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Web-Based Monitoring and Control System for Aquaponics Using IoT and Fuzzy Logic

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Abstract

Aquaponics integrates aquaculture and hydroponic cultivation to improve resource efficiency and support food security under constraints of limited land and water. Water quality is a critical determinant of aquaponics productivity; however, many small-scale systems still rely on manual and periodic monitoring, which limits timely intervention. This study proposes an Internet of Things (IoT)–enabled, web-based aquaponics monitoring and control system for catfish (Clarias gariepinus) cultivation integrated with water spinach (Ipomoea aquatica). The system acquires water quality parameters including temperature, pH, dissolved oxygen, and ammonia using multiple sensors connected to an Arduino Mega. Sensor data are transmitted in real time via an ESP communication module using the MQTT protocol through the HiveMQ broker and stored in a MongoDB database for real-time visualization and historical analysis. In addition, pump actuator control is implemented using fuzzy logic based on water temperature and ammonia concentration to regulate water circulation and provide an interpretable qualitative assessment of water quality. Experimental validation confirms reliable sensing, transmission, storage, and web-based monitoring in an aquaponics pond scenario. The end-to-end transmission delay from the microcontroller to the web application achieves an average of 0.369 s (369 ms), indicating near real-time performance suitable for continuous monitoring and control.

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1. Introduction

According to projections reported by the Pew Research Center, Indonesia ranked as the fourth most populous country in the world in 2020, with an estimated population of 274 million people an increase of more than 290% compared to 1950 [1], [2]. Rapid population growth directly intensifies pressure on food availability, requiring continuous improvements in food production systems. When population growth is not matched by proportional increases in agricultural productivity, food demand and supply imbalance becomes unavoidable. These challenges are further exacerbated by global climate change, limited land availability, and increasing pressure on water and natural resources. Consequently, innovative and resource-efficient food production approaches are required to ensure long-term food security.

Conventional aquaculture practices typically require extensive land areas and abundant water resources. In addition, aquaculture water quality can deteriorate due to metabolic waste produced by fish, particularly toxic compounds such as ammonia and nitrogen, which necessitate frequent water replacement. However, fish waste also contains nutrients essential for plant growth. Hydroponic cultivation can utilize these nutrients while simultaneously acting as a natural biofilter that improves water quality before it is recirculated back into the fish pond. This symbiotic relationship not only reduces water consumption but also eliminates the need for chemical nutrient solutions commonly used in standalone hydroponic systems, which must be replaced periodically to prevent salt accumulation and phytotoxicity.

The integration of aquaculture and hydroponics is known as aquaponics. Aquaponics enables simultaneous fish and vegetable production within a single recirculating system, offering improved resource efficiency and dual economic benefits for farmers. As a result, aquaponics has emerged as a promising solution to land limitations and sustainability challenges in food production systems, while also contributing to food security resilience [3], [4].

Despite its advantages, many aquaponics systems in Indonesia still rely on conventional monitoring practices. Water quality assessment often requires farmers to physically inspect ponds at regular intervals, resulting in non-real-time observations and delayed responses to adverse conditions. These limitations become more critical under unstable climatic and environmental conditions, which can accelerate bacterial growth and increase the risk of disease outbreaks, leading to reduced productivity or even mortality of fish and plants. Manual monitoring is also time-consuming and inefficient, particularly for systems operated at multiple or remote locations.

To address these limitations, several studies have proposed technology-based aquaponics monitoring solutions. Kazadi et al. [5] developed a mobile-based monitoring and control system, while Perumal et al. [6] implemented aquaponics observation using a mobile application integrated with a Firebase database. Roy et al. [7] presented a mobile-based monitoring system utilizing an Intel Edison module as the controller. Akhtar et al. [8] employed an Arduino-based system; however, real-time data visualization through web or online platforms was not provided, limiting remote accessibility. Vanaraj et al. [9] proposed a water quality classification and monitoring approach using electronic nose and tongue systems, but the study focused on classification rather than integrated real-time monitoring and control.

Although existing studies demonstrate the potential of digital technologies for aquaponics monitoring, limitations remain in terms of real-time data accessibility,

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integration between sensing, control, and web-based visualization, and system scalability. Therefore, this study proposes a web-based aquaponics monitoring system that integrates real-time sensor data acquisition, MQTT-based communication, fuzzy logic–based actuator control, and web visualization to support continuous monitoring and efficient water quality management. The proposed system aims to provide a practical, extensible, and remotely accessible solution for aquaponics operations under real-world conditions.

2. Methods

This section describes the methodological framework used to design, implement, and evaluate the proposed web-based aquaponics monitoring system. The methods are structured to ensure reproducibility and objective performance assessment, encompassing system architecture, aquaponic media configuration, sensing and actuation components, data transmission mechanisms, and fuzzy-based actuator control. The overall approach integrates sensor-based data acquisition, MQTT-based real-time communication, and web-based visualization to support continuous monitoring and control of aquaponic water quality under operational conditions.

Figure 1 illustrates the overall system architecture employed in this study. The system consists of sensing nodes, communication modules, backend services, and a web-based monitoring interface that collectively enable data acquisition, transmission, processing, visualization, and actuator control.

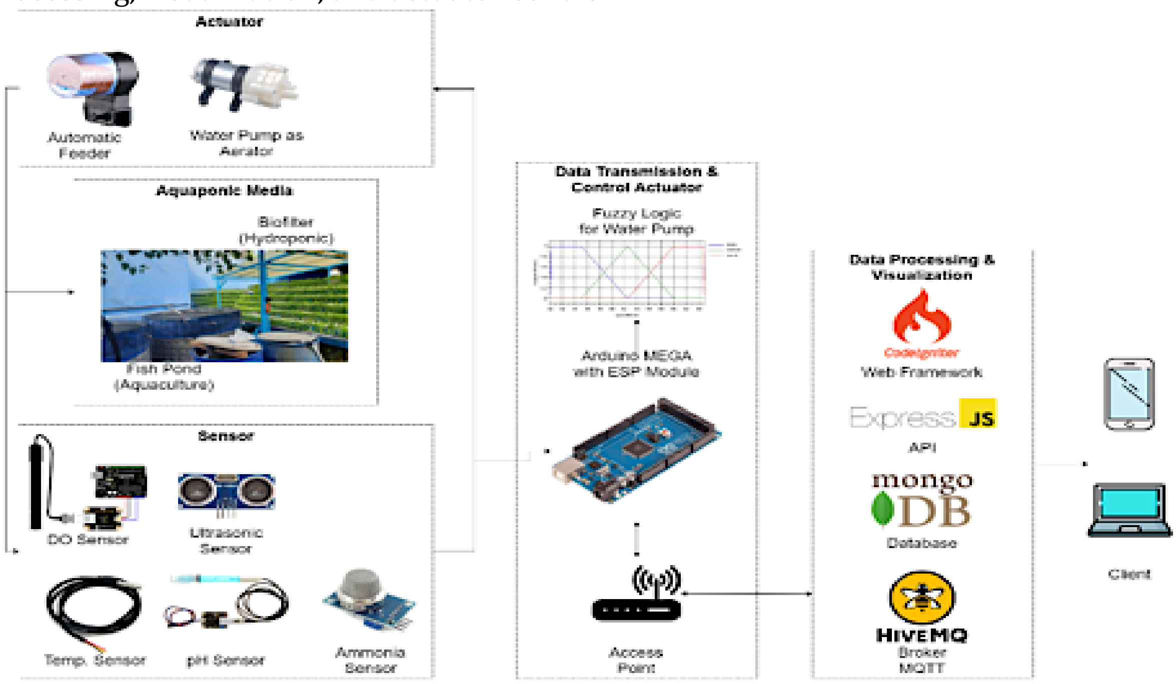

Fig. 1. System Design

In general, the system operates as follows: sensors connected to an Arduino microcontroller measure water quality parameters, and the collected data are transmitted via an ESP communication module over the Internet using the MQTT protocol. Through the web application, users select registered devices to subscribe to corresponding MQTT topics and monitor sensor readings in real time. Fish feeding is performed automatically at fixed intervals of 8 hours in accordance with Indonesian

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National Standards (BSNI), while water circulation between the fish pond and hydroponic beds is regulated by a pump actuator controlled using fuzzy logic rules.

2.1 Aquaponic Media

The aquaponics system implemented in this study combines aquaculture and hydroponics, consisting of a fish pond integrated with hydroponic cultivation that functions as a biological filter. This configuration enables nutrient recycling, where waste generated from fish metabolism is utilized by plants, thereby improving water quality in the pond.

The fish species cultivated in this system is African catfish (Clarias gariepinus), which has specific water quality requirements regulated by the Ministry of Marine Affairs and Fisheries of the Republic of Indonesia through SNI 6484.3:2014 issued by the National Standardization Agency (BSN) [10], [11]. These standards define acceptable ranges for key water quality parameters relevant to catfish cultivation.

Water brightness was not included as an observed parameter in this study. Although turbidity sensors commonly provide measurements in nephelometric turbidity units (NTU), conversion to centimeter-based visibility is highly dependent on external lighting conditions and pond depth, resulting in inconsistent and unreliable measurements. Furthermore, several water quality parameters exhibit interdependencies; for instance, elevated ammonia concentrations are often associated with increased water temperature. Therefore, this study focuses on parameters with more stable and interpretable sensor measurements.

The hydroponic component cultivates water spinach (*Ipomoea aquatica*), selected due to its suitability as a biological filter capable of absorbing nitrogen compounds, particularly ammonium (NH_4^+) and nitrate (NO_3^-). This characteristic contributes to the reduction of nitrogen concentration in the aquaponic water, thereby supporting water quality stabilization [12], [13].

2.2 Sensor

The sensing subsystem collects water quality and feedstock data using the following sensors:

a. Dissolved Oxygen (DO) Sensor: measures the concentration of dissolved oxygen in the pond water.
b. pH Sensor: measures the acidity or alkalinity level of the water.
c. Temperature Sensor: measures the water temperature in the fish pond.
d. Ammonia Sensor: measures ammonia concentration to assess potential toxicity levels.
e. Ultrasonic Sensor: measures the height of available feedstock in the feeder container.

These sensors provide the primary inputs for both real-time monitoring and fuzzy-based actuator control.

2.3 Actuator

Two main actuators are employed in the system:

a. Automatic Feeding System, which dispenses feed at predefined intervals to support consistent fish growth and productivity.
b. Water Pump, which circulates water between the fish pond and the hydroponic beds. This circulation enables reuse of nutrient-rich wastewater, reduces overall water consumption, and enhances filtration through plant uptake.

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The pump operating speed is dynamically adjusted based on water quality conditions. When water quality degrades, the pump operates at a higher speed to accelerate waste transfer to the hydroponic system and return filtered water to the fish pond more rapidly. Water loss from the system is primarily caused by evaporation and minor shrinkage.

2.4 Data Transmission & Actuator Control

Water quality parameters measured by the sensors are acquired by an Arduino microcontroller and transmitted via an ESP communication module connected to a wireless Internet network. Data transmission employs the Message Queuing Telemetry Transport (MQTT) protocol, which provides lightweight and reliable message delivery suitable for IoT-based monitoring applications [14].

The sensor data are transmitted using a standardized message format to ensure interoperability across IoT nodes that share the same parameter sequence and control logic. Each data packet consists of a sequence of sensor values separated by a # delimiter and can be expressed as Equation (1)

$$S = [U_1, pH, T, DO, NH_3, U_2, D] \tag{1}$$

where U_1 and U_2 denote ultrasonic feedstock level measurements, T is water temperature, , DO is dissolved oxygen, NH_3 represents ammonia concentration, and D is the duty cycle corresponding to pump motor speed. An example of received sensor data along with its reception timestamp is shown in Figure 2. Sensor data are published at 15-second intervals.

10:50:32 - 0#7#26#16#52.53#0#55#

10:50:16 - 0#7#26#16#52.52#0#55#

10:50:00 - 0#7#26#16#52.10#0#55#

Fig. 2. Example of sensor data and reception time displayed by the MQTT client

Pump actuator control is implemented using a fuzzy logic control system with two input variables water temperature (T) and ammonia concentration (NH_3) and one output variable representing pump motor speed (M). The temperature input variable is defined by four fuzzy sets (*cold*, *good*, *warm*, and *hot*), as illustrated in Figure 3.

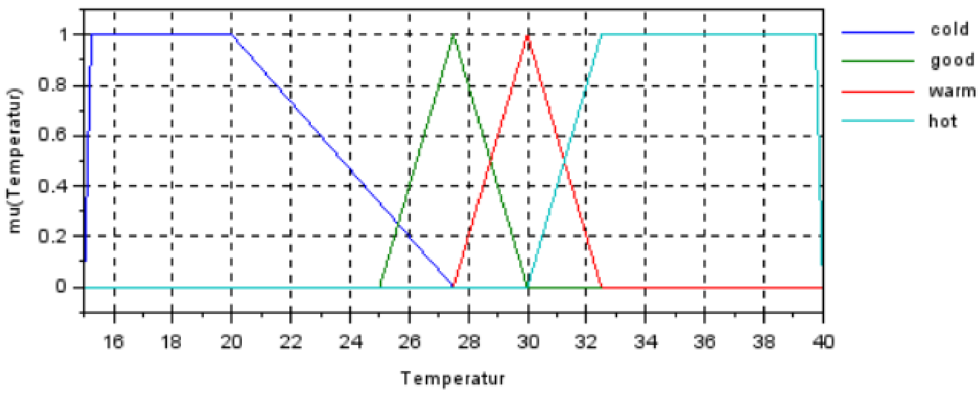

Fig. 3. Membership functions of the temperature variable

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The ammonia input variable is defined using three fuzzy sets *safe*, *warning*, and *toxic* as shown in Figure 4.

