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Calibration of Dissolved Oxygen Sensors in IoT Systems for Water Quality Monitoring in Aquaculture

Gema Parasti Mindara[1,*], Walidatush Sholihah[2], Inna Novianty[1], Lathifunnisa Fathonah[1], Faldiena Marcelita[1], Ridwan Siskandar[1], Dodik Ariyanto[1], Bayu Widodo[1], Aep Setiawan[1], Naufal Rizqullah Firdaus[1]

[1]*Computer Engineering Technology, Vocational School, IPB University, Indonesia*
[2]*Faculty of Science and Engineering, University of Groningen, Netherlands*

*Corresponding Author Email: gemaparasti@apps.ipb.ac.id

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ABSTRACT

Dissolved Oxygen (DO) is an important parameter for maintaining water quality in aquaculture systems. The accuracy of DO sensors significantly affects the reliability of Internet of Things (IoT)-based monitoring systems. This study aimed to calibrate the DO sensor using a two-point calibration method and evaluate the accuracy of the sensor readings compared with those of a reference device (standard DO meter). A key novelty of this study lies in its multi-media calibration, performed directly on six distinct aquaculture water types, providing field-realistic validation conditions not commonly explored in previous studies. Furthermore, the accuracy of the calibrated sensor is evaluated quantitatively using MAE, RMSE, and percentage deviation to ensure rigorous performance assessment. The system was developed using an ESP32 microcontroller, DO sensor (SEN0237), DS18B20 temperature sensor, and ADS1115 ADC module. Testing was performed on six types of aquaculture water media and compared with a standard DO meter using a comparative approach. In total, n = 6 field measurement points (one stabilized reading per water medium) were used to compute MAE, RMSE, and percentage deviation. The comparison results showed that the calibrated sensor had high accuracy, with a Mean Absolute Error (MAE) of 0.1083 mg/L and a Root Mean Square Error (RMSE) of 0.2654 mg/L. Significant deviations occurred only in one type of water medium, whereas the other five showed results consistent with the reference device, indicating stable sensor readings. These findings confirm that proper calibration can improve the accuracy and reliability of IoT systems used for water-quality monitoring. Regular calibration is required to maintain the sensor performance, particularly for long-term use in dynamic aquaculture water environments.

Keywords: DO sensor accuracy, IoT, calibration, dissolved oxygen sensor, aquaculture, water quality monitoring

INTRODUCTION

Water quality is a crucial factor in aquaculture production that directly affects the sustainability and success of businesses [1]. Fluctuations in environmental water conditions and unpredictable weather often pose major challenges for cultivators [2]. One of the parameters for maintaining optimal water quality is the level of dissolved oxygen (DO) [3]. The optimal DO to support the metabolism and health of freshwater fish ranges between 5-8 mg/L, with a value of 6.77 mg/L identified as the most ideal level for Pelteobagrus fulvidraco juveniles [4]. Meanwhile, a lack of DO can cause physiological stress, decreased food intake, metabolic disturbances, and even mass mortality, negatively affecting the function of aerobic microorganisms in maintaining water quality [5]. Low levels of dissolved oxygen (DO) significantly impact fish physiology, causing behavioral changes such as frequent surfacing and reduced appetite. This results in slow growth, increased vulnerability to disease, and higher mortality rates, especially in the early developmental stages and intensive farming systems [6-7].

The IoT-based water quality monitoring system uses dissolved oxygen (DO) sensors for the early detection of oxygen level fluctuations, allowing quick responses. Historical data support trend analysis and predictive decision-making, improving aquaculture management and ensuring optimal conditions for aquatic species [8-9].

The effectiveness of IoT monitoring is heavily dependent on sensor accuracy [10]. Optical oxygen sensors have advantages such as high sensitivity, fast response time, no oxygen consumption, and long-term stability, making them suitable for various applications, including Internet of Things (IoT) systems [11]. In the implementation of IoT systems, DO sensors are designed to support real-time data acquisition, energy efficiency, and easy integration with software and hardware [12]. Other key characteristics include resistance to biofouling and wireless data transmission capabilities to support responsive decision-making [13]. Several studies have reported that integrating advanced machine learning and optimization techniques such as LSTM, ensemble learning, GRU, and remote sensing significantly enhances the accuracy and reliability of dissolved oxygen prediction for aquaculture water quality monitoring [26-30].

Nonetheless, the accuracy of sensor readings is highly influenced by environmental factors such as temperature [14], pressure [15], and internal sensor conditions [16]. Therefore, calibration is an essential step in maintaining data precision. Calibration methods for DO sensors generally include single-point calibration (referring to oxygen-saturated air) [17] , two-point calibration (using zero and saturation values) [18], and offset correction to adjust the reading deviations caused by sensor drift. Periodic calibration enhances the long-term reliability of sensors and ensures the integrity of the data used in IoT-based water quality monitoring systems.

Several studies have developed Internet of Things (IoT)-based water quality monitoring systems for aquaculture environments, focusing primarily on sensor installation, data acquisition, and the real-time integration of environmental parameters. For example, Huan et al. [19] designed an NB-IoT-based system for aquaculture monitoring that used STM32 microcontrollers and various environmental sensors, such as temperature, pH, and dissolved oxygen (DO). The system demonstrated high accuracy (±0.12 °C for temperature and ±0.55 mg/L for DO) and achieved low packet loss (less than 0.5 %) over a 3 km range, with data transmission occurring every 30 min to a telecom cloud platform. This study is a prime example of how IoT systems can provide reliable water quality monitoring through accurate sensor calibration, efficient data acquisition, and seamless integration into cloud platforms.

In another study, Mohd Jais et al. [10] proposed a low-cost IoT-based water quality monitoring system for Asian seabass aquaculture, utilizing Arduino Uno, DFRobot sensors, and Wi-Fi connectivity via ESP8266. Their system was calibrated using linear regression to improve the sensor accuracy, achieving a significant enhancement from 76 % to 97 %. This improvement, validated against YSