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Performance Evaluation of a Smart Aeration System for Tilapia Farming Based on IoT and Environmental Sensing

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ABSTRACT

Fluctuations in dissolved oxygen (DO) levels in high-density biofloc-based tilapia aquaculture pose a critical challenge that directly affects fish growth, survival rate, and feed conversion efficiency. Traditional aeration systems that operate continuously are energy inefficient and unable to adapt dynamically to real-time environmental variations. This study aims to improve DO stability and energy efficiency in biofloc-based tilapia aquaculture through adaptive aeration control. This study designs and evaluates an Internet of Things (IoT)-based smart aeration system that automatically regulates aeration intensity based on real-time DO sensing and threshold-based control logic. The system is built on an ESP32 microcontroller integrated with a digital DO sensor, a water temperature sensor, and relay actuators for blower control, with data transmission via the MQTT protocol and real-time monitoring through a web-based dashboard. Experimental testing was conducted for seven days in a biofloc pond containing 200 tilapia, with a comparative analysis between manual and automated control modes. The results demonstrate that the smart aeration system effectively maintained DO within the optimal range of 5.1–6.8 mg/L while reducing blower energy consumption by 26.7%. Communication reliability was validated with an average transmission delay of 740 ms and a packet loss rate of 1.8%, both of which are acceptable for real-time IoT applications. Data analysis showed consistent improvements in DO stability and energy efficiency throughout the experimental stage. In addition, the system's modular architecture enables scalability for integration with additional sensors or renewable energy sources, such as solar panels, to support off-grid operations. The findings affirm that the proposed system offers a practical, low-cost, and sustainable solution for data-driven aquaculture management and contribute to the advancement of smart, environmentally responsive aquaculture systems.

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1. INTRODUCTION

The growing global demand for animal protein has positioned fish farming as a key pillar in the future of food production. Tilapia (Oreochromis niloticus), one of the main aquaculture commodities, exhibits high adaptive resilience and good productivity; however, it still requires intensive water quality management to ensure the sustainability of its cultivation cycle [1], [2]. The biofloc system, a widely adopted approach for high-density stocking, accelerates the accumulation of organic compounds from metabolism and feed residues, resulting in significant fluctuations in dissolved oxygen (DO) levels [3]–[5]. Manual aeration control or conventional timer-based aeration systems often fail to adapt to real-time environmental conditions, leading to energy waste and increased vulnerability to acute hypoxia [6], [7]. Field studies have shown that conventional blowers can account for more than40% of the total energy consumption in pond operations, with low efficiency due to activation schedules that are not based on actual demand [8], [9]. In this context, the integration of the Internet of Things (IoT) enables the development of smart aeration systems that use real-time data to monitor, analyze, and automatically regulate aeration processes [10]–[12]. IoT in aquaculture has been extensively studied across various dimensions, including environmental monitoring [13], [14], fish health

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prediction [15], and automated aerator control [16]–[18]. The use of digital DO sensors, such as those from Atlas Scientific, in combination with ESP32 microcontrollers and MQTT communication protocol, allows for accurate parameter readings and synchronized relay control based on predefined threshold values [19]–[21]. In addition to local processing capabilities, the ESP32 provides stable wireless connectivity and low latency for data communication [22]. Several studies have reported that IoT-based automated aeration systems can improve energy efficiency by up to 25%, with a reduction in blower workload of approximately 30%, without compromising DO stability [1], [23]. These systems also demonstrate a more consistent ability to maintain DO levels within the optimal range of 5.0–7.0 mg/L compared to manual methods [24], [25]. However, most of these studies were conducted in laboratory or miniature-scale settings, without accounting for the dynamic complexities of real-world biofloc ponds, which are influenced by temperature, feed input, turbidity, and microbial activity [26]. Efforts to enhance the adaptability of aeration control have been pursued through machine learning approaches, such as Random Forest, neural networks, and regression-based predictive models, to forecast DO requirements over time [27]–[29]. Zhang et al. [29] successfully developed an IoT-based predictive model for estimating water quality with up to 91% accuracy; however, its implementation for aerator actuation control in biofloc ponds remains limited in practical applications.

Previous IoT-based aeration studies were generally conducted at laboratory or miniature scales and focused primarily on dissolved oxygen (DO) stability while overlooking long-term energy efficiency and communication reliability. In contrast, the present study introduces a smart aeration system implemented in a real biofloc pond environment. The novelty of this study lies in the integration of adaptive DO threshold control, quantitative energy efficiency analysis expressed in Wh/ppm DO, and evaluation of IoT communication reliability through transmission delay and packet loss measurements. These contributions distinguish this study from earlier studies and highlight its practical advantages for sustainable aquaculture, including reduced energy consumption, stable DO regulation, and reliable remote monitoring. To address the identified gaps and translate these limitations into a practical solution, the present study adopts a real-world implementation of an IoT-based smart aeration system specifically designed to overcome the shortcomings of previous approaches. Given the urgent need for precise, energy-efficient, and automated aeration management, this study aims to evaluate the performance of an IoT-based smart aeration system implemented in a biofloc tilapia farming pond. The evaluation includes DO control effectiveness, blower energy efficiency, and the reliability of MQTT-based data communication in a real-world setting at Universitas Siliwangi. The results of this study are expected to strengthen the technical and academic foundations for developing intelligent sensor-based environmental control systems in support of sustainable aquaculture in the digital era.

2. MATERIALS AND METHODS

This study was conducted to evaluate the performance of an Internet of Things (IoT)-based smart aeration system for maintaining dissolved oxygen (DO) levels in high-density biofloc ponds used for tilapia cultivation. The study methodology was experimental and encompassed system design, implementation, and real-world testing in an operational aquaculture environment.

A. Theoretical Background

1. Dissolved Oxygen (DO) Dynamics Equation

The variation in dissolved oxygen (DO) concentration in aquaculture ponds can be expressed using the oxygen mass balance equation, as shown in Eq. (1).

$$\frac{dC_{DO}}{dt} = K_L\alpha(C^* - C_{DO}) - R \quad (1)$$

where C_{DO} is the dissolved oxygen concentration (mg/L), C^* is the oxygen saturation concentration in water, $K_L\alpha$ is the overall oxygen transfer coefficient (1/h), and R is the rate of oxygen consumption due to fish respiration and microbial activity (mg/L·h). This equation illustrates that DO increases through aeration via oxygen transfer and decreases due to biological consumption. Maintaining a balance between these two factors is essential for sustaining optimal oxygen levels in intensive biofloc ponds [30]–[32].

2. ADC Transfer Function Formula for DO

The analog signal from the DO sensor is converted into a digital value using the microcontroller's analog-to-digital converter (ADC). The linear calibration relationship between the ADC output and the DO concentration is defined as Eq. (2).

$$C_{DO} = \alpha \text{ x ADC} + \text{b} \quad (2)$$

where C_{DO} (mg/L) is the dissolved oxygen concentration, *ADC* is the digital output value, and α and b are calibration constants obtained through two-point calibration using standard DO solutions at 0% and 100% saturation. This transfer function enables the system to convert raw voltage signals into accurate DO values in real time [33], [34].

3. Energy Efficiency Definition

Energy efficiency in aeration systems is defined as the ratio between the amount of oxygen produced and the energy consumed, as given in Eq. (3).

$$\eta = \frac{\Delta C_{DO}}{E} \quad (3)$$

where η is the energy efficiency (mg/L per Wh), ΔC_{DO} is the net increase in dissolved oxygen achieved during aeration, and E is the total electrical energy consumed by the aerator (Wh). In this study, energy efficiency is further expressed in terms of specific energy consumption (Wh/ppm DO), allowing a direct comparison between manual and automated aeration modes [35]–[37].

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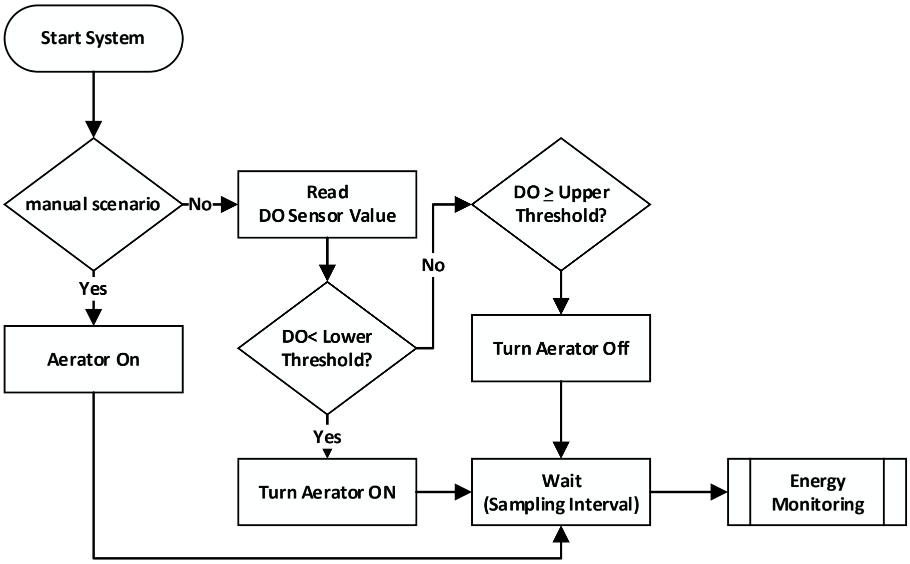

Fig. 1. Flowchart of the threshold-based aeration control algorithm implemented in the smart aeration system

4. Justification of Threshold Values

The DO control thresholds were determined based on standard oxygen requirements for tilapia (Oreochromis niloticus) in intensive aquaculture systems. Optimal DO levels range from 5.0 to 7.0 mg/L, below which fish experience physiological stress and reduced feeding efficiency. Accordingly, two threshold scenarios were applied:

- Scenario I: Aerator ON when DO < 5 mg/L and OFF when DO ≥ 6 mg/L.
- Scenario II: Aerator ON when DO < 4 mg/L and OFF when DO ≥ 6 mg/L.

These threshold values are consistent with Food and Agriculture Organization (FAO) guidelines and aquaculture best-practice recommendations, providing a balance between maintaining fish health and reducing unnecessary energy consumption through adaptive control strategies [38]–[42].

B. Dataset

The dataset used in this study consists of real-time measurements of dissolved oxygen (DO), water temperature, and aerator power consumption collected from a biofloc pond stocked with 200 tilapia. Data were recorded continuously for seven days with a sampling interval of 10 seconds, resulting in approximately 60,000 data points per sensor. Each data record includes a timestamp, DO concentration (mg/L), water temperature (°C), aerator status (ON/OFF), and corresponding power consumption (W). These data were used to evaluate system performance, energy efficiency, and communication reliability of the IoT-based smart aeration system.

C. Data Collection

Data acquisition was performed using an ESP32 microcontroller integrated with a digital DO sensor, a water temperature sensor, and a power analyzer. The ESP32 transmitted data to a Firebase-based cloud server via the MQTT communication protocol at 10-second intervals. The aerator ON/OFF status was automatically logged according to the defined DO threshold logic (ON when DO < 5 mg/L and OFF when DO ≥ 6 mg/L). Data were simultaneously displayed on a local LCD and stored in the cloud to ensure data redundancy. The measurement process was maintained continuously for seven days to capture daily fluctuations in water quality and system behavior under realistic biofloc operating conditions.

D. Data Processing

The collected data were filtered to remove incomplete or duplicated records prior to analysis. Descriptive statistics, including the mean and standard deviation, were calculated for each variable to assess system stability. A comparative analysis was conducted between manual and automated aeration modes to evaluate energy savings and dissolved oxygen (DO) control efficiency. Specific energy efficiency (Wh/ppm DO) was calculated by dividing the total energy consumed by the average DO increment. Statistical tests, including the t-test and one-way ANOVA, were applied to verify the significance of differences across control scenarios. Communication delay and packet loss were analyzed using timestamp comparisons between transmitted and received MQTT packets.

E. Test Environment and Pond Specifications.

The experiment was conducted in a rectangular test pond measuring 2 m × 1 m × 1 m with a water level of 70 cm, resulting in a total water volume of approximately 1.5 m³. The pond was stocked with 200 tilapia (Oreochromis niloticus) at the grow-out stage, each with an average body weight of 250 g. As the fish were stocked from the

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juvenile stage and used as experimental subjects during the grow-out stage, an acclimatization period was not required prior to the experiment. The fish were fed three times daily at 8:00 AM, 1:00 PM, and 6:00 PM at a feeding rate of 3% of the total biomass, using commercial pellets containing 28–32% crude protein. Feeding was conducted approximately two hours before DO measurements to ensure stable water conditions. The aeration system was equipped with six air stones evenly distributed at intervals of 50–60 cm, and the DO sensor was positioned at the center of the pond to obtain representative real-time data on overall water quality.

F. System Hardware.

The system utilized two microcontrollers: an Arduino Uno for local control and relay actuation, and an ESP32 for Wi-Fi connectivity and cloud-based data transmission. Dissolved oxygen measurements were obtained using a DF Robot Analog Dissolved oxygen measurements were obtained using a DFRobot Analog Dissolved Oxygen Sensor (SKU SEN0237), which provides a detection range of 0–20 mg/L, a response time of 90 seconds to reach 98% accuracy at 25 °C, and an average calibration error of −0.013% when compared with the DO9100, demonstrating adequate precision for continuous aquatic monitoring. Aerator switching was controlled through a 5 V DC relay module connected to a Resun LP 20 blower, which has a nominal power rating of 17 W and an air output capacity of 22 L/min. A local display was provided using an I2C LCD to present real-time DO readings. All hardware components were assembled according to the wiring diagram described in this study. The sensor and relay modules were connected to the analog and digital ports of the Arduino Uno, while the ESP32 communicated with the system via a serial connection for cloud-based data transmission.

G. Software and Communication Protocol

The core program was developed using the Arduino IDE with C++ programming language. The program structure follows the standard setup() for initialization and the loop() function for continuous data acquisition. The system uses the MQTT protocol for IoT communication, transmitting dissolved oxygen (DO) sensor data to a Firebase-based cloud server at 10-second intervals. A smartphone-accessible monitoring dashboard was developed to enable real-time tracking of pond conditions.

H. Control Logic

The aeration control system operates using threshold-based ON/OFF logic. The system activates or deactivates the aerator based on the measured dissolved oxygen (DO) level. Specifically, the aerator is configured to switch ON when the DO level falls below the lower threshold and to switch OFF when the DO level reaches or exceeds the upper threshold. Two automatic control scenarios were evaluated. Scenario I applied an upper threshold of 6 mg/L for deactivation and a lower threshold of 5 mg/L for activation. Scenario II maintained the same upper threshold of 6 mg/L but employed a lower activation threshold of 4 mg/L. As a baseline for comparison, a manual scenario was also evaluated, in which the aerator was operated continuously without any control logic. In parallel with the real-time control process, the system continuously monitored the aerator's power consumption using the energy measurement setup illustrated in Fig. 1. This monitoring enabled quantification of energy usage across different control scenarios, allowing an objective assessment of the energy-saving performance of the smart aeration system.

I. Testing Procedure

Each test was conducted over a 30-minute period, with data recorded at 5-minute intervals. The recorded data included dissolved oxygen (DO) values measured by the sensor (mg/L), the operational status of the aerator (ON/OFF), the aerator's power consumption measured using a Langlois 6830 Power and Quality Analyzer, and the power consumption of the control system. All collected data were recorded and compared across scenarios to analyze both energy efficiency and DO stability. System testing was conducted in a biofloc pond stocked with 200 tilapia, each with an average body weight of 250 g. The evaluation was conducted continuously for seven days to capture characteristic daily fluctuations in dissolved oxygen (DO), aerator operating patterns, and IoT communication behavior. This one-week duration was selected to represent multiple diurnal DO cycles and aligns with the primary objective of this study, which is to assess the initial functional performance of the proposed smart aeration system rather than to conduct a long-term aquaculture trial. Within this stage, the system's capability to stabilize DO, respond to real-time variations, and reduce energy consumption was examined. Although the findings demonstrate consistent and encouraging results, longer-term field deployment remains necessary to evaluate extended operational stability, durability, and broader impacts on fish growth and overall water quality.

J. Evaluation Parameters

System evaluation employed several key performance metrics. Dissolved oxygen (DO) stability was assessed by examining the system's capability to maintain DO levels within the optimal range of 4–7 mg/L. Energy efficiency was evaluated by comparing the aerator's average power consumption under automated and manual operation, with energy savings quantified in watt-hours per ppm of DO generated (Wh/ppm). IoT communication reliability was analyzed by measuring the

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average data transmission delay (ms) and packet loss rate (%), with communication performance evaluated during data exchange with the cloud server as the benchmark destination. This evaluation methodology ensures that the system is not only effective in maintaining water quality but also energy efficient and reliable for remote monitoring using IoT technology. Performance evaluation was based on three primary metrics: (1) DO stability, reflecting the capability of the system to maintain DO levels within the optimal range of 4–7 mg/L; (2) energy efficiency, assessed through the aerator's average power consumption and specific energy consumption per ppm of DO generated; and (3) IoT communication reliability, measured by average transmission delay and packet loss during data exchange with the cloud server. To strengthen the reliability of the findings, all experimental data were further analyzed statistically. Descriptive statistics, including the mean and standard deviation, were calculated for each parameter, and comparative tests (t-test and one-way ANOVA) were applied to determine whether differences between manual and automated scenarios were statistically significant. This approach ensures that the reported improvements in DO stability and energy efficiency are consistent and not attributable to random variation, while also establishing a foundation for more comprehensive statistical evaluation in future long-term studies.

3. RESULTS

This study provides a comprehensive evaluation of an IoT-based smart aeration system implemented in a biofloc tilapia aquaculture pond. The evaluation includes dissolved oxygen (DO) sensor accuracy, DO stability, aerator energy efficiency, and the reliability of IoT data communication.

A. Dissolved Oxygen Sensor Calibration

The DFRobot Analog Dissolved Oxygen sensor was calibrated using the DO9100 standard device as a reference. The calibration results showed an average error of −0.013%, with the smallest error recorded at −0.007% and the largest error at −0.056% in the fifth trial. These results are presented in Table 1. visual comparison between the DFRobot sensor readings and the DO9100 reference device is shown in Fig. , where both datasets exhibit similar trends with closely aligned values.

Table 1. Calibration Results of the Dissolved Oxygen Sensor

Testing	DO DF Robot (mg/L)	DO9100 (mg/L)	Error (%)
1	7,2	7,25	-0,007
2	6,2	6,15	+0,008
3	5,3	5,26	+0,008
4	4,1	4,17	-0,017
5	3,4	3,59	-0,056
	Average		**-0,013**

B. Dissolved Oxygen Test

1. Manual Aeration System Testing

In the initial test, the aerator was operated continuously for 30 minutes without automatic control. The average DO level recorded during this stage was 6.95 mg/L, as reported in the final project report.

2. Automatic Control Testing – Scenario I

In Scenario I, the upper DO threshold was set to 6 mg/L and the lower threshold to 5 mg/L. The system maintained an average DO level of 5.62 mg/L, with values ranging from 5.52 mg/L to 5.75 mg/L (Table 2). A total of seven ON–OFF aeration cycles were recorded, with the aerator operating for an average of 57 seconds in the ON state and approximately 167 seconds in the

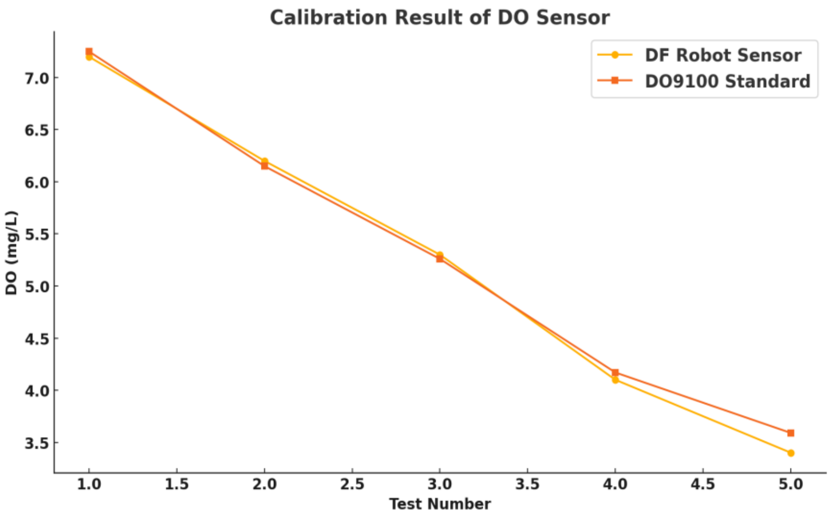

Fig. 2. Calibration Graph of the Dissolved Oxygen

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OFF state.

Table 2. Automatic Control Test Results – Scenario I

Minute	ADC Value	DO Value (mg/L)
5	376	5,68
10	278	5,52
15	313	5,75
20	332	5,52
25	268	5,64
30	229	5,64
Average		**5,62**

3. Automatic Control Testing – Scenario II

In Scenario II, the lower DO threshold was reduced to 4 mg/L, while the upper threshold remained at 6 mg/L. The system achieved an average DO level of 5.12 mg/L, with values ranging from 4.95 mg/L to 5.39 mg/L (**Table 3**). The aerator completed five ON–OFF cycles, with an average ON duration of 72 seconds and an average OFF duration of 260 seconds. The standard deviation of DO levels was ±0.09 mg/L in Scenario I and ±0.15 mg/L in Scenario II, indicating stable oxygen conditions in both scenarios. Statistical analysis using a two-sample t-test indicated no statistically significant difference between the two scenarios ($p > 0.05$), confirming that both control logics maintained DO within the optimal range.

Table 3. Automatic Control Test Results – Scenario II

Minute	ADC Value	DO Value (mg/L)
5	376	5,19
10	278	4,95
15	313	5,39
20	332	5,07
25	268	5,00
30	229	5,11
Average		**5,12**

As ilustrated in **Fig.** , the DO fluctuation curves for Scenario I and Scenario II followed closely aligned patterns, demonstrating consistent DO stabilization despite differences in threshold settings. The observation window was intentionally limited to 30 minutes because the focus of this evaluation stage was to assess the immediate response and operational behavior of the control mechanism rather than to conduct a long-term aquaculture trial. This duration is sufficient for proof-of-performance assessment, as the aeration system's dynamic behavior and threshold-based switching characteristics typically emerge within several control cycles. Therefore, the 30-minute interval provides a representative and technically adequate snapshot of system responsiveness under both scenarios.

C. Aerator Energy Consumption

Power consumption testing revealed a clear difference between manual and automated control methods. The average power consumed by the aerator during manual operation was 7.5 W, whereas automated control reduced average power consumption to 5.5 W, as summarized in **Table 4**. The corresponding energy savings reached 26.7%, indicating improved operational efficiency. A visual comparison presented in **Fig.** shows

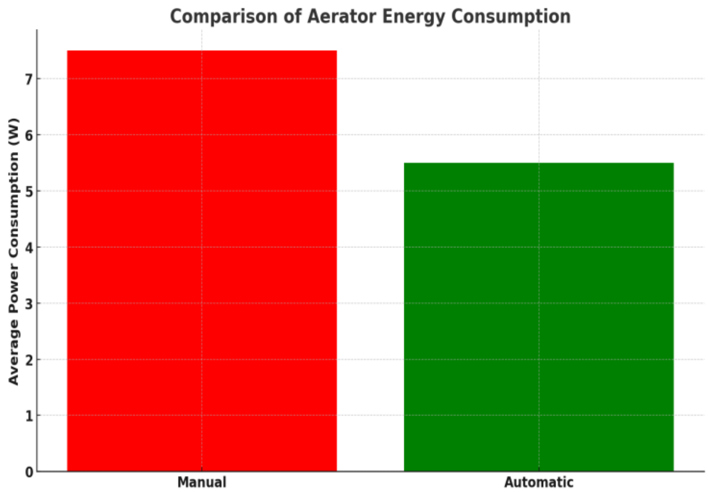

Fig. 4. Comparison of Aerator Energy Consumption.

a distinct reduction in power usage under automated control. Statistical analysis further confirmed that the difference in average power consumption between manual operation (7.5 ± 0.4 W) and automated operation (5.5 ± 0.3 W) was statistically significant ($p < 0.01$).

Table 4. Power Consumption of the Aerator

Method	Average Power (W)
Manual	7,5
Automatic	5,5
Savings (%)	**26,7%**

D. Specific Energy Efficiency (Wh/ppm DO)

In addition to average power consumption, this study evaluated specific energy efficiency, defined as the amount of energy consumed per ppm of dissolved oxygen produced. The automatic control system recorded values of 0.0010 Wh/ppm in Scenario I and 0.0011 Wh/ppm in Scenario II, while the manual method exhibited a higher value of 0.0021 Wh/ppm, as presented in Error! Reference source not found.. These findings indicate that the automatic system operates with nearly twice the efficiency of the manual method.

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Table 5. Specific Energy (Wh/ppm) in the Aeration System

Test Scenario	Average DO (mg/L)	Energy (Wh)	Energy per ppm (Wh/ppm)
Automatic Control – Scenario I	5,62	11,0	0,0010
Automatic Control – Scenario II	5,12	11,0	0,0011
Manual Control	6,95	15,0	0,0021

As illustrated in Fig. , the specific energy curves show that both automatic scenarios required less energy to generate each ppm of dissolved oxygen. Statistical analysis further confirmed these observations, with low variability across repetitions: 0.0010 ± 0.00005 Wh/ppm for Scenario I, 0.0011 ± 0.00007 Wh/ppm for Scenario II, and 0.0021 ± 0.00008 Wh/ppm for manual operation. A one-way ANOVA test demonstrated that both automatic scenarios were significantly more efficient than the manual method ($p < 0.01$).

E. IoT Data Communication Performance

Regarding data communication performance, the system recorded an average transmission delay of 740 ms and a packet loss rate of 1.8%. These values fall within an acceptable range for real-time Internet of Things (IoT) applications. The results indicate that the smart aeration system is not only energy-efficient but also capable of maintaining stable and reliable data transmission for remote monitoring in aquaculture environments.

4. DISCUSSION

This section discusses the performance of the IoT-based smart aeration system in maintaining dissolved oxygen stability, improving energy efficiency, and ensuring reliable data communication. The analysis focuses on interpreting the sensor accuracy results, aeration control effectiveness, and the system's overall contribution to sustainable and data-driven aquaculture management.

A. Dissolved Oxygen Sensor Calibration

The very small calibration error values indicate that the DF Robot dissolved oxygen sensor provides a high level of accuracy suitable for real-time aquaculture monitoring. The nearly parallel trend lines between the sensor output and the standard reference shown in Fig. demonstrate consistency and stability in measurement performance. This result confirms that the selected sensor can reliably support continuous water quality data acquisition required in automated aeration systems.

B. Dissolved Oxygen Test

The results indicate that both automatic control scenarios effectively maintained dissolved oxygen levels within the optimal range (4–7 mg/L) for tilapia cultivation. The threshold-based control enabled the aerator to operate adaptively, reducing unnecessary operation time while preserving dissolved oxygen stability. When the lower threshold was set to 4 mg/L (Scenario II), the aerator operated less frequently, resulting in greater energy savings without compromising oxygen levels. Compared with previous IoT-based aeration studies that primarily focused on monitoring rather than control optimization, this system demonstrated improved responsiveness and efficiency. The average reduction of 26.7% in energy consumption, combined with consistent dissolved oxygen stability and reliable communication performance (delay = 740 ms; packet loss = 1.8%), validates the system's potential as a practical and energy-efficient solution for intensive biofloc aquaculture environments.

