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Implementation of Fuzzy Tsukamoto on Node MCU ESP8266 to optimize monitoring of water flow in pipes

April firman Daru[1], Alaudin maulana Hirzan[2*], Muhammad Alfian Badrud Duja[3] , Paminto Agung Christianto[4],

[1,2,3]Faculty of Information and Communication Technology, Universitas Semarang, Tlogosari Kulon, 50196 Kota Semarang, Jawa Tengah, Indonesia
[4]Departmentof Informatics STMIK Widya Pratama, Patriot No.25, Pekalongan, Jawa Tengah,Indonesia

*Corresponding author: maulanahirzan@usm.ac.id
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Abstract— The issue of excessive and uncontrolled artesian water consumption has become a critical concern that requires immediate attention. The lack of real-time monitoring mechanisms often leads to significant water wastage, particularly in urban areas where demand is high. Recent data on artesian water usage indicate a 20% increase in consumption in 2023 compared to the previous year, with approximately 25% of the total distributed water being wasted. To address this issue, an Internet of Things (IoT)-based monitoring system for well water consumption has been developed, integrating the Tsukamoto fuzzy logic method. This system employs a NodeMCU ESP8266 microcontroller to collect water consumption data from a flow sensor. The data is then processed using the Tsukamoto fuzzy logic method to classify water usage into three categories: efficient, normal, and excessive. The categorized water usage information is displayed on a 16x2 LCD and a mobile application, enabling users to monitor their water consumption patterns in real-time.By providing continuous monitoring and intelligent classification of water usage, this system aims to enhance user awareness of sustainable water consumption practices. The results of this study demonstrate that the application of fuzzy logic in the monitoring model enables accurate and adaptive water consumption predictions, which can be adjusted based on environmental conditions. The fuzzy logic values obtained in this study are low flow (0.0), normal flow (0.5), and high flow (0.0). This system is expected to contribute to reducing the risk of excessive water consumption, promoting more efficient resource management, and fostering a culture of conservation among users.

Keywords— Internet of Things (IoT), NodeMCU ESP8266, Tsukamoto Fuzzy Logic, Artesian Monitoring.

I. Introduction

The Internet of Things (IoT) is one of the most significant and revolutionary technological innovations in the current digital era[1]. The IoT concept refers to a network of physical devices connected to the internet and able to communicate with each other, collect and exchange data, and interact with their surrounding environment[2]. In current IoT packet data capture, a new model exists, namely using the scalable traffic capture concept. With this model, packet capture can be done simultaneously, not only on one interface but together with just one command[3]. Attack detection in the IoT currently uses machine learning, meaning that the attack model already uses artificial intelligence so that the detection accuracy of the attack is better than before[4] [5].

Water is a vital resource essential for living things. Thus, as the population increases, so does the need for water that must be met. No human does not need water[6]. The role of water is crucial, such as for daily needs, transportation, and as an energy source for hydropower plants[7]. The inability to monitor water usage in real-time often results in significant waste, especially in urban areas[8].

Water meters are very commonly found in each of their customer's homes, whether in residential, office or industrial environments, which act as a counter for the amount of water used by customers each month[9]. In general, water meters are installed in each house that subscribes to artesian as a water provider that meets the water needs of the population[10].

The main problem faced in artesian water management is the lack of real-time information regarding community water consumption patterns. This causes difficulties in predicting water demand, identifying leaks, and optimizing water distribution efficiently [11]. In addition, awareness of wise water use also still needs to be improved among users.

The use of the IoT in water monitoring systems provides significant benefits because it can connect sensors installed in the water distribution network with a data management system directly. This allows for monitoring and controlling water consumption in real-time and provides accurate information to artesian for better decision making.

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The fuzzy logic method, especially fuzzy Tsukamoto, was chosen because of its ability to handle uncertainty and complexity in water usage data. Fuzzy Tsukamoto can integrate various input variable factors such as the number of residents, weather, and time in a flexible and interpretable way. This method is also capable of providing more intuitive and easily understood recommendations or decisions by users and artesian managers. By combining IoT technology and fuzzy logic methods in an artesian water usage monitoring tool, it is hoped that it can improve water management efficiency, reduce waste, and raise public awareness of the importance of sustainable water use. Previous studies have primarily focused on the automation of monitoring artesian water usage using microcontrollers and WaterFlow sensors, categorizing water consumption into two levels: low and high. However, this study aims to enhance the monitoring system by implementing the Tsukamoto Fuzzy Logic Method, which classifies water flow into three distinct categories: low, medium, and high. This approach enables a more precise and detailed analysis of water usage, improving the overall accuracy and efficiency of the monitoring system.

II. Related Work

Fuzzy logic, particularly the Tsukamoto method, has been widely implemented in various monitoring and control systems, including water management. In [12], a real-time water quality monitoring system was developed using the Tsukamoto fuzzy algorithm integrated into an Internet of Things (IoT)-based framework. This system enhances decision-making by categorizing water quality levels, providing timely and accurate data for users. Similarly, in [13], [14], an IoT-based system was designed using the Fuzzy Tsukamoto method to monitor drinking water quality, incorporating turbidity sensors and cloud-based data storage for real-time assessment. In the agricultural sector, a smart farming system utilizing Tsukamoto Fuzzy Logic was proposed in [15], [16], where input parameters such as pH, humidity, air temperature, and soil temperature were used to automate irrigation decisions. This approach demonstrated efficiency in optimizing water usage. Additionally, in [17], a water monitoring device was developed to determine the feasibility of water using pH and turbidity sensors processed through an Arduino-based Tsukamoto fuzzy model, leading to better water management. Further applications of Tsukamoto fuzzy logic include energy-efficient water distribution, as seen in [18], where a fuzzy-based control system managed water flow rates to reduce waste and optimize consumption. Another study [19] implemented fuzzy logic in water purification systems, demonstrating improved filtration efficiency by adjusting treatment parameters dynamically. The integration of fuzzy logic in smart cities was also explored in [20], where a water resource management system utilized fuzzy decision-making for sustainable urban water distribution. Moreover, Tsukamoto fuzzy logic has been applied in industrial water monitoring, as detailed in [21], where a system controlled chemical dosing in water treatment plants, optimizing resource utilization. In [22], an automated leakage detection system used fuzzy logic to identify anomalies in water pipelines, reducing water loss. Lastly, a hybrid fuzzy-PID approach was introduced in [23] to regulate water pressure in distribution networks, achieving stable and efficient operation. These studies highlight the flexibility and effectiveness of the Tsukamoto fuzzy logic method in diverse water management applications. The integration with IoT and smart control systems further enhances real-time monitoring and decision-making capabilities, making it a promising solution for optimizing water usage.

III. Research Methodology

A circuit block diagram is an important component in designing electronic equipment because it allows one to understand the overall working principle of the electronic circuit being created. This allows the entire tool block to be created to form a system that can be used or a system that runs according to design.

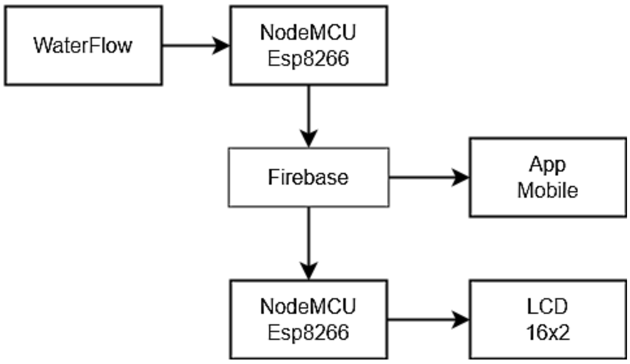

Fig. 1 Circuit Block Diagram

The WaterFlow sensor measures the water flow rate in customer pipelines. It comprises a plastic valve body, a water rotor, and a Hall-effect sensor. As water flows through the rotor, it spins at a speed proportional to the water flow. The Hall-effect sensor detects pulse signals from the rotor, which are then processed by a microcontroller. The NodeMCU ESP8266 functions as the central processing unit, executing pre-programmed instructions, controlling devices, and collecting sensor data. The collected data is processed using fuzzy logic for more accurate readings. To ensure real-time accessibility, Firebase is employed as a cloud-based database, allowing mobile and web

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applications to retrieve sensor data remotely. In the prototype development, two NodeMCU ESP8266 units are utilized to enhance the sensitivity of sensor readings. A 16x2 LCD is incorporated to display essential information such as water flow rate, cost, and total water volume. Additionally, a mobile application visualizes real-time data, including water speed, total volume, and billing information, enabling remote monitoring and management.

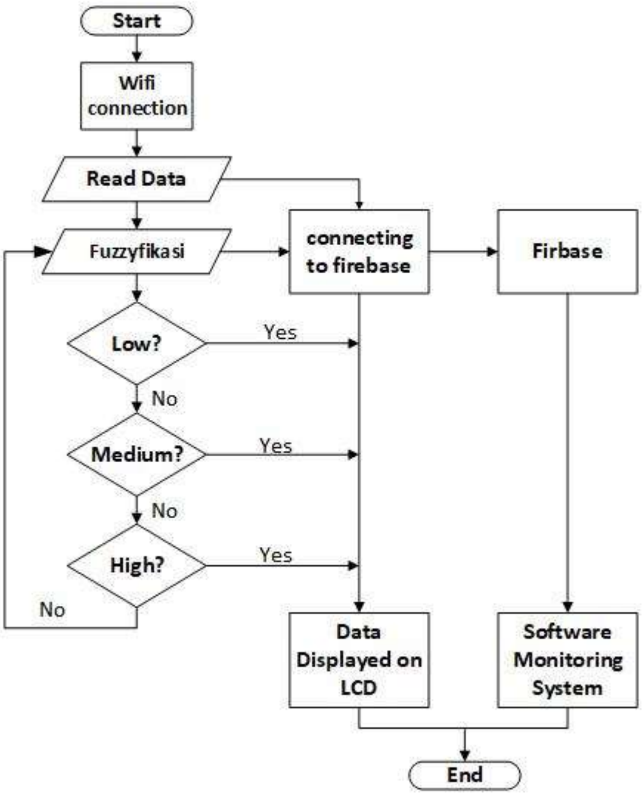

Fig. 2 Flow chart of the system work process

Figure 2 illustrates the working process connecting the device to a power source. Once the device is turned on, it connects to the internet via Wi-Fi. After establishing an internet connection, the sensor operates to collect data. The water flow sensor then measures the water discharge flowing through the artesian pipe. The discharge data is transmitted to the NodeMCU ESP8266, which processes it using the Tsukamoto fuzzy logic method to classify water usage into three categories: low, medium, and high. The water consumption data (including discharge and usage category) is displayed on a 16x2 LCD. Additionally, the data is sent to the Firebase Realtime Database. A mobile application retrieves the water consumption data from the Firebase Realtime Database and displays realtime water consumption and usage categories.

Figure 3 presents the circuit schematic designed for data display. This circuit consists of several key components, including the NodeMCU ESP8266, which functions as a microcontroller and a receiver for data from Firebase, subsequently transmitting it to the LCD. The baseboard plays a crucial role in facilitating the connection and control of electronic components. Additionally, it serves as a power extender since the NodeMCU provides only 3V, which is insufficient for specific components. To ensure stable operation, the baseboard requires an additional 12V adapter. Within this schematic, the LCD functions as an output device that displays the data retrieved from Firebase and transmitted by the NodeMCU. The integration of these components ensures efficient data processing and realtime visualization.

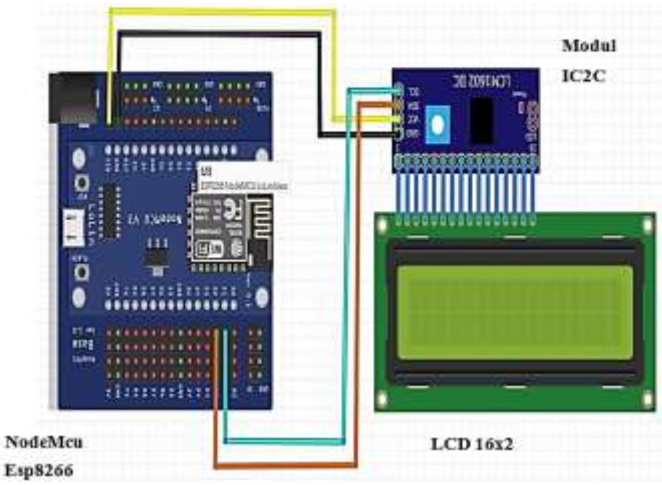

Fig. 3 Circuit Schematic Displaying Data

IV. FUZZY TSUKAMOTO IMPLEMENTATION ON ESP8266

Fuzzy logic is a computational approach that mimics human reasoning by handling uncertainty and imprecise data, making it suitable for various control applications. Implementing fuzzy logic on the ESP8266 microcontroller enhances decision-making processes in embedded systems, particularly when dealing with dynamic sensor data. The Tsukamoto fuzzy inference method is commonly used in embedded systems because it provides a crisp output by applying monotonic membership functions. This method consists of three main stages: fuzzification, rule evaluation, and defuzzification.[24], [25]. In the fuzzification stage, input variables—such as sensor readings—are converted into fuzzy sets based on predefined membership functions. The rule evaluation stage applies if-then rules to determine intermediate fuzzy values. Finally, the defuzzification stage converts these fuzzy values into a numerical output, allowing the ESP8266 to make precise control decisions. Integrating fuzzy logic into the ESP8266 is widely utilized in IoT applications, including water consumption monitoring, environmental sensing, and automated control systems[26]. The microcontroller processes sensor data, applies fuzzy

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logic rules, and classifies outputs such as "low," "medium," and "high." This classification enables real-time decision-making, enhancing the efficiency and adaptability of IoT systems. By leveraging fuzzy logic, the ESP8266 can effectively manage complex decision-making processes with limited computational resources, making it a powerful solution for intelligent embedded systems.

Fuzzy Tsukamoto is a fuzzy inference system that uses a monotonic membership function for the output. The output of each rule is a crisp value, which is calculated based on the α-predicate of the rule. The final output of the system is the weighted average of the crisp outputs of all the rules. Fuzzy Tsukamoto is similar to fuzzy Sugeno in that it uses a crisp value for the output of each rule. However, fuzzy Sugeno uses a constant or linear function to determine the crisp output, while fuzzy Tsukamoto uses a monotonic membership function. Fuzzy Tsukamoto is also different from fuzzy Mamdani, which uses a fuzzy set for the output of each rule. Fuzzy Mamdani then uses a defuzzification method to convert the fuzzy set into a crisp value. Figure 3 is a table summarizing the differences between the three fuzzy inference systems:

TABLE I
DIFFERENCES BETWEEN FUZZY METHODS

Feature	Fuzzy Tsukamoto	Fuzzy Sugeno	Fuzzy Mamdani
Output of each rule	Crisp value	Crisp value	Fuzzy set
Calculation of crisp output	Monotonic membership function	Constant or linear function	Defuzzification method
Final output	Weighted average of crisp outputs	Weighted average of crisp outputs	Crisp value after defuzzification

The Tsukamoto Fuzzy Method is widely applied in various domains, including temperature control systems, prediction models, decision-making processes, and other complex systems. Its effectiveness lies in its ability to handle uncertainty and complexity, making it a suitable approach for systems requiring adaptive and intelligent decision-making. The Tsukamoto fuzzy method follows a structured mathematical formulation, which is expressed as follows:

a. *Low* (Low): Low value.
b. *Medium* (Normal) : Normal value.
c. *High* (High) : High value.

V. RESULT AND EVALUATION

The tool's implementation is a phase conducted after the system analysis and design stages. This phase focuses on the system's hardware and software. The hardware consists of several modules and fundamental electronic components, while the software involves using Arduino IDE as the programming editor and Firebase as the database management tool. Figure 4 shows the finished circuit created to monitor artesian water usage using the Internet of Things (IoT).

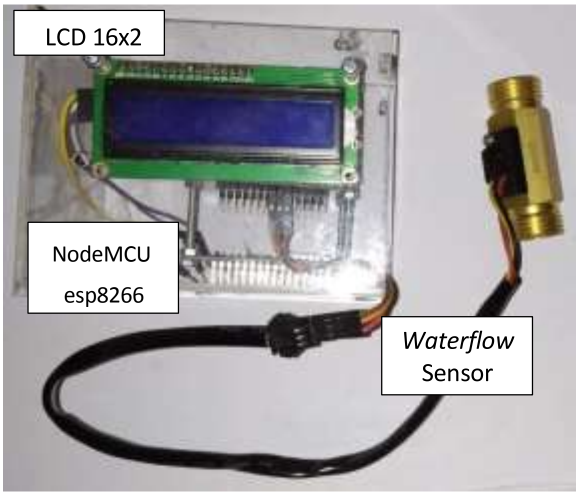

Fig. 4 Finished Circuit

Figure 5 illustrates the use of Firebase Realtime Database for storing water usage data obtained from sensors. The data is collected in realtime from water sensors and transmitted to Firebase. The Tsukamoto Fuzzy Logic algorithm processes this data to classify water usage patterns. Implementing the Tsukamoto Fuzzy Logic method in the water usage monitoring model, utilizing Firebase Realtime Database, enables efficient data collection, storage, and analysis. Firebase provides a robust platform for realtime data management, which is crucial for monitoring and control applications that require rapid and accurate responses. The collected data facilitates realtime water usage monitoring and offers valuable insights for future analysis and decision-making.