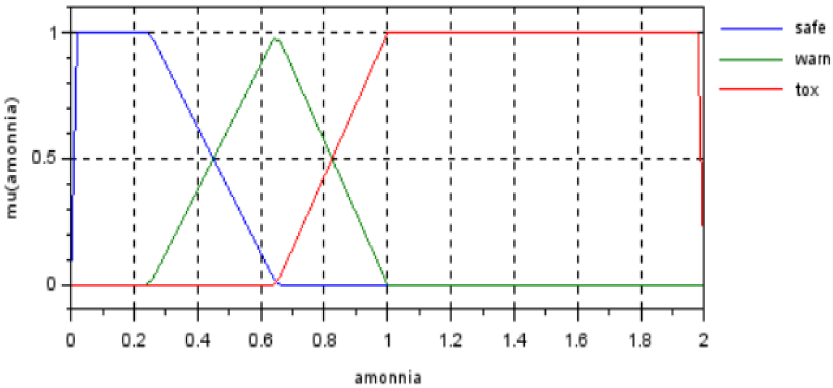

Fig. 4. Membership functions of the ammonia variable

The output variable, pump motor speed, consists of three fuzzy sets: *slow*, *normal*, and *quick*, as illustrated in Figure 5.

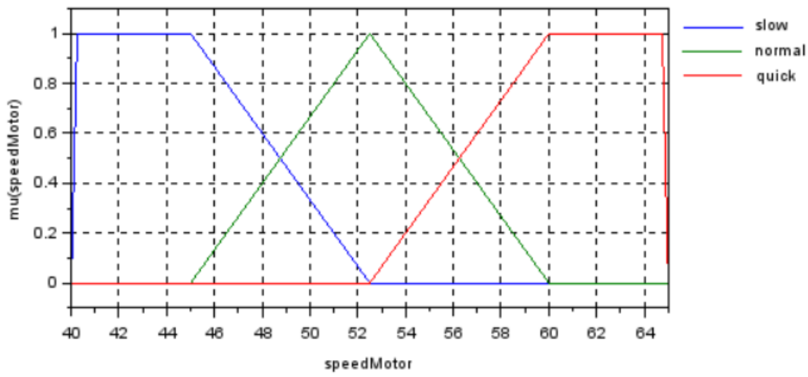

Fig. 5. Membership functions of the motor speed variable

Fuzzy inference is performed using a rule base summarized in Table 1, which maps combinations of temperature and ammonia conditions to the appropriate pump motor speed. The same rule base is implemented in the API layer to provide qualitative water quality classification, where *slow*, *normal*, and *quick* motor speeds correspond to good, moderate, and poor water quality conditions, respectively.

The defuzzified motor speed output M^* is obtained using the centroid method, expressed as Equation (2).

$$M^* = \frac{\sum_{i=1}^{n} \mu_i(M) M_i}{\sum_{i=1}^{n} \mu_i(M)} \tag{2}$$

where $\mu_i(M)$ is the membership degree of the output fuzzy set M_i.

Table 1. Fuzzy control rules for pump motor speed determination

Rule		**Temperature**			
		Cold	***Good***	***Warm***	***Hot***
Ammonia	Safe	Slow	Slow	Normal	Quick
	Warning	Slow	Normal	Normal	Quick
	Toxic	Quick	Quick	Quick	Quick

2.5 Data Processing & Visualization

2.5.1 MQTT Broker

The Message Queuing Telemetry Transport (MQTT) protocol is a lightweight messaging protocol operating over the TCP/IP stack. It is characterized by minimal packet overhead typically as low as 2 bytes making it suitable for resource-constrained IoT environments and reducing power consumption during data transmission [15], [16]. MQTT is a data-agnostic protocol that supports the transmission of various data formats, including binary data, plain text, XML, and JSON [17].

Unlike conventional client–server communication models, MQTT adopts a publish/subscribe architecture in which data publishers and subscribers are decoupled through an intermediary broker. This architecture provides both *space decoupling*, where publishers and subscribers do not need to be aware of each other, and *time decoupling*, which allows clients to disconnect temporarily without losing data. In offline mode, a client can reconnect to the broker and receive pending messages published during its disconnection period. These characteristics make MQTT particularly well suited for real-time sensor data delivery in distributed aquaponics monitoring systems.

2.5.2 Database Design

The database functions as the primary storage layer for both raw input data and processed outputs generated by the monitoring system [18], [19]. This study uses MongoDB because its document-oriented model and schema flexibility are well suited for semi-structured IoT data. Unlike relational databases that depend on SQL-based tables, MongoDB stores records as JSON-like documents, enabling efficient ingestion and retrieval of sensor streams and user-related information.

Three main collections are implemented: Users, Feeders, and Monitorings. The Users collection stores user attributes, including idUser, name, username, email, hashed password, address, phone number, gender, and photoURL, as well as a devices array. Each device entry contains idDevice which also corresponds to the MQTT topic used for subscription along with metadata such as pond name and fish type. The Feeders collection records feeding activities for each device and includes fields such as idDevice, number of fish, fish age (days), and feed quantity (kg). Figure 6 presents the document structure of the Users and Feeders collections, illustrating how user accounts are linked to devices and how feeding logs are recorded per device.

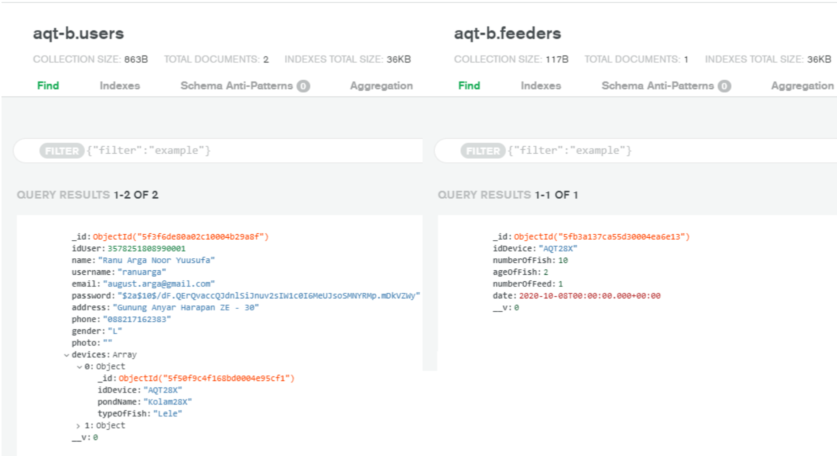

Fig. 6. Structure of Users and Feeders collections.

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The Monitorings collection stores all received sensor data. Its fields include idDevice and timestamp, along with sensor parameters such as feed-level readings from ultrasonic sensors, pH, temperature, dissolved oxygen (DO), ammonia concentration, and dutyCycle, which represents the pump motor speed used for system control [20], [21]. Figure 7 shows the schema of the Monitorings collection used to persist timestamped sensor streams and control-related variables for historical retrieval and analysis.

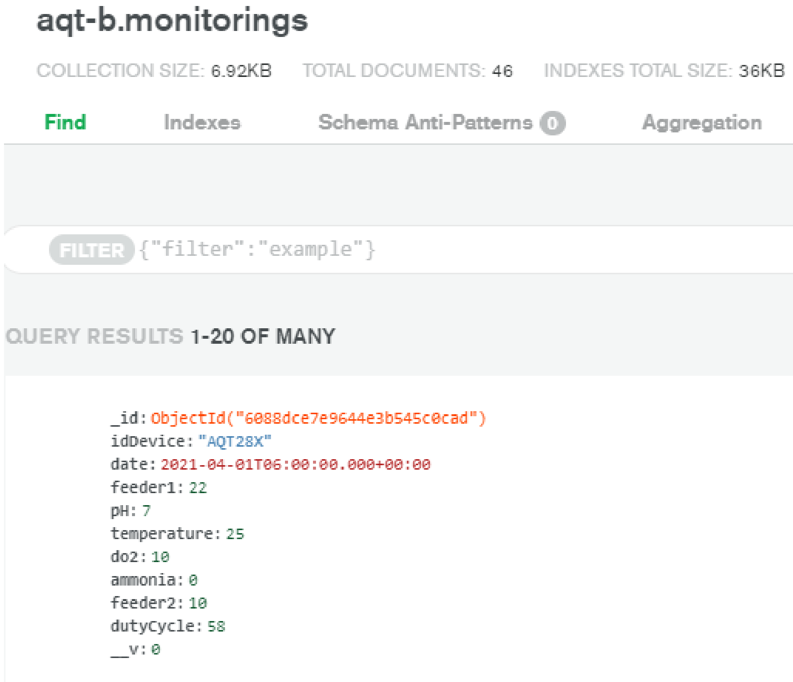

Fig. 7. Structure of the Monitorings collection

2.5.3 Application Programming Interface (API)

In addition to the web application, a RESTful Application Programming Interface (API) is developed to support extensibility and cross-platform integration. The API facilitates future enhancements, including feature expansion and integration with additional client applications. All endpoints return JSON responses and implement token-based authentication using JSON Web Tokens (JWT) [22], [23]. The main API functionalities implemented in this study include:

a. Authentication Services: login and registration endpoints that validate user credentials and issue JWT tokens for secure access to protected resources.
b. User Profile Management: endpoints for retrieving and updating user profile information, including a dedicated endpoint for password modification.
c. Device Management: endpoints for retrieving, adding, updating, and deleting aquaponics devices associated with a user account.
d. Feeding Log Management: endpoints for managing feeding records, including retrieval, creation, modification, and deletion of feed logs.
e. Sensor Data History Management: endpoints for storing sensor data history, retrieving historical records based on device identifiers and dates, and deleting stored records when required.

For historical data retrieval, the API also provides basic statistical summaries minimum, maximum, average, and median for water-quality parameters. These summaries are then interpreted using the same fuzzy logic rules applied in actuator control, enabling automated qualitative assessment of water-quality conditions.

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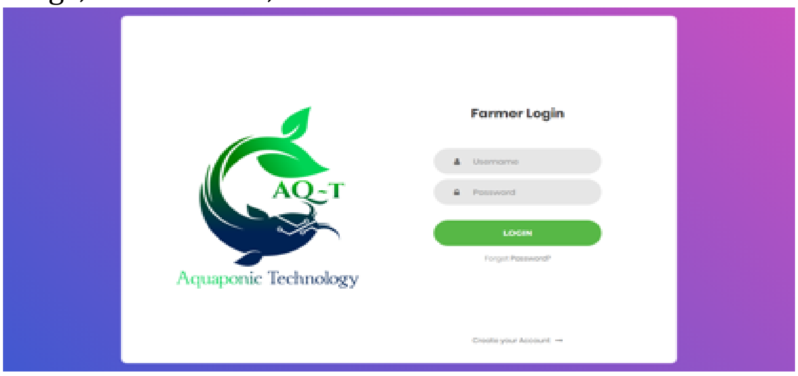
3. Results and Discussion

This section presents the experimental results obtained from the implementation and testing of the proposed aquaponics monitoring system, followed by an analytical discussion of the findings. The results focus on system functionality, data transmission performance, and operational stability during real-time monitoring. The discussion interprets the observed results in relation to system design choices, communication mechanisms, and practical constraints, highlighting both system strengths and limitations in comparison with existing IoT-based monitoring approaches.

3.1 Web-Based Monitoring Interface and Functional Verification

The proposed system includes a web-based monitoring interface to verify real-time functionality and data accessibility. The interface provides user authentication, device and feed-log management, real-time visualization of sensor readings, and historical analysis to support secure access and continuous monitoring.

After login/registration, users access the monitoring dashboard, which displays current sensor values and time-series graphs that automatically update when new device data are published, confirming end-to-end delivery from sensors to the web application. The system also enables users to manage devices and feeding records and export data (CSV, Excel, PDF). Historical data can be reviewed by device and date, supported by tabular and graphical views with basic statistics (min, max, average, median) and fuzzy-based qualitative water quality interpretation [24]. Overall, the interface confirms reliable data acquisition, storage, visualization, and user interaction in near real time.



(a)

(b)

Fig. 8. Authentication interface of the web application: (a) login page and (b) registration page.

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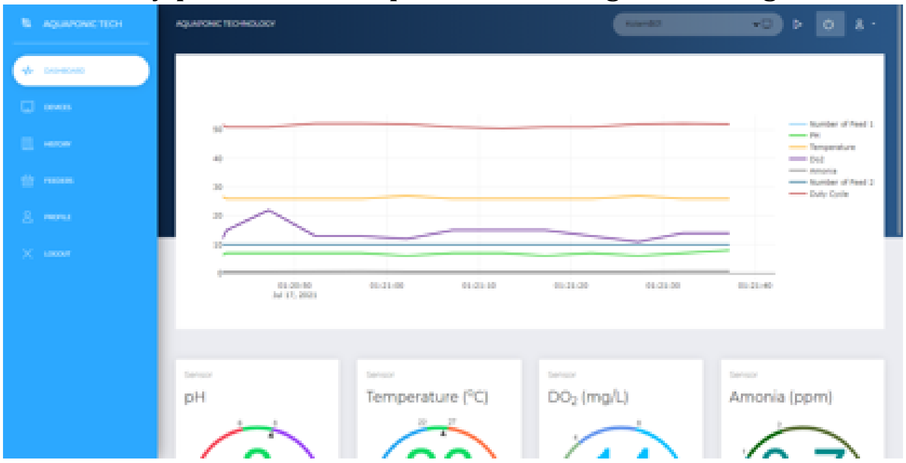
Figure 8 illustrates the authentication module that manages user access and session continuity. Successful authentication redirects users to the dashboard and provides a secure entry point for subsequent monitoring and management functions.



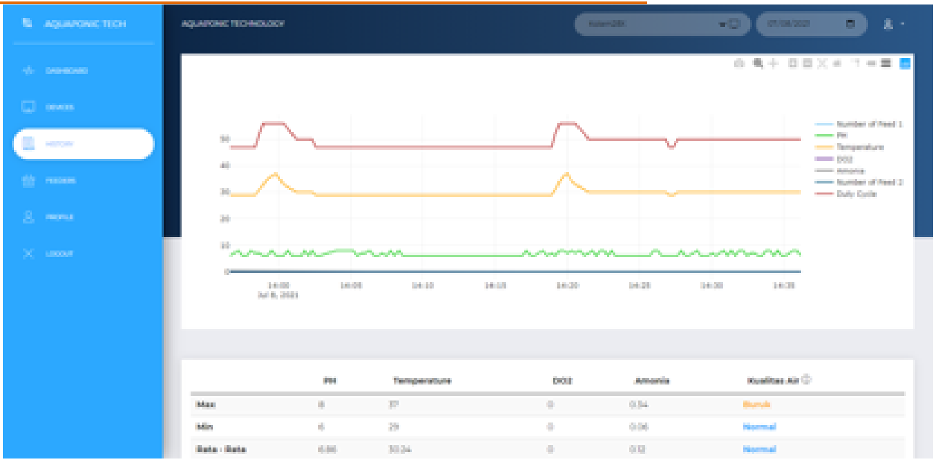
(a)

(b)

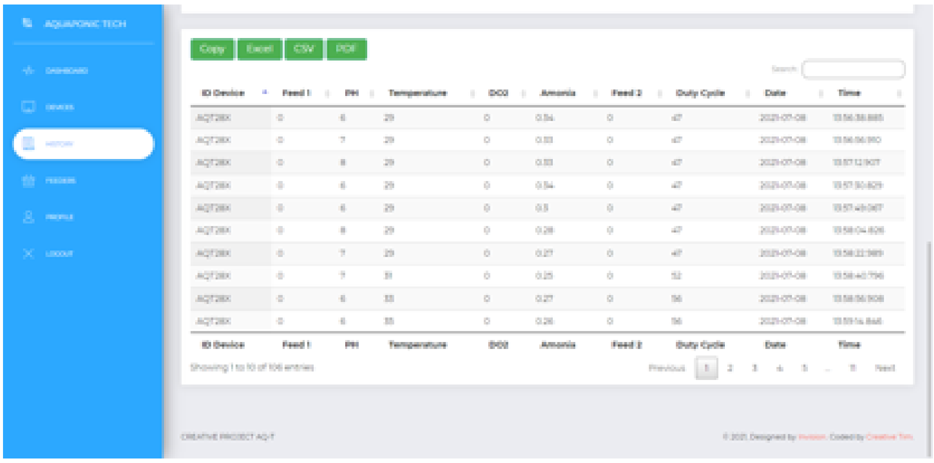
Fig. 9. Real-time monitoring interface displaying (a) time-series sensor graphs and (b) current sensor readings.

As shown in Figure 9, sensor values are displayed alongside time-series plots that refresh automatically upon new device publications, indicating successful end-to-end delivery and rendering. This behavior verifies that the acquisition–transmission–storage-visualization pipeline operates reliably for real-time monitoring.

In addition to real-time monitoring, the system provides historical visualization to support retrospective assessment and trend analysis. Users can retrieve device-specific data over selected periods and obtain summary statistics to facilitate interpretation of water quality dynamics.



(a)



(b)

(c)

Fig. 10. Historical monitoring features: (a) sensor history graph, (b) sensor history table, and (c) statistical and fuzzy-based water quality summary.

Figure 10 presents the historical module, combining graphical trends, tabular records, and descriptive statistics (minimum, maximum, average, and median). The same fuzzy rule base used for actuator control is applied to summarize water quality conditions from historical patterns, demonstrating that the system supports both data logging and interpretable monitoring outputs over time.

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3.2 Water Quality Sensor Test

This subsection presents the results of water-quality sensor testing conducted to evaluate sensor behavior under operational aquaponics conditions. The experiment was carried out on January 27, 2021, from 10:00 to 11:00 a.m., using pond water collected from a post-harvest African catfish (Clarias gariepinus) cultivation system. The test environment exhibited elevated ammonia levels, representing unfavorable water-quality conditions. Sensor measurements were transmitted from the device to the web application at 15 s intervals. Figure 11 shows the water-quality sensing module and the field test setup, including the sensors used and their placement during pond testing.

(a) (b)

Fig. 11. Water quality sensing module and test setup: (a) sensors used in the system and (b) sensor placement during pond testing.

Sensor performance was summarized using descriptive statistics, including the minimum, maximum, mean, and median values. The arithmetic mean for each parameter was calculated using Equation (3).

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (3)$$

where x_i denotes the sensor reading at sample iii and N is the total number of samples. The median value represents the middle observation after the data are sorted in ascending order.

During the observation period, pH readings ranged from 6 to 8, with a mean value of 6.875 and a median of 7, as shown in Figure 12. These results indicate moderate pH stability despite elevated ammonia concentrations.

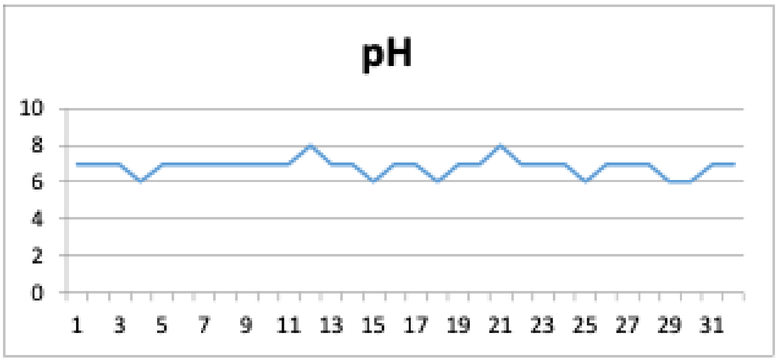

Fig. 12. pH sensor readings during the test period

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Temperature measurements were collected from 32 samples. Most readings were 26°C, with only four observations reaching 27°C. The mean and median temperatures were 26.125°C and 26°C, respectively, as shown in Figure 13.

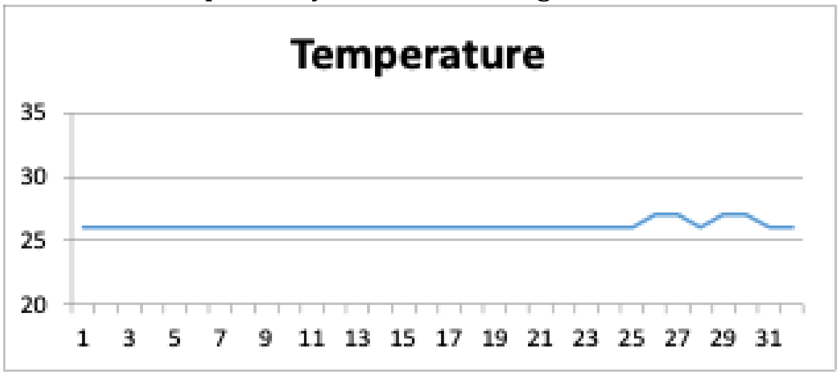

Fig. 13. Water temperature sensor readings during the test period

Dissolved oxygen (DO) values ranged from 11 mg/L to 22 mg/L. The lowest DO concentration coincided with a temporary increase in water temperature to 27°C. Overall, the mean DO concentration was 14.16 mg/L, with a median of 14 mg/L, as illustrated in Figure 14.

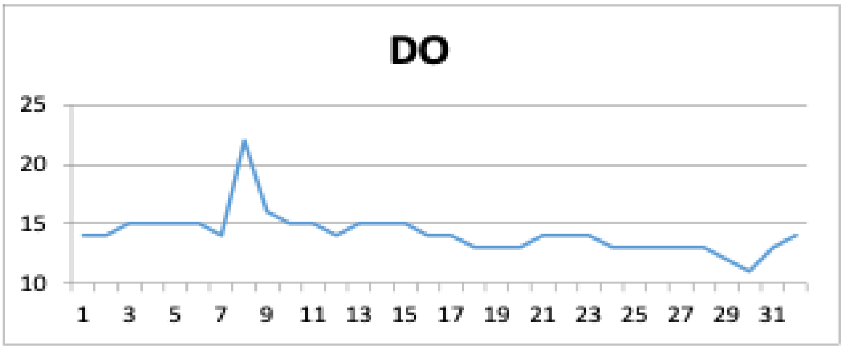

Fig.14. Dissolved oxygen sensor readings during the test period

In contrast, ammonia concentrations measured during the test were consistently high, indicating poor water quality conditions. Ammonia values ranged from 53.39 ppm to 71.85 ppm, with an average of 61.27 ppm and a median of 59.38 ppm, as shown in Figure 15. These results confirm that the test environment successfully represented unfavorable water quality scenarios relevant for evaluating system response.

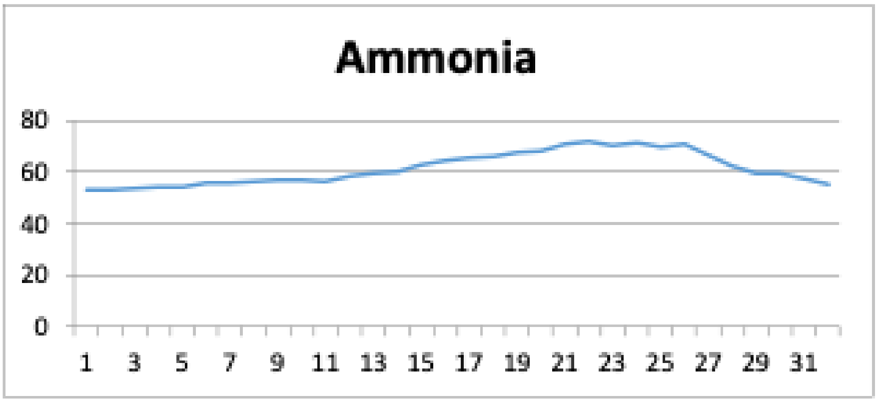

Fig. 15. Ammonia sensor readings during the test period

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3.3 Testing the Delay Time of Data Delivery from the Microcontroller to the Web Application

This subsection evaluates the end-to-end delay of sensor data delivery from the microcontroller to the web application. Sensor measurements were published by the microcontroller via the MQTT protocol using the HiveMQ broker, and the web application subscribed to the corresponding idDevice topics. The transmission delay, Δt, was calculated as the difference between the reception time at the subscriber and the publication time at the device, as expressed in Equation (4).

$$\Delta t = t_{recv} - t_{pub} \tag{4}$$

where t_{pub} is the timestamp when the data packet is published by the microcontroller and t_{recv} is the timestamp when the same packet is received by the web application. Figure 16 shows the sending and receiving delay graph used in this evaluation.

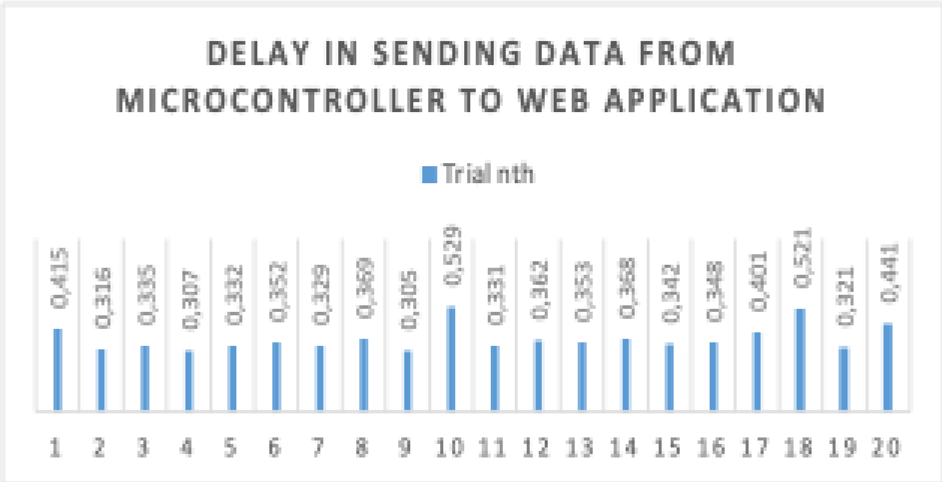

Fig. 16. Sensor Data Sending and Receiving Delay Graph

As shown in Figure 16, the average transmission delay was 0.369 s (369 ms), with a median delay of 0.350 s (350 ms). The maximum and minimum observed delays were 0.529 s (529 ms) and 0.305 s (305 ms), respectively. These results demonstrate that the MQTT-based communication mechanism provides near real-time data delivery suitable for continuous aquaponics monitoring.

3.4 REST API Response Time Testing

This subsection presents the performance evaluation of the RESTful API developed for sensor data storage and retrieval. Two representative endpoints were selected for testing: Add History and Get History by idDevice and Date. The Add History endpoint represents frequent write operations triggered during real-time monitoring, whereas Get History by idDevice and Date represents read operations that may involve larger datasets and higher computational load.

Performance testing was conducted using the RESTful Stress application, which supports automated load generation and performance visualization. For each endpoint, 30 iterations were executed with a 100 ms inter-request interval. For the Add History endpoint, the server response was intentionally configured to return a zero-byte payload, providing only HTTP status codes (200 OK or 400 Bad Request) to reduce processing overhead during high-frequency write operations. Figure 17 shows the request performance graph for the Add History endpoint.

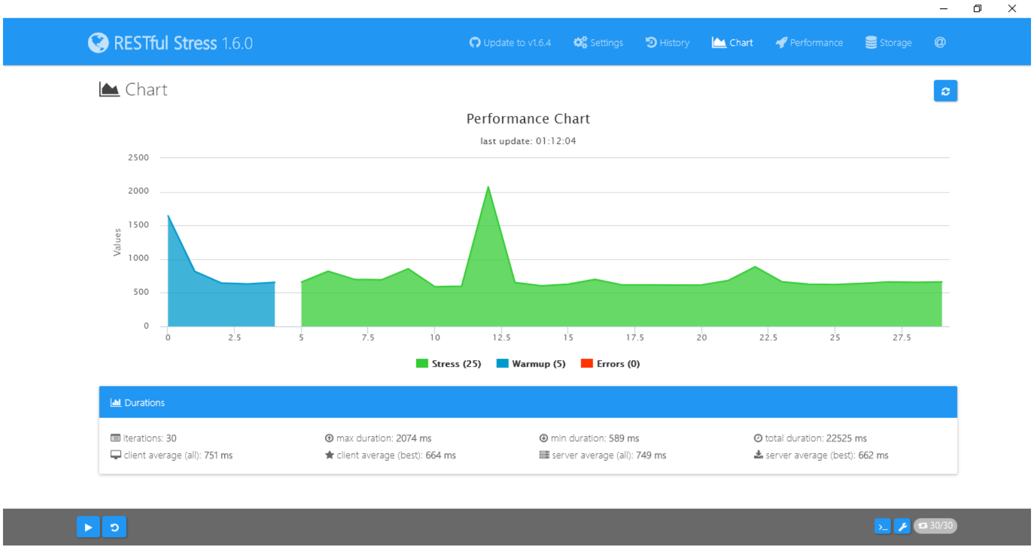

Fig. 17. Request performance graph for the *Add History* endpoint.

The *Add History* endpoint achieved an average response time of 751 ms, with a minimum response time of 589 ms and a maximum response time of 2074 ms, as shown in Figure 18.

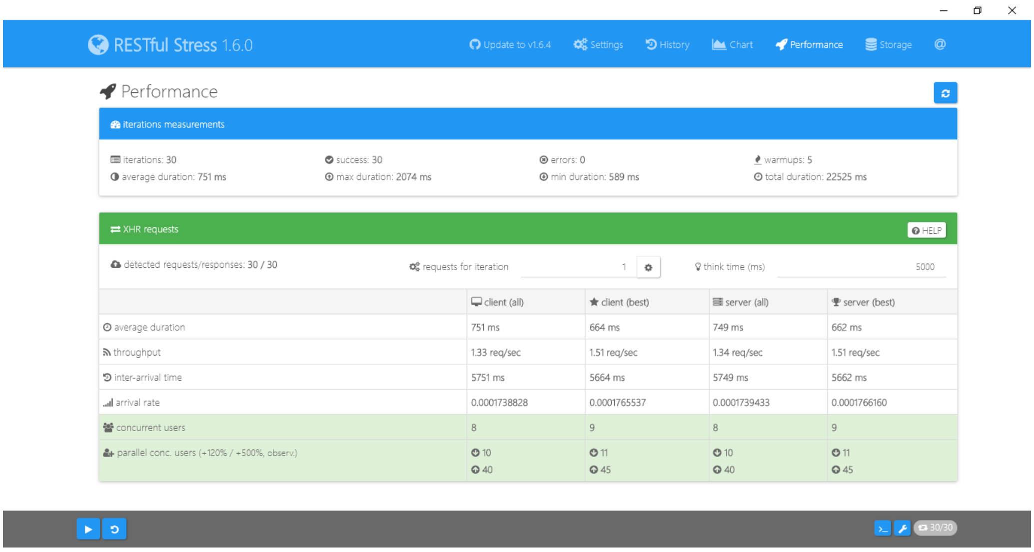

Fig. 18. Estimated performance metrics for the *Add History* endpoint

Based on the stress-test results, the system is estimated to support 8 concurrent users under normal conditions. With parallel processing, the concurrent capacity ranges from 10 users in the worst case to 40 users in the best case, with a throughput of approximately 1.33 requests/s.

For the Get History by idDevice and Date endpoint, the response payload was approximately 19,839 bytes, containing 106 sensor records collected on July 8, 2021, for device ID AQT28X. The response also included statistical summaries (minimum, maximum, average, and median) as well as a fuzzy logic–based qualitative classification of water-quality conditions. Figure 19 presents the request graph for this endpoint.

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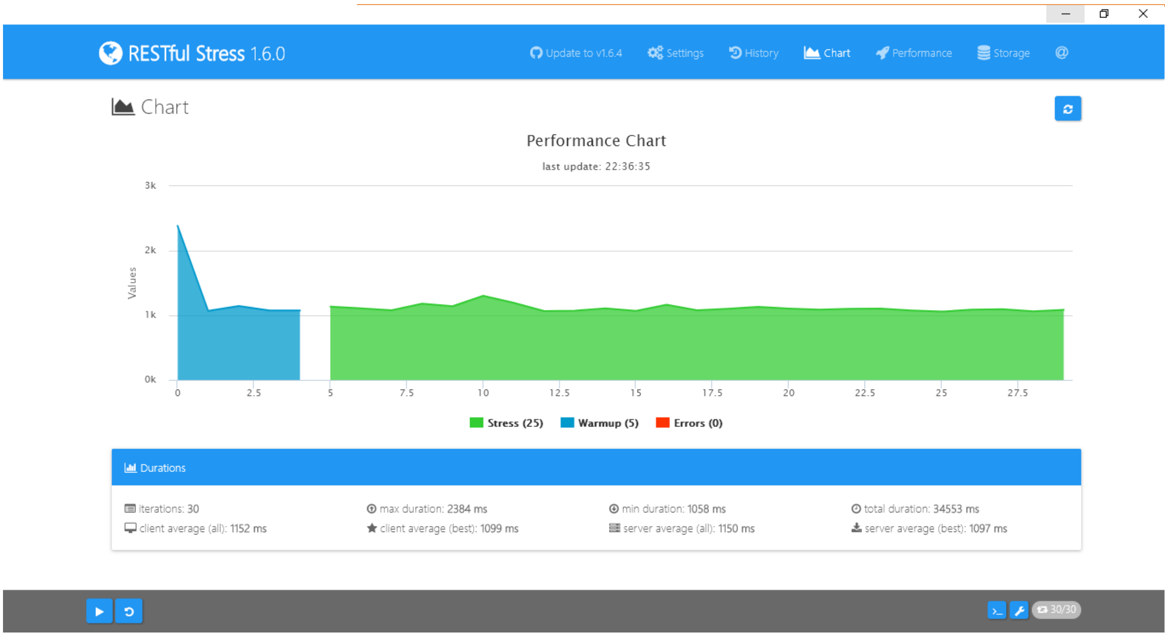

Fig. 19. Request Graph on getting History by idDevice and Date

The average response time for this endpoint was 1152 ms, with a minimum of 1058 ms and a maximum of 2384 ms, as shown in Figure 20.

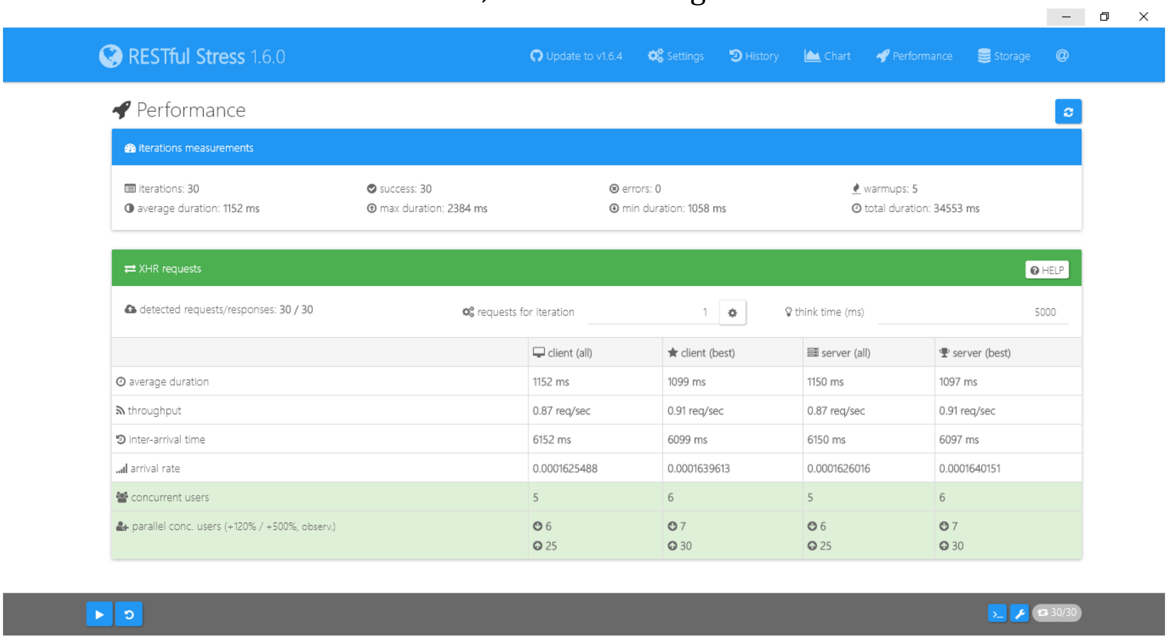

Fig. 20. Estimated Performance Get History by idDevice and Date

This endpoint is estimated to support 5 concurrent users under normal conditions. With parallel processing, the concurrent capacity ranges from 6 users in the worst case to 25 users in the best case, and the measured throughput is approximately 0.87 requests/s.

3.5 Application Functionality Testing

The web application was tested to verify core functionality for real-time monitoring and historical data management. Users authenticate through a login/registration flow and register their devices prior to monitoring. During operation, users select a device ID and start monitoring via the dashboard controls. The interface displays current sensor readings and time-series graphs that refresh automatically when

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new MQTT messages are received, confirming correct end-to-end integration between the device, broker, and web client.

During active monitoring, incoming sensor records are stored as historical data to enable retrospective analysis. The application provides device management (add/update/delete devices) and data export capabilities (CSV/Excel/PDF). It also supports feed-log management for recording feeding events per device. Historical data can be queried by device ID and date and presented as tables and plots, accompanied by descriptive statistics (minimum, maximum, mean, and median). Water quality is then categorized using the same fuzzy rule base applied for pump control, where slow, normal, and quick correspond to good, moderate, and poor conditions, respectively [25].

3.6 Aquaponic System Sustainability Testing

Testing the sustainability of the aquaponics system is carried out by running the system for a long period, specifically starting from the beginning of November 2020 to January 2021 while continuing to develop and improve applications and tools according to the capacity of the research focus and the ability of the author. From the tests carried out the application has been able to do its job of monitoring. Overall the aquaponics system can be said to run quite well with a note found that some minor problems can be handled.

The MiFi module had detached from its place which may be due to the heat so the glue melted, but it can be returned to its place again using duct tape. The feed actuator was removed because the aquaponics cultivator who was able to operate it was unable to stay in place for days and no one could replace it. The floated sensor had toppled over which might have been due to being hit by a fish but it was still safe because it was protected by plastic and could be returned to the correct position. The sensor value obtained is sometimes less accurate due to the presence of moss/dirt and the solution is that the sensor surface can be cleaned about once a week.

4. Conclusion

This study developed and evaluated an IoT-enabled, web-based aquaponics monitoring and control system that integrates multi-sensor acquisition, MQTT-based real-time communication, database-backed visualization, and fuzzy logic–based pump control. The system achieved near real-time delivery with an average end-to-end delay of 369 ms, and the API performance evaluation showed average response times of 751 ms for data insertion and 1152 ms for history retrieval with statistical summaries and fuzzy-based qualitative interpretation.

The main contribution of this work is a complete and reproducible end-to-end architecture that couples real-time monitoring with an interpretable fuzzy control mechanism, enabling both operational actuation (pump speed regulation) and human-readable water quality categorization from the same rule base.

Future work will benchmark the fuzzy logic–based classification/control against alternative approaches (e.g., decision tree, SVM, k-NN, or neural models) using labeled datasets and control-oriented metrics to quantify accuracy, robustness, and operational impact.

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