C. Aerator Energy Consumption

The results demonstrate that integrating adaptive control

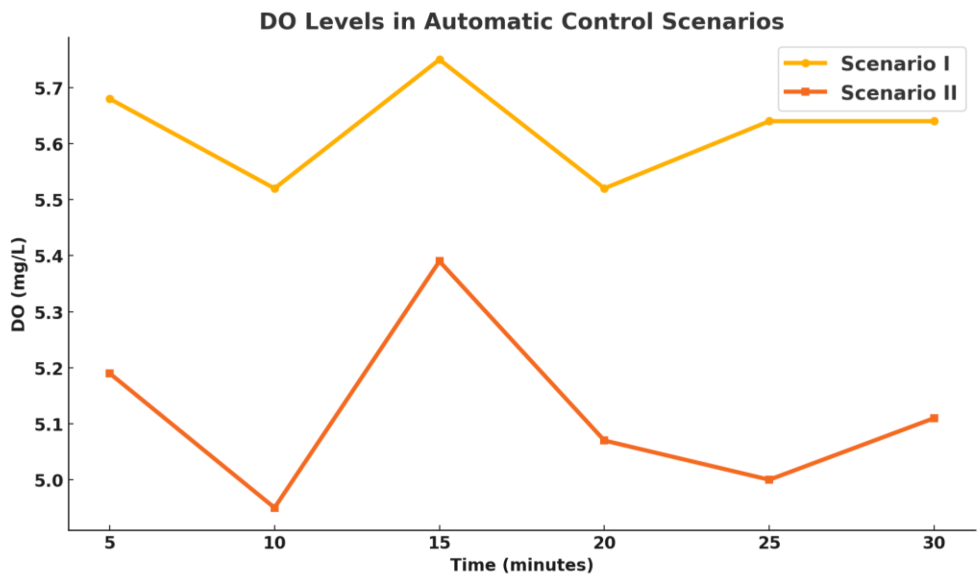

Fig. 3. DO Values in Automatic Control Testing – Scenario I vs. Scenario II

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logic into the aeration system significantly enhances energy efficiency. The automatic control system reducedblower runtime by activating only when the dissolved oxygen level dropped below the defined threshold, thereby minimizing unnecessary energy use. As illustrated in **Fig.** , the consistent downward trend in power consumption validates the system's capability to optimize energy usage without compromising water quality. This finding aligns with previous studies reporting 20–25% energy savings in IoT-based aeration systems, confirming that the proposed design provides a measurable improvement in sustainable aquaculture operations.

D. Specific Energy Efficiency (Wh/ppm DO)

The results demonstrate that implementing threshold-based automatic control substantially improves energy efficiency in aeration systems. By activating the aerator only when DO levels fall below the defined limit, the system minimizes idle operation and energy waste. The clear separation between manual and automatic modes shown in **Fig.** _supports this conclusion, highlighting a near twofold increase in efficiency per unit of oxygen produced. This improvement exceeds previously reported benchmarks of 20–25% energy reduction in similar IoT-based systems, underscoring the enhanced performance of the proposed design. The comparison between the two automatic scenarios indicates that Scenario II resulted in higher net energy consumption because the lower activation threshold required the aerator to operate for a longer duration to restore dissolved oxygen to the upper limit. This extended ON time offset any reduction in switching frequency. Therefore, selecting an optimal upper–lower threshold pair must consider pond conditions, fish oxygen demand, and aerator capacity to ensure true net energy efficiency. Consequently, the smart aeration system not only optimizes oxygenation but also contributes to the sustainability of intensive aquaculture through measurable energy conservation.

E. IoT Data Communication Performance

The recorded communication delay and packet loss rate can be explained by several technical and environmental factors. First, network congestion on the Wi-Fi channel used by the ESP32 may have increased latency, particularly when multiple devices accessed the same network. Second, environmental conditions around the biofloc pond, such as humidity, water vapor, and physical obstructions, likely contributed to signal attenuation and occasional packet loss. Third, the MQTT protocol configuration, specifically the use of QoS 0, prioritizes transmission speed over guaranteed delivery, allowing minor data losses. Finally, the 10-second data transmission interval may have introduced buffering delays during periods of network instability. These combined factors justify the observed performance metrics and demonstrate that, despite minor transmission constraints, the system meets the reliability requirements for real-time IoT-based aquaculture monitoring. Future work should include testing under different network conditions to further evaluate system robustness and optimize communication quality.