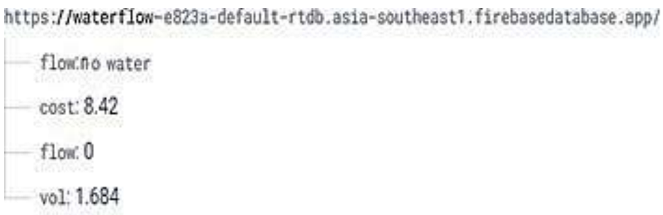

Fig. 5 Firebase Database View

An IoT-based monitoring system for artesian water usage has been developed to measure water flow within pipes and deliver realtime data on flow speed, volume, and billing via a dedicated application. The system employs a Waterflow sensor and a NodeMCU ESP8266 microcontroller to achieve this functionality. The microcontroller processes the acquired data and transmits it to a Firebase database, ensuring seamless integration and realtime updates within the application interface. This design facilitates efficient water usage monitoring while maintaining precision and accessibility of information. Upon establishing a connection with Firebase, the NodeMCU retrieves input from the

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Waterflow sensor and digital pins to calculate flow speed and volume. These parameters are critical for accurate measurement and are summarized in Table 2. By leveraging IoT technology, the system ensures cohesive data flow between hardware and software components, enhancing reliability and user experience. This structured approach underscores the system's ability to effectively provide actionable insights into water consumption patterns.

TABLE II
SENSOR READING SCRIPT EXPLANATION

Information	**Script**
Digital water flow pin	const int flowSensorPin = D5;

Flow Rate Data liters per minute	float flowRate = 0.0; // Flow rate in liters per minute
	float vol = 0.0, l_minute;

Data *Flow* Volume	unsigned long lastMillis = 0; unsigned long currentMillis; int currentDay = 0; float price = 5.0 ; float totalcost = 0.0 ;

Flow sensor *delay*	int botRequestDelay = 1000; unsigned long lastTimeBotRan; unsigned long previousMillis = 0;
	// Variables for flow rate calculation
	unsigned long lastFlowRateCalcMillis = 0;
	const unsigned long flowRateCalcInterval = 1000; // 1 second

The water flow monitoring system in Table 2 employs several key variables and constants to facilitate accurate data acquisition, flow rate computation, and cost estimation. The digital flow sensor is interfaced through the constant flowSensorPin, which is configured to the microcontroller's digital pin D5. This pin captures pulse signals emitted by the flow sensor, each corresponding to a specific volume of water. To compute and store the instantaneous flow rate and the total accumulated water volume, the variables flowRate, vol, and l_minute are initialised. These allow the system to represent real-time data in litres per minute and integrate flow measurements over time.

Temporal tracking is managed through the variables lastMillis, currentMillis, and currentDay. These parameters are crucial for determining elapsed time, segmenting data daily, and managing measurement intervals. The cost estimation mechanism is implemented using the variable price, set to a predefined value (e.g., 5.0 currency units per litre), and total cost, which accumulates the monetary cost based on the total volume of water used. To prevent excessive processing and allow scheduled external communications, the system utilises timing control variables such as botRequestDelay, lastTimeBotRan, and previousMillis. These parameters define the delay interval between data handling or transmission tasks and keep track of the last execution times of related processes.

Additionally, accurate flow rate calculations are governed by lastFlowRateCalcMillis and flowRateCalcInterval, where the latter is fixed at a 1000-millisecond interval (equivalent to one second). This fixed sampling rate ensures consistent temporal resolution for calculating the flow rate using the pulses counted from the flow sensor. Overall, these variables form the core computational structure for a real-time water flow monitoring system suitable for Internet of Things (IoT)-based environmental monitoring applications. Such a design is consistent with best practices in embedded system development and has been applied in related studies focusing on resource management and automated fluid control systems.

