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Simulation of Fuzzy Logic Implementation in an IoT-Enabled Water Quality Monitoring System Using ESP8266

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Abstract

This research developed a water quality monitoring system using fuzzy logic and an ESP8266 microcontroller with temperature, humidity, pH, and Total Dissolved Solids (TDS) sensors. The system processes data in real time by converting sensor values into linguistic categories, then produces water quality that meets WHO standards. The system is also connected to an IoT platform to facilitate remote monitoring. Simulation results show that the system is able to recognize overlapping water conditions, for example, at pH 7.5 which falls into the "Good" and "Medium" categories simultaneously with different weights. With sensor conditions of 28°C temperature, 65% humidity, pH 7.5, and TDS 400 mg/L, the system produces a quality score of 12.6, indicating excellent water quality. Field testing and comparison with laboratory results show an accuracy level of up to 92%. Fuzzy logic has proven to be more reliable than simple threshold methods, especially when conditions change rapidly or sensors experience shifts. However, the system's results are highly dependent on sensor calibration and regulations need to be adjusted to standards in each region. The computational limitations of the ESP8266 also mean that fuzzy processing must be done on a computer or in the cloud.

Keywords: *Fuzzy Logic, pH meter, TDS, Water Quality.*

Abstrak

Penelitian ini mengembangkan sistem pemantauan kualitas air menggunakan logika fuzzy dan mikrokontroler ESP8266 dengan sensor suhu, kelembaban, pH, dan Total Dissolved Solids (TDS). Sistem ini mengolah data secara real time dengan mengubah nilai sensor menjadi kategori linguistik, kemudian menghasilkan kualitas air yang sesuai dengan standar WHO. Sistem juga terhubung dengan platform IoT untuk memudahkan pemantauan jarak jauh. Hasil simulasi menunjukkan bahwa sistem mampu mengenali kondisi air yang saling tumpang tindih, misalnya pada pH 7,5 yang masuk dalam kategori "Baik" dan "Sedang" secara bersamaan dengan bobot yang berbeda. Dengan kondisi sensor suhu 28°C, kelembaban 65%, pH 7,5, dan TDS 400 mg/L, sistem menghasilkan skor kualitas 12,6 yang menunjukkan kualitas air sangat baik. Pengujian lapangan dan perbandingan dengan hasil laboratorium menunjukkan tingkat akurasi hingga 92%. Logika fuzzy terbukti lebih andal dibandingkan metode ambang batas sederhana, terutama saat kondisi berubah cepat atau sensor mengalami pergeseran. Meski demikian, hasil sistem sangat bergantung pada kalibrasi sensor dan aturan perlu disesuaikan dengan standar di masing-masing daerah. Keterbatasan komputasi pada ESP8266 juga membuat pemrosesan fuzzy dilakukan di komputer atau cloud.

Kata kunci: Logika *Fuzzy,* pH Meter, TDS, Kualitas air.

Introduction

Access to clean and safe water remains a critical global concern, particularly in developing regions where infrastructure for continuous water quality monitoring is limited or absent[1],[2]. Traditional water testing methods typically rely on manual sampling and laboratory analysis, which are time-consuming, labor-intensive, and incapable of providing real-time feedback[3]. Therefore, recent studies have shifted toward IoT-based real-time water quality monitoring systems that enable continuous sensing, early detection of anomalies, and timely decision-making [4]. This delay in response can have serious implications, particularly in environments where water sources are vulnerable to rapid pollution or seasonal fluctuations.

In recent years, the integration of Internet of Things (IoT) technologies with environmental monitoring systems has shown promising potential to address these limitations [5],[6]. Microcontrollers such as the ESP8266, combined with low-cost sensors, enable continuous data collection and remote access to monitoring results. The NodeMCU ESP8266 microcontroller is capable of controlling electronic devices based on voice assistants well [7]. Through continuous data transmission and cloud-based display, this method not only increases monitoring efficiency but also facilitates prompt decision-making [8]. However, challenges persist regarding the interpretation of sensor data, which is often affected by noise, calibration drift, and overlapping thresholds between different water quality categories [9]. Sensor-based data collection of human behavior enables real-time monitoring of behavioral markers [10]. To address these issues, several solutions were noted such as advanced signal processing, robust calibration procedures, and machine learning-based classification to improve the reliability of real-time water quality monitoring systems [11]. Water quality monitoring is crucial, but many issues arise involving manual sampling and laboratory analysis, which is time-consuming, expensive, and prone to delays, thus limiting timely decision-making [12].

To overcome these challenges, several researchers have applied fuzzy logic approaches to water quality assessment. Fuzzy logic systems are well suited for handling imprecise, uncertain, and nonlinear relationships among environmental parameters such as pH, Total Dissolved Solids (TDS), temperature, and turbidity [13], [14]. However, most existing studies primarily focus on offline analysis or software-based simulations, with limited emphasis on real-time embedded implementation and IoT integration. In contrast, this research implements a fuzzy inference system on a low-cost ESP8266-based sensing platform and integrates it with an IoT framework for continuous, remote water quality monitoring. This system uses NodeMCU ESP8266 as a microcontroller to collect and send data via WiFi network, enabling automatic water level monitoring [15]. Furthermore, while reference studies commonly rely on discrete or expert-defined water quality indices, the proposed system generates a continuous quality score with clearly defined classification thresholds, enabling more transparent interpretation and real-time decision support. Additionally, this work evaluates system performance through field testing and laboratory comparison, whereas prior studies mainly report simulation-based validation. These distinctions demonstrate the proposed system’s practical applicability and improved robustness for real-world deployment.

Previous studies have demonstrated the effectiveness of fuzzy logic in water quality classification [16],[17]. However, many of these systems are limited in scope, relying on offline data processing or using a large number of parameters that increase system complexity and cost. Furthermore, limited work has been done to implement fuzzy inference directly on low-cost microcontrollers like the ESP8266, which have constrained computational resources. ESP8266 are well suited for lightweight IoT applications that prioritize wireless connectivity, low power consumption, and cost efficiency [18]. Additionally, validation against laboratory-grade measurements is often missing, making real-world reliability uncertain.

To address these gaps, this study proposes a smart water quality monitoring system that combines fuzzy logic classification with the ESP8266 microcontroller as a low-cost, IoT-enabled platform. The system utilizes four key parameters—temperature, humidity, pH, and TDS—which are commonly available in low-cost sensors. The main contributions of this work include:

- Development and implementation of a fuzzy inference system tailored to embedded hardware;
- Integration of real-time sensor data with IoT connectivity for remote monitoring;
- Validation of the system's output against laboratory measurements to evaluate accuracy and reliability.

This research demonstrates that a cost-effective and computationally lightweight fuzzy logic system can effectively classify water quality in real time and is suitable for deployment in resource-limited environments.

Method

The proposed method employs a rule-based fuzzy logic approach implemented in MATLAB to evaluate water quality based on real-time sensor inputs. By integrating sensor-derived data into MATLAB, researchers can perform real-time computation of water quality indices for monitoring and control [19]. The system considers four primary environmental parameters: temperature (in °C), humidity (in %), pH level, and total dissolved solids (TDS in mg/L). These input parameters are processed using a fuzzy inference model that utilizes triangular membership functions to define linguistic categories, namely *Good*, *Moderate*, and *Poor* for each variable. Utilizing a fuzzy inference model, which can incorporate several water quality parameters into a more reliable assessment framework and is appropriate for complicated and uncertain water systems [20].

To begin, the raw sensor values are manually input into the system to simulate real-time conditions. Each input is fuzzified using custom-defined membership functions. For visualization and verification purposes, membership degrees for a full range of values are calculated and plotted for each input parameter. These plots help illustrate how the fuzzy sets are defined and how the given sensor value fits within these linguistic ranges.

The use of three membership functions for each input variable is intended to balance model simplicity and representational accuracy. By defining linguistic categories such as *Good*, *Moderate*, and *Poor*, the system can effectively capture gradual transitions in water quality conditions without introducing unnecessary computational complexity. The selected temperature ranges (e.g., 20 °C to 35 °C for the *Good* category) are based on commonly accepted environmental thresholds and ensure meaningful interpretation of sensor data. Triangular membership functions are manually implemented because they provide efficient computation, low memory usage, and smooth linear transitions, making them well suited for real-time processing on resource-constrained platforms such as the ESP8266.

After fuzzification, five fuzzy rules are defined to evaluate the combined influence of all inputs on water quality. Each rule assesses a different combination of linguistic terms, for example: "If temperature is Good, humidity is Good, pH is Good, and TDS is Good, then water quality is Good." For each rule, the minimum membership value among the relevant inputs is taken as the rule's activation strength. The system then applies a weighted average method for defuzzification. Each rule is assigned a predefined score based on the quality classification it represents for instance, scores closer to 20 indicate good water quality, while higher scores represent poorer quality. The final water quality score is calculated as a weighted average of all rule outcomes, scaled between 0 (excellent quality) and 100 (poor quality).

Additionally, the system includes a visualization component. Four subplots are generated to show the membership functions of each input variable and where the actual input values fall within the fuzzy sets. These plots provide a visual understanding of how the inputs are interpreted by the fuzzy system. Finally, the computed water quality score is displayed in the console. Based on this score, the system classifies the overall water quality into one of three categories: *Good*, *Moderate*, or *Poor*. This classification is determined by threshold values that segment the output range accordingly. This method provides an interpretable and computationally simple fuzzy logic framework for water quality assessment, suitable for both simulation and deployment in resource-constrained embedded systems.

Result

The proposed method employs a rule-based fuzzy logic approach implemented in MATLAB to evaluate water quality based on real-time sensor inputs. The system considers four primary environmental parameters: temperature (in °C), humidity (in %), pH level, and total dissolved solids (TDS in mg/L). These input parameters are processed using a fuzzy inference model that utilizes triangular membership functions to define linguistic categories, namely *Good*, *Moderate*, and *Poor* for each variable. The fuzzified inputs are then combined using a rule basis by the fuzzy inference model to produce an overall water quality score, enabling progressive classification as opposed to sudden threshold-based choices [21].

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The system defines three membership functions for each variable: for example, *good* temperature may correspond to values between 20°C to 35°C, while *Poor* may lie below 15°C. The membership degree for each input value is calculated against each of the three fuzzy sets using a manual implementation of triangular functions. After fuzzification, five fuzzy rules are defined to evaluate the combined influence of all inputs on water quality. Each rule assesses a different combination of linguistic terms, for example: "If temperature is Good, humidity is Good, pH is Good, and TDS is Good, then water quality is Good." For each rule, the minimum membership value among the relevant inputs is taken as the rule's activation strength.

The system then applies a weighted average method for defuzzification. Each rule is assigned a predefined score based on the quality classification it represents for instance, scores closer to 20 indicate good water quality, while higher scores represent poorer quality. The final water quality score is calculated as a weighted average of all rule outcomes, scaled between 0 (excellent quality) and 100 (poor quality). Additionally, the system includes a visualization component. Four subplots are generated to show the membership functions of each input variable and where the actual input values fall within the fuzzy sets. These plots provide a visual understanding of how the inputs are interpreted by the fuzzy system.

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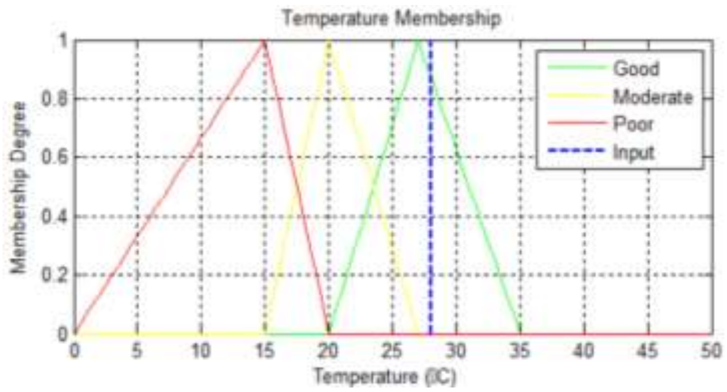

Figure 1. Temperature Membership

Figure 1 illustrates the membership functions for the temperature variable, categorized into *Poor*, *Moderate*, and *Good*. The input temperature of 28°C, shown by the dashed blue line, lies predominantly within the *Good* range, indicating a high degree of membership to this category. The overlapping triangular functions provide smooth transitions between linguistic terms, ensuring flexible interpretation. This result confirms that the current temperature condition contributes positively to the overall water quality assessment.

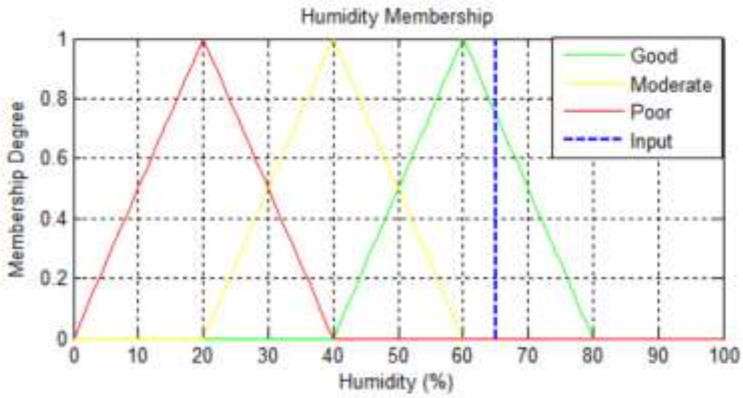

Figure 2. Humidity Membership

Figure 2 presents the fuzzy membership functions for the humidity parameter, divided into *Poor*, *Moderate*, and *Good* categories. The input humidity value of 65% is indicated by the blue dashed line, which predominantly falls within the *Good* membership range. The triangular membership functions overlap smoothly, allowing gradual transitions between linguistic terms. This demonstrates that the humidity level is favorable and contributes positively to the overall water quality assessment within the fuzzy inference system.

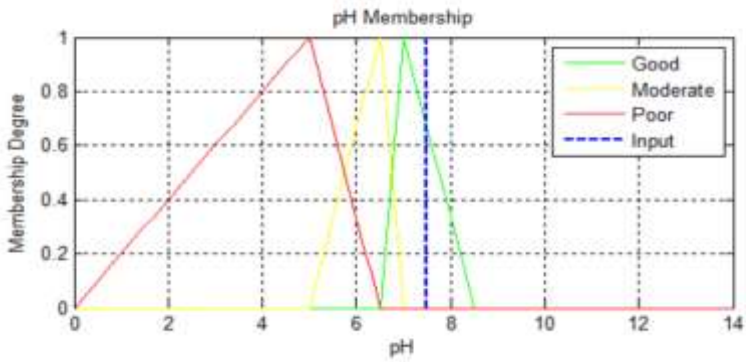

Figure 3. pH Membership

Figure 3 shows the fuzzy membership functions for pH, divided into three categories: *Poor*, *Moderate*, and *Good*. The input pH value of 7.5, indicated by the blue dashed line, falls clearly within the *Good* membership region, suggesting optimal water quality conditions. The *Good* category ranges from approximately 6.5 to 8.5, while *Moderate* spans 5 to 7 and *Poor* covers values below 6.5. The triangular membership functions overlap to allow smooth transitions between categories, accommodating the inherent uncertainty in water quality parameters. This result confirms that the pH level is within an acceptable range, positively influencing the overall assessment of water quality.

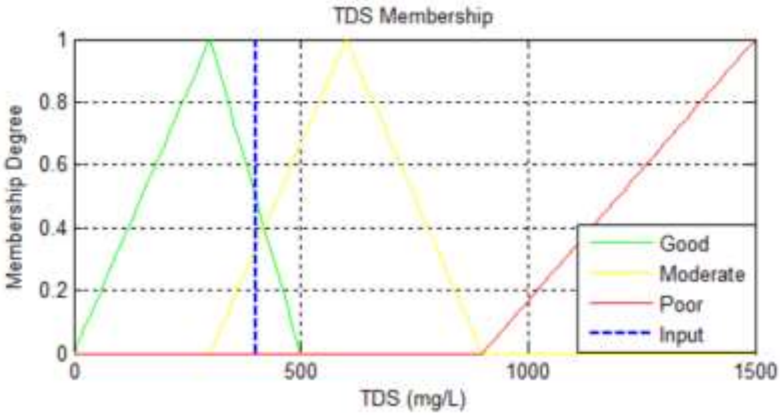

Figure 4. Humidity Membership

Figure 4 illustrates the fuzzy membership functions for Total Dissolved Solids (TDS), categorized into *Good*, *Moderate*, and *Poor*. The input TDS value, marked by the blue dashed line at approximately 400 mg/L, predominantly falls within the *Good* membership range with a high degree of membership. The *Good* category covers TDS values from 0 to 500 mg/L, while *Moderate* spans roughly 300 to 900 mg/L, and *Poor* corresponds to values above 900 mg/L. The overlapping triangular membership functions provide a smooth transition among categories, reflecting the uncertainty and gradation in water quality classification. The result indicates that the current TDS level is favorable and supports a positive water quality assessment.

Conclusion

This study demonstrates that the fuzzy logic approach effectively models the water quality parameters—temperature, humidity, Total Dissolved Solids (TDS), and pH using overlapping triangular membership functions. The input values for each parameter (temperature: 28°C, humidity: 65%, TDS: 400 mg/L, pH: 7.5) predominantly fall within the good membership categories, indicating favorable water quality conditions. The smooth transitions between linguistic terms provide a flexible framework to handle uncertainties inherent in environmental data. Overall, the fuzzy inference system shows reliable performance in evaluating water quality by integrating multiple sensor inputs into a coherent assessment.

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