

# IMPLEMENTATION OF ESP8266 AND TURBIDITY SENSOR IN WATER TURBIDITY MONITORING MODEL USING FUZZY TSUKAMOTO

A.P. Daru<sup>1</sup>, A.M. Hirzan<sup>1</sup>, F.B. Saputra<sup>1</sup> and P.A. Christianto<sup>2</sup>

<sup>1</sup>Faculty of Information and Communication Technology,  
Universitas Semarang, Tlogosari Kulon, 50196 Kota Semarang, Jawa Tengah,  
Indonesia.

<sup>2</sup>Department of Informatics  
STMIK Widya Pratama, Patriot No.25, Pekalongan, Jawa Tengah, Indonesia.

Corresponding Author's Email: [maulanahirzan@usm.ac.id](mailto:maulanahirzan@usm.ac.id)

**Article History:** Received 30 September 2024; Revised 28 October 2024;

Accepted 25 November 2024

**ABSTRACT:** Drinking water quality is a critical concern for public health. The 2020 Household Drinking Water Quality Study (SKAMRT) by the Indonesian Ministry of Health revealed that 70% of households consume water contaminated with bacteria, including *Escherichia coli* (*E. coli*). Despite 93% of the population having access to adequate drinking water, only 11.9% meet safety standards. Regular quality testing, particularly for turbidity, is crucial given the increasing water consumption, yet effective real-time monitoring remains a challenge. This research develops an IoT-based system for drinking water quality monitoring using the Fuzzy Tsukamoto method. The system integrates a turbidity sensor, NodeMCU ESP8266 microcontroller, and Firebase for data storage. Turbidity values, measured in Nephelometric Turbidity Units (NTU), are processed by the Fuzzy Tsukamoto method to assess water quality. The results showed that bottled drinking water, with a turbidity level of 0.83 NTU, meets the standards set by the Indonesian Minister of Health Regulation 492/Menkes/Per/IV/2010 and SNI 01-3553-2006, confirming it is safe. Additionally, one-way ANOVA results demonstrated significant differences in water quality across various turbidity categories, with p-values of 1.353e-38 for clean water, 2.733e-38 for slightly turbid water, and 2.380e-26 for moderately turbid water, indicating substantial variations in water quality based on turbidity levels.

**KEYWORDS:** *Firestore, Fuzzy Tsukamoto, Internet of Things, Water Turbidity.*

## **1.0 INTRODUCTION**

Water is essential for human life, particularly for daily consumption, yet poor drinking water quality poses significant health risks. The 2020 Household Drinking Water Quality Survey (SKAMRT) by the Indonesian Ministry of Health revealed that 70% of households consume water contaminated with *Escherichia coli* (E. coli). Although 93% of the population has access to potable water, only 11.9% can access water deemed truly safe for consumption, underscoring a critical gap in water safety[1]. Turbidity, measured in Nephelometric Turbidity Units (NTU), is a key parameter for evaluating water quality. It reflects the concentration of suspended particles, including silt, minerals, and pathogenic microorganisms. Elevated turbidity levels often indicate a higher risk of microbiological contamination, potentially causing waterborne diseases[2]. Thus, monitoring turbidity is essential, especially in regions with inadequate sanitation infrastructure [3], [4].

Contaminated drinking water can carry horrendous diseases like cholera, trachoma, schistosomiasis, and helminthiasis [5], [6]. Even light contamination may cause diarrhoea and dehydration as an aftereffect. Thus, contaminated drinking water must be treated carefully and seriously to ensure hygiene. However, ensuring water quality is safe is difficult. Traditional methods such as laboratory tests are accurate but time-consuming and costly. Thanks to the Internet of Things technology, it is possible to create a low-cost[7], faster[8] and more efficient water turbidity monitoring system[9]. The application of IoT has become more precise and accurate due to the integration of artificial intelligence (AI). As examples, IoT often used for scalable data traffic capture[10], or attack classification with recent algorithm[11].

Many studies have proposed numerous model to monitor the water turbidity using Internet of Things technology. For instance, on article published in 2021[12] has developed a laser-based sensor that allows real-time turbidity measurement. Additionally, Trevathan utilized IoT technology to integrate turbidity sensors into a remote monitoring system [13]. The model result from article[14] successfully created a water quality monitoring using Internet of Things. In 2022, there was a turbidity monitoring model using NodeMCU paired with Android application[15]. Meanwhile, within the same year there was another model using light sensor as the turbidity sensor with high accuracy detection[16]. The last model as the state-of-the-art in this study was

proposed in 2023 done in rural areas[7].

These findings highlight the critical need for innovative turbidity monitoring technologies to sustain aquatic ecosystems. Existing models primarily focus on monitoring turbidity levels but lack the capability to determine water safety, representing a significant limitation.

To address this gap, this study proposes an IoT-based water quality monitoring system incorporating NodeMCU ESP8266, a turbidity sensor, and decision-making functionality using the Fuzzy Tsukamoto method. The study's novelty lies in three key aspects: leveraging the Fuzzy Tsukamoto algorithm for decision-making, employing NodeMCU ESP8266 to reduce costs and energy consumption, and utilizing Google Firebase as a versatile database for IoT, web, desktop, and mobile platforms.

This study utilizes NodeMCU ESP8266 for several reasons, primarily due to its integrated Wi-Fi capabilities, which enable direct connectivity between sensor devices and cloud platforms. The turbidity sensor, used to measure water turbidity, integrates seamlessly with the NodeMCU ESP8266, facilitating the creation of an automated monitoring system. Sensor data is transmitted to the cloud in real-time for further analysis, enhancing efficiency and reliability[17]. The Fuzzy Tsukamoto method was selected for turbidity data analysis due to its capability to manage uncertain or ambiguous data effectively. This method represents each fuzzy rule with a monotonic fuzzy set, and inference results are numerically determined through specific formulas. Such an approach offers enhanced flexibility in addressing variations in water quality parameters, including turbidity[18].

The system is expected to provide an efficient, economical, and real-time water quality monitoring solution, thereby supporting the improvement of drinking water quality in society. Moreover, this system can be applied on various scales, both at the household level and on a larger scale, such as water resource management in rural or urban areas[19].

## 2.0 METHODS

This research utilizes a turbidity sensor to measure water turbidity, displaying results on an LCD and monitoring them through a custom Android application. System development involves component selection, device design, programming, and testing to ensure accurate performance. Both hardware and software requirements are analyzed during the design phase to meet system objectives.

### 2.1 Block Design model

This sub section explains the block design for the proposed model. The block design will explain how the connectivity between peripherals are connected. Figure 2 contains the illustration for the proposed model:

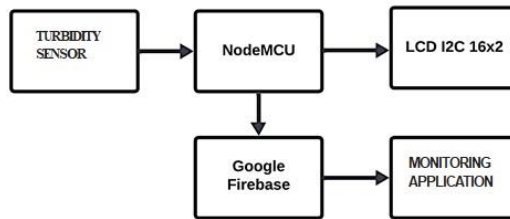


Figure1: Block Diagram

Figure 1 illustrates the system's block design. The turbidity sensor measures liquid turbidity, indicating the concentration of suspended particles such as silt, microorganisms, and insoluble substances. NodeMCU ESP8266 processes the sensor data using fuzzy logic before transmitting it to the output. The processed data is displayed on a 16x2 I2C LCD and sent to Google Firebase, enabling monitoring via a custom application.

### 2.2 Model Circuit Schematic

This subsection explains the wiring schematic of the proposed model. This model is needed to ensure the reproduction of the model and to avoid mistakes during wiring process. Figure 2 contains the illustration for the wiring schematic.

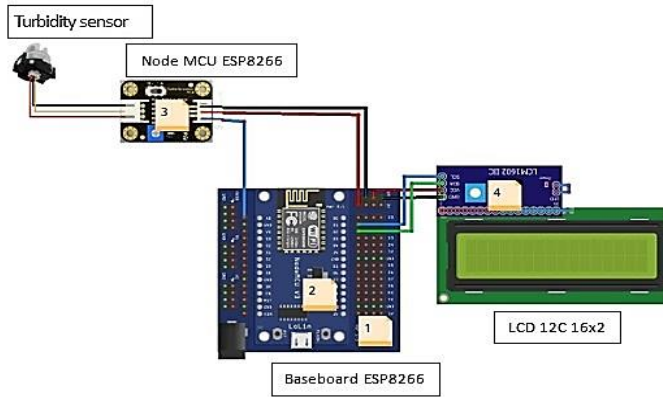


Figure 2: Model Circuit Schematic

Figure 2 shows the configuration of the Turbidity Sensor system. It includes a turbidity sensor, NodeMCU ESP8266, a baseboard for ESP8266 expansion, and an LCD with I2C connectivity. The sensor's VCC pin is connected to the baseboard's 3V pin, and its Ground pin to the baseboard's Ground. To prevent overvoltage, the sensor is powered by 3V, not 5V. The sensor's analog output is connected to the A0 pin of the NodeMCU, as using a digital pin could damage the component. The NodeMCU processes data from the Turbidity Sensor, which is then sent to Firebase and displayed on an I2C LCD. The ESP8266 baseboard houses the NodeMCU, simplifying VCC and Ground connections. The output data is shown on a 16x2 I2C LCD, with the following connections: SCL to D1, SDA to D2, VCC to Vin, and Ground to the NodeMCU's Ground pin.

### 2.3 Model Workflow

This subsection contains the explanation about how the proposed model works. The explanation start on how the model initialize the network, start sensor reading, fuzzify the data and submit the result to the database. Figure 3 contains the illustration of the model's workflow.

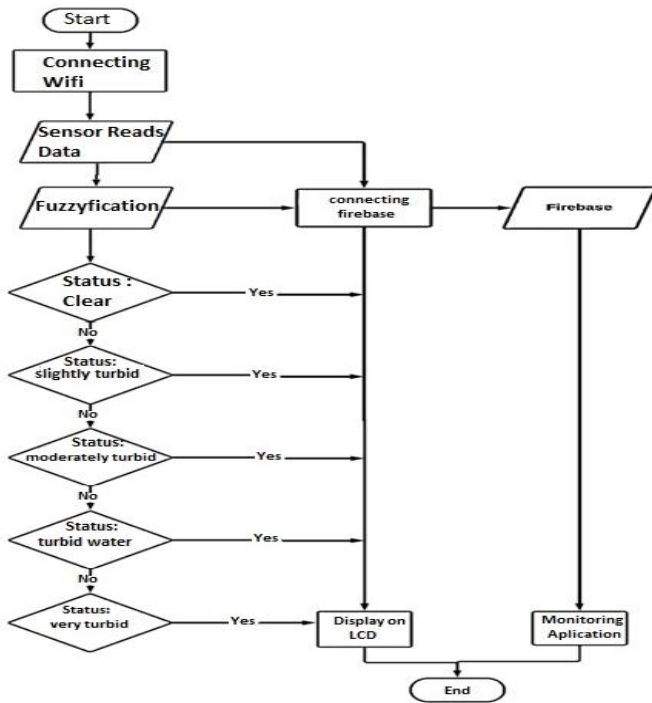


Figure 3: System Workflow Flow Chart

Figure 3 illustrates the system workflow, starting with data input. The system then establishes a Wi-Fi connection for internet access, enabling communication and data transfer via the microcontroller. The sensor reads the data, which is processed through fuzzyfication to generate fuzzy logic. This logic determines membership categories: clear, slightly turbid, moderately turbid, turbid, and highly turbid. Finally, the results are sent to Firebase and displayed on an LCD or monitoring application.

The system relies on internet connectivity, first establishing a Wi-Fi connection before reading data. Once connected, it links to Firebase for sensor readings. The turbidity sensor, connected to the NodeMCU, transmits analog values, which are converted to NTU (Nephelometric Turbidity Units) to assess water clarity. The system uses fuzzy logic to classify turbidity levels into five categories: 1. Clear Water, 2. Slightly Turbid Water, 3. Moderately Turbid Water, 4. Turbid Water, and 5. Very Turbid Water. The processed data is displayed on an LCD and sent to Firebase for real-time monitoring via the application.

## 2.4 Fuzzy Tsukamoto Model

This subsection explains the creation of the Fuzzy Tsukamoto model. The model itself is written in C programming language and executed via the Arduino IDE. In the development process, the fuzzy logic system requires the definition of fuzzy membership functions. Table 1 outlines the fuzzy set memberships applied in the system.

Table 1: Fuzzy Membership

Information	Resistance Value (NTU)
Clear Water	0-5
Slightly Cloudy	5-10
Moderate Cloudy	10-50
Murky	50-80
Very Cloudy	80-100

The fuzzy membership in the water turbidity monitoring system serves to convert numerical turbidity values into degrees of membership within a fuzzy set. In the case of water turbidity, fuzzy membership is defined through fuzzy sets such as "clear" (0-5 NTU), "slightly turbid" (5-10 NTU), "moderately turbid" (10-50 NTU), "turbid" (50-80 NTU), and "very turbid" (80-100 NTU), each represented by triangular or trapezoidal membership functions.

Table 2: Fuzzy Weights

Information	Value Weight
Clear	2,5
Slightly Cloudy	7,5
Moderate Cloudy	30
Murky	50
Very Cloudy	100

The clear range is between 0 and 5, the slightly turbid range is from 5 to 10, the moderately turbid range is from 10 to 50, the turbid range is between 50 and 80, and the highly turbid range is from 80 to 100. This test uses Fuzzy Tsukamoto, there are 3 memberships in each sensor module.

After obtaining the threshold values, this study create an illustration

how the Fuzzy Tsukamoto's membership for water turbidity. Figure 5 contains the membership value for this model.

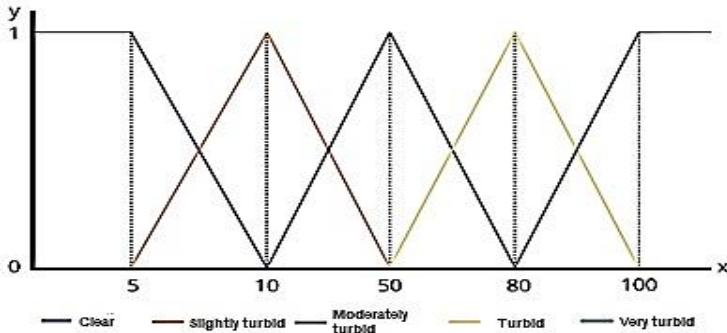


Figure 4: Collection of Water Turbidity

Figure 4 illustrates fuzzy membership functions in a Tsukamoto fuzzy inference system, demonstrating how inputs are categorized into linguistic terms based on their membership degrees. The x-axis represents the input variable (e.g., turbidity level) ranging from 0 to 100, while the y-axis shows the degree of membership, from 0 to 1. Five fuzzy sets are defined: "Clear," "Slightly turbid," "Moderately turbid," "Turbid," and "Very turbid," each represented by triangular membership functions. These functions are characterized by three points: a start (membership 0), a peak (membership 1), and an end (membership 0).

### 3.0 RESULTS AND DISCUSSION

In this section, the study will explain the evaluation result of the proposed model. The explanation starts from the prototype of the model, the detection and the evaluation results. Figure 5 is the prototype of the proposed model

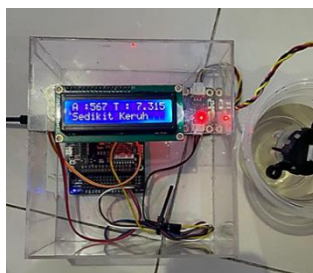


Figure 5: IoT Based Water Turbidity Monitoring Model



Figure 5 shows the assembled system encased in a plastic enclosure for protection. During the evaluation, the sensor is submerged in water samples with varying turbidity levels. The results are displayed on the I2C screen and stored for further analysis. The evaluation tests five sensor readings to verify whether the system functions correctly based on the obtained data. Table 3 presents the results of the data reading trials.

Table 3: Test Result

No	Testing	Samples	Average	Category
1	Bottled Water	0.825	0.831	Clear
		0.827		
		0.826		
		0.839		
		0.838		
2	Refillable Mineral Water	0.876	0.871	Clear
		0.873		
		0.866		
		0.874		
		0.866		
3	Treated Drink Water	3.741	3.736	Clear
		3.743		
		3.732		
		3.731		
		3.732		
4	Spring Source	0.942	0.941	Clear
		0.941		
		0.947		
		0.937		
		0.936		
5	Rainwater	7.308	7.31	Slightly Cloudy
		7.302		
		7.316		
		7.310		
		7.313		
6	Pool Water	6.985	6.981	Slightly Cloudy
		6.986		
		6.973		
		6.976		
		6.989		
7	Well Water	6.811	6.811	Slightly Cloudy
		6.813		
		6.815		
		6.804		
		6.814		
8	Drilled well water	5.313	5.320	Slightly

