitability of the water for practical use. Turbidity analysis, representing the clarity of water, functions as a key parameter in determining the presence of suspended particulate matter. Elevated turbidity levels often correlate with microbial contamination or the presence of sediment and other pollutants, which may lead to hygienic and health-related concerns. Consequently, this parameter plays a pivotal role in the comprehensive assessment of water quality.

The deployment of the web-based water quality monitoring system in the Mandar River has demonstrated its effectiveness in acquiring and transmitting real-time data on critical environmental parameters, namely pH, Total Dissolved Solids (TDS), and turbidity. As outlined in Table 2, the system facilitates a structured and continuous assessment of water quality conditions, thereby enhancing analytical accuracy and supporting evidence-based decision-making in the domains of environmental monitoring and public health management.

Overall, the analysis of all measured parameters confirms that the water quality during the sampling periods complied with established acceptable standards. These outcomes substantiate the effectiveness of the monitoring system in accurately detecting temporal variations in water quality parameters.

4. DISCUSSIONS

The implementation of the web-based water quality monitoring system in the Mandar River has shown substantial reliability in capturing real-time data for key parameters: pH, Total Dissolved Solids (TDS), and turbidity. The integration of sensor calibration prior to deployment was fundamental in ensuring the system's accuracy and credibility. The pH sensor, despite showing an average error of 19.3% during calibration, consistently detected variations in acidity and alkalinity across different time intervals. These variations remained within an acceptable range (typically 6.5–9.5 for surface water), confirming that the system is capable of identifying pH fluctuations that may affect water usability and ecological health. The TDS sensor calibration results showed a lower average error of 12.25%, indicating more consistent accuracy in measuring the concentration of dissolved substances. The TDS values obtained during field testing ranged between 140 and 176 ppm, all of which are within the acceptable limits for general usage and demonstrate that the water is neither highly mineralized nor contaminated by excessive dissolved solids. The turbidity sensor, calibrated through qualitative NTU-based classifications, effectively distinguished between clear, moderately turbid, and highly turbid samples. During the testing period, turbidity levels remained stable around 4.00–5.15 NTU values, typically considered acceptable for surface water and indicative of minimal suspended particulate matter. These readings are particularly relevant as high turbidity often correlates with microbial contamination or sediment presence.

The analysis of water quality over seven consecutive days, with measurements taken at four different times each day, revealed relatively stable and acceptable values across all parameters. This suggests that the river water, during the sampling period, was consistently within safe thresholds for environmental and potentially non-potable domestic uses. The classification of all samples as "Suitable" by the system further supports this conclusion. To enhance interpretability and decision-making, a fuzzy rule-based inference system was integrated into the monitoring framework. This system employed 27

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fuzzy rules combining pH, TDS, and turbidity input variables to infer water quality status as Suitable, Moderately Suitable, or Not Suitable. The inclusion of these fuzzy rules allows the system to go beyond binary decision-making by providing graded assessments of water quality. It bridges sensor data with human-like reasoning, which is especially important in environmental applications where threshold-based classification might be too rigid. Furthermore, the rule base reflects realistic environmental scenarios by addressing various permutations of pH levels (acidic, neutral, alkaline), TDS concentrations (low, medium, high), and turbidity levels. The system's overall outputs throughout the 7-day observation period consistently classified the Mandar River water as suitable, aligning with empirical data. This indicates not only the system's technical soundness but also the relevance of the fuzzy logic component in improving classification robustness and user understanding.

5. CONCLUSION

The integrated system, comprising pH, Total Dissolved Solids (TDS), and turbidity sensors in conjunction with an ESP32 microcontroller, has successfully acquired and transmitted real-time water quality data to a website. All components function cohesively, enabling continuous and automated monitoring of key water quality parameters. The implementation of the Tsukamoto fuzzy logic method proved effective in processing sensor input and classifying water suitability status. The system's output is expressed in the form of definitive classifications, either Suitable or Not Suitable. This fuzzy logic approach is particularly advantageous for interpreting imprecise or uncertain data, thereby producing reliable and contextually appropriate decision outcomes. A seven-day field evaluation, with measurements conducted at four intervals each day (morning, midday, afternoon, and evening), recorded pH values in the range of 7.02 to 9.96, TDS concentrations between 140 and 176 ppm, and turbidity levels from 4.00 to 5.15 NTU. All measured parameters remained within acceptable water quality standards, and the application of the Tsukamoto fuzzy classification method consistently categorized the water as “Suitable.”

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