The prototype tool testing for this Final Project employs the Tsukamoto Fuzzy Logic method. In the Artesian Water Usage Monitoring system, there are membership functions that are detailed in the following table: This approach ensures a systematic and structured analysis of water usage patterns by leveraging fuzzy logic principles. The membership functions serve as a critical component in translating input variables into meaningful outputs, thereby facilitating accurate monitoring and decision-making within the system. The subsequent table provides an overview of these memberships, which are integral to the functioning of the Tsukamoto Fuzzy Logic framework.

TABLE III
FUZZY INPUT VARIABLES

Category	**Range**
Low water flow	0-10
Medium water flow	>10-<20
High water flow	>20-<60

In Table 3, the fuzzy variable data shows that when the Waterflow sensor generates a value, it is categorized into three variables: low, medium, and high. After determining the membership values, the next step is to carry out fuzzy calculations. To perform fuzzification based on the fuzzy set above (low, medium, high) with the following boundaries:

1. Low : 0-10
2. Medium : 10-20
3. High : 20-60 Variable

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In the Tsukamoto fuzzy model, the membership functions for each fuzzy set are defined based on predetermined boundaries. Given the specified ranges:

1. Low : 0 < X < 10
2. Medium : 10 < X < 20
3. High : X>20 to X < 60

In the Tsukamoto fuzzy inference system, membership functions define the degree of belonging of a crisp input X to specific fuzzy sets based on predetermined boundaries. The classification consists of three fuzzy sets: Low, Medium, and High, each representing a distinct range of values. The Low fuzzy set covers values from 0 to 10. Within this range, X has full membership (μ=1) when it is at the lower bound and gradually decreases as X approaches the upper limit. Beyond 10, the membership value becomes zero. The Medium fuzzy set applies to values greater than 10 but less than 20. The membership degree increases linearly from zero at 10 to full membership at the midpoint and then decreases symmetrically as X approaches 20. This ensures a smooth transition between the Low and High categories. The High fuzzy set represents values greater than 20 up to 60. Membership starts increasing from zero at 20, reaching its peak as X approaches the upper limit.

For a given input X=15, the membership functions are calculated as follows:

- **Low Set Membership** ($\mu_{low}(X)$), Since X=15 falls outside the range of the "low" fuzzy set (0≤X≤100), the membership degree is $\mu_{low}(X)=0$.
- **Medium Set Membership** ($\mu_{medium}(X)$), The "medium" fuzzy set is defined between 10 and 20, with a linear transition. The membership function for increasing values is given by: $\mu_{\text{medium}}(X) = \frac{20 - X}{20 - 10}$

  Substituting X=15:

  $$\mu_{\text{medium}}(15) = \frac{20 - 15}{10} = \frac{5}{10} = 0.5$$
- **High Set Membership** ($\mu_{high}(X)$), Since X=15 is below the lower boundary of the "high" fuzzy set (X>20), the membership degree is $\mu_{High}(X)=0$.

Thus, for X=15, the corresponding fuzzification results are:

$\mu_{\text{low}}(15) = 0$

$\mu_{\text{medium}}(15) = 0.5$

$\mu_{\text{high}}(15) = 0$

In the Tsukamoto fuzzy inference system, the output value (Y) is determined using the weighted average defuzzification method. Given the predefined fuzzy sets for input (X), the membership degrees for X=15 were calculated as follows: $\mu_{low}=0$, $\mu_{medium}=0.5$ and $\mu_{high}=0$. These membership values indicate that X=15 belongs partially to the "medium" fuzzy set with a degree of 0.5, while it does not belong to the "low" or "high" fuzzy sets. To determine the crisp output (Y), it is assumed that the corresponding output values are Y=10 for "low," Y=30 for "medium," and Y60 for "high."

Applying the inference rules:

1. Rule 1: IF X is Low, THEN Y is Low (Y=10) → Not active since $\mu_{low}=0$.
2. Rule 2: IF X is Medium, THEN Y is Medium (Y=30) → Active with $\mu_{medium}=0.5$.
3. Rule 3: IF X is High, THEN Y is High (Y=60) → Not active since $\mu_{high}=0$.