F. Comparative Analysis with Prior Studies

To strengthen the interpretation of the results, this subsection provides a structured comparison between

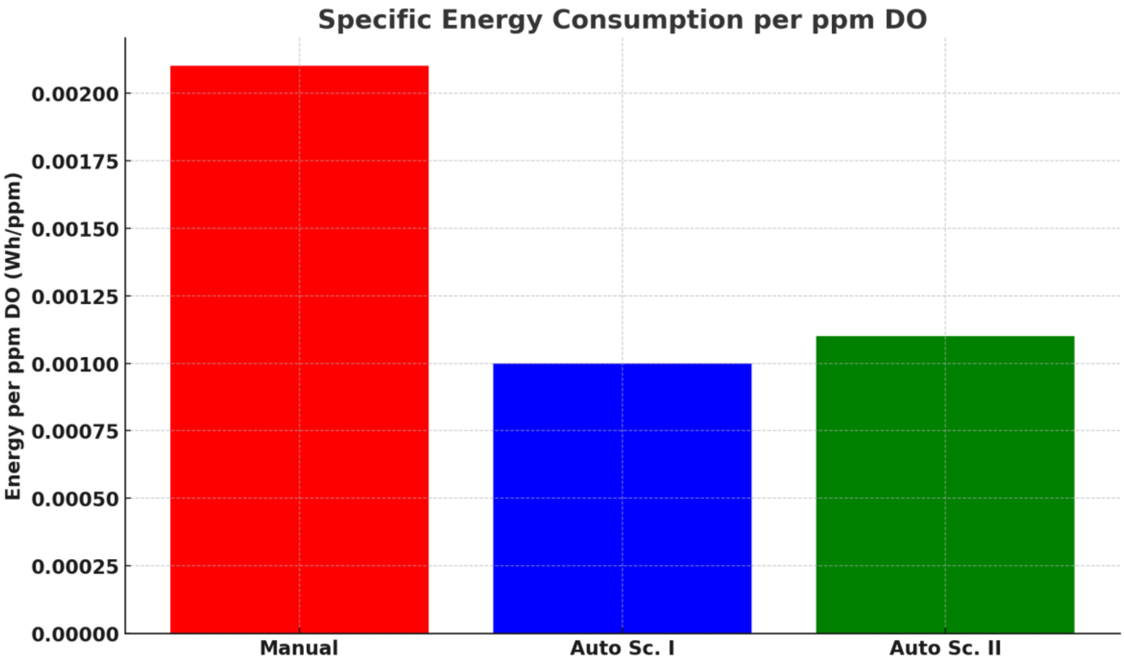

Fig. 5. Specific Energy Consumption per ppm of Dissolved Oxygen

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Table 6. ***Comparative summary between this study and selected prior IoT-based aquaculture systems.***
System

Study	DO Stability (mg/L)	Scale / Duration	Key Limitation
This study	5.1–6.8	Biofloc pond, 7 days	Short trial duration, energy Saving 26,7%
[5]	4.7–6.3	Intensive fish farm	No energy-per-DO analysis
[7]	4.8–6.4	Pond-scale	No aeration energy measurement
[8]	4.5–6.5	Lab-scale	No energy-per-DO analysis

the proposed system and representative IoT-based aquaculture studies. While prior studies have reported advances in water quality monitoring and automated aeration, Table 6 summarizes their key performance metrics including DO stability, energy efficiency, communication reliability, and experimental scale relative to the present study. The proposed smart aeration system achieved higher energy savings and reported more comprehensive communication metrics compared to existing systems. Unlike earlier studies that focused primarily on sensing, this study integrates real-time DO control with energy and network evaluation under biofloc conditions, highlighting its distinct contribution to practical, data-driven aquaculture.

5. CONCLUSION

This study successfully addresses the identified gaps by providing real-world validation of a smart aeration system based on microcontroller technology that integrates dissolved oxygen (DO) control, energy efficiency evaluation, and communication reliability assessment in an operational biofloc pond environment. The system demonstrated its ability to measure and regulate DO levels using the Gravity Analog Dissolved Oxygen Sensor Meter Kit for Arduino, supported by ESP32 and Wi-Fi communication in a closed-loop mechanism between sensor and actuator nodes. Stable data exchange between the nodes was consistently achieved, with the DO sensor maintaining an acceptable error margin (≤5%), and the communication delay of 740 ms with a 1.8% packet loss rate remaining feasible for real-time monitoring. The use of battery–solar-powered sensor nodes enabled flexible deployment in areas without direct power access, while the modular architecture supports scalability according to pond size. The observed improvements in DO stability and aerator energy efficiency were statistically validated, confirming that the system performed reliably under real operating conditions and effectively met the need for adaptive, data-driven aeration management.

While full IoT-based remote monitoring has not yet been implemented due to funding constraints, this study establishes a foundational proof of performance that directly contributes to the development of smarter and more energy-efficient aquaculture systems. Future work will focus on completing IoT integration, conducting extended field trials in commercial ponds, and performing deeper statistical evaluation of system durability, energy dynamics, and impacts on fish growth. Additional water quality parameters, such as pH and turbidity, will also be incorporated to enhance decision-making in smart aquaculture management.

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