		5.321		Cloudy
		5.318		
		5.326		
		5.323		
		23.677		
		23.684		
9	River water	23.685	23.682	Moderate Cloudy
		23.689		
		23.676		
		10.798		
		10.796		
10	Sea water	10.791	10.793	Moderate Cloudy
		10.794		
		10.785		

Table 3 shows the water turbidity test results from the Pati Regency area, where the highest turbidity value was found in river water at 23.68 NTU, categorized as moderately turbid, and the lowest was bottled drinking water at 0.83 NTU, classified as clear. The results indicate that bottled drinking water, with a turbidity level of 0.83 NTU, meets the standards set by Indonesian Minister of Health Regulation 492/Menkes/Per/IV/2010 and SNI 01-3553-2006, confirming its safety based on turbidity levels.

A one-way ANOVA was conducted to assess differences between various water sources categorized by turbidity. The results showed significant differences in each category: for clean water sources, the p-value was 1.353e-38; for slightly turbid water, the p-value was 2.733e-38; and for moderately turbid water, the p-value was 2.380e-26, all indicating significant variations.

This subsection discusses the research gap, the novelty of the study, the proposed model, and its evaluation results. Previous models could only monitor water turbidity but lacked decision-making capability, which this study addressed by integrating the Fuzzy Tsukamoto algorithm. The evaluation showed that the model accurately monitored water turbidity and categorized samples. In river water, the turbidity reached 23.68 NTU, indicating unsafe drinking water, while bottled water had 0.83 NTU, confirming it as safe. One-way ANOVA revealed significant differences in water quality across turbidity categories, with p-values of 1.353e-38 for clean water, 2.733e-38 for slightly turbid, and

2.380e-26 for moderately turbid water. Compared to previous models, this study's model improves by providing decisions on water clarity. However, the model cannot detect bacteria, viruses, or dissolved chemicals, and the evaluation was limited to a local area. The river water test results may differ in other regions. In conclusion, the proposed model effectively determines water turbidity but does not guarantee water safety.

## 4.0 CONCLUSION

The integration of a turbidity sensor with the ESP8266 microcontroller enables real-time water quality monitoring, with data displayed on an LCD and sent to Firebase via a dedicated application. The system uses the Fuzzy Tsukamoto method to assess turbidity levels (NTU), providing faster and more accurate analysis. Testing showed a maximum turbidity of 23.68 NTU in river water, classifying it as moderately turbid, while bottled water had 0.83 NTU, classified as clear. One-way ANOVA results indicated significant differences in water quality across turbidity categories. Future research could explore alternative sensors, the ESP32 microcontroller, and other fuzzy logic methods to enhance water quality assessments.

## REFERENCES

- [1] J. Irianto *et al.*, "Studi Kualitas Air Minum Rumah Tangga di Indonesia," Puslitbang Upaya Kesehatan Masyarakat, Jakarta, Research Result, 2020. [Online]. Available: <https://repository.badankebijakan.kemkes.go.id/4936/1/Laporan%20SKAM-RT%20Balitbangkes.pdf>
- [2] W. H. Organization, *Guidelines for drinking-water quality: fourth edition incorporating the first and second addenda*, 4th ed. World Health Organization, 2022. [Online]. Available: <https://books.google.co.id/books?id=x3RyEAAAQBAJ>
- [3] F. Jan, N. Min-Allah, and D. Düştögör, "IoT Based Smart Water Quality Monitoring: Recent Techniques, Trends and Challenges for Domestic Applications," *Water*, vol. 13, no. 13, 2021, doi: 10.3390/w13131729.
- [4] S. Bijekar *et al.*, "The State of the Art and Emerging Trends in the Wastewater Treatment in Developing Nations," *Water*, vol. 14, no. 16, 2022,

doi: 10.3390/w14162537.