The defuzzification process is performed using the formula:

$$Y = \frac{\sum(\mu_i \times y_i)}{\sum \mu_i} \tag{1}$$

Substituting the given values:

$$Y = \frac{(0 \times 10) + (0.5 \times 30) + (0 \times 60)}{0 + 0.5 + 0} = \frac{15}{0.5} = 30$$

The graph represents the fuzzy sets in the Tsukamoto fuzzy inference system, categorized into three groups: Low (blue), Medium (green), and High (red). The dashed line indicates the position at X = 15, where the membership degree in the Medium fuzzy set is 0.5, while the membership degrees in the Low and High fuzzy sets are zero, as shown in Figure 6.

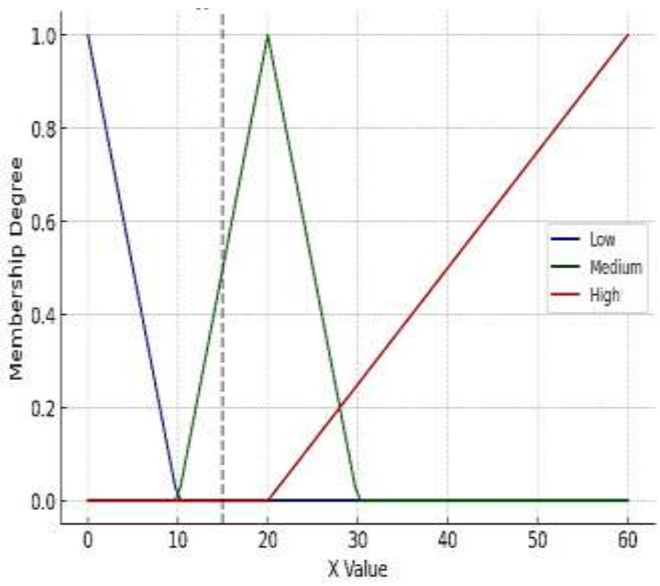

Fig. 6 Fuzzy Set

This testing is conducted to ensure that the device performs as expected. The evaluation includes testing the sensor data reading process and observing whether the device operates by the acquired sensor data. Table 4 presents the results of the sensor data reading test.

TABLE IV
IOT MODEL TEST RESULTS

No	*Sensor output* (m³)	Measuring cup method (m³)	Difference
1	0.0004884	0.0005	0.0000116 m³
2	0.0004876	0.0005	0.0000124 m³
3	0.0004640	0.0005	0.0000360 m³
4	0.0004976	0.0005	0.0000024 m³
5	0.0004793	0.0005	0.0000207 m³
Total difference = 0.0000831 m³ (83.1ml)			

TABLE V
PRECISION TEST RESULTS

No	*output Values* sensor (m³)	Values *actual* (ml)	$\|(xi - , x)2\|$
1.	0.0004884	0.0005	0,0058081
2.	0.0004876	0.0005	0,0040401
3.	0.0004640	0.0005	0,000979
4.	0.0004976	0.0005	0,000701
5.	0.0004793	0.0005	0,000214
Average 0.00048358 m³			

$$SD = \sqrt{\frac{\Sigma(x_i - \bar{x})^2}{n-1}} \quad (2)$$

Where SD is the standard deviation, $\bar{x}$ is the average value of the sensor measurement results, xi is the value of each measurement and n is the number of measurements performed. The results of the precision test can be seen in Table 5.

VI. Conclusions

This study proposes a monitoring system for artesian water usage supervised through a mobile application. The system employs the Tsukamoto fuzzy logic method to classify water usage levels based on data from sensors integrated into the mobile device. The findings indicate that the Internet of Things (IoT)-based Artesian Water Usage Monitoring System functions effectively. The Water Flow sensor operates as expected, ensuring accurate data collection. Communication between NodeMCU and Firebase is successfully established, and data transmission from Firebase to the mobile application functions correctly, allowing real-time data visualization within the application interface.

Furthermore, water usage levels—categorized as low, medium, and high—are classified based on preprocessed data using the fuzzy logic method. The device successfully measures water consumption with a minimal deviation, achieving an average difference of 0.00048358 m³ between sensor output values and actual measurements. These results demonstrate the system's reliability in accurate monitoring and classifying water usage. Future research can apply this system to real artesian water pipes and test its level of accuracy.

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Conflict of Interest

The authors declare that there is no conflict of interest

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