- [5] L. Lin, H. Yang, and X. Xu, "Effects of Water Pollution on Human Health and Disease Heterogeneity: A Review," *Frontiers in Environmental Science*, vol. 10, 2022, doi: 10.3389/fenvs.2022.880246.
- [6] M. Fida, P. Li, Y. Wang, S. M. K. Alam, and A. Nsabimana, "Water Contamination and Human Health Risks in Pakistan: A Review," *Exposure and Health*, vol. 15, no. 3, pp. 619–639, Sep. 2023, doi: 10.1007/s12403-022-00512-1.
- [7] R. Bogdan, C. Paliuc, M. Crisan-Vida, S. Nimara, and D. Barmayoun, "Low-Cost Internet-of-Things Water-Quality Monitoring System for Rural Areas," *Sensors*, vol. 23, no. 8, 2023, doi: 10.3390/s23083919.
- [8] P. S. Munoz, N. Tran, B. Craig, B. Dezfouli, and Y. Liu, "Analyzing the Resource Utilization of AES Encryption on IoT Devices," in *2018 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, Honolulu, HI, USA: IEEE, Nov. 2018, pp. 1200–1207. doi: 10.23919/APSIPA.2018.8659779.
- [9] W.-J. Li, C. Yen, Y.-S. Lin, S.-C. Tung, and S. Huang, "JustIoT Internet of Things based on the Firebase real-time database," in *2018 IEEE International Conference on Smart Manufacturing, Industrial & Logistics Engineering (SMILE)*, IEEE, 2018, pp. 43–47.
- [10] K. Dwi Hartomo, A. Firman Daru, and H. Dwi Purnomo, "A new approach of scalable traffic capture model with Pi cluster," *IJECE*, vol. Vol 13, No 2: April 2023, no. 2, 2023, doi: 10.11591/ijece.v13i2.pp2186-2196.
- [11] A. F. Daru, K. D. Hartomo, and H. D. Purnomo, "IPv6 flood attack detection based on epsilon greedy optimized Q learning in single board computer," *IJECE*, vol. 13, no. 5, pp. 5782–5791, 2023, doi: <http://doi.org/10.11591/ijece.v13i5.pp5782-5791>.
- [12] M. M. Rahman and Others, "Laser-Based Turbidity Sensor Development," *Environmental Monitoring and Assessment*, vol. 193, no. 12, pp. 1–12, 2021, doi: 10.1007/s10661-021-09723-4.
- [13] J. Trevathan, W. Read, and A. Sattar, "Implementation and calibration of an IoT light attenuation turbidity sensor," *Internet of Things*, vol. 19, p. 100576, 2022, doi: 10.1016/j.iot.2022.100576.
- [14] P. Mahajan and P. Shahane, "An IoT Based System for Water Quality Monitoring," *SSRN Electronic Journal*, no. Iicicnis, 2021, doi: 10.2139/ssrn.3769765.
- [15] A. R. Zain, M. Agustin, P. Oktivasari, N. F. Soelaiman, and M. F. Fahroji, "Design of Monitoring System for Water Levels and Turbidity Water Canals Based on Nodemcu," in *2022 16th International Conference on Telecommunication Systems, Services, and Applications (TSSA)*, Oct. 2022, pp. 1–4. doi: 10.1109/TSSA56819.2022.10063905.
- [16] J. Trevathan, W. Read, and A. Sattar, "Implementation and Calibration of an

- IoT Light Attenuation Turbidity Sensor,” *Internet of Things*, vol. 19, p. 100576, 2022, doi: <https://doi.org/10.1016/j.iot.2022.100576>.
- [17] H. Rachmat, I. Putra, and A. Wicaksono, “Monitoring System for Water Turbidity Using IoT Technology,” *Indonesian Journal of Electrical Engineering and Informatics*, vol. 9, no. 3, pp. 402–410, 2021.
- [18] L. A. Zadeh, “Fuzzy logic,” in *Granular, Fuzzy, and Soft Computing*, Springer, 2023, pp. 19–49.
- [19] G. D. Astudillo, L. E. Garza-Castañon, and L. I. Minchala Avila, “Design and Evaluation of a Reliable Low-Cost Atmospheric Pollution Station in Urban Environment,” *IEEE Access*, vol. 8, pp. 51129–51144, 2020, doi: [10.1109/ACCESS.2020.2980736](https://doi.org/10.1109/ACCESS.2020.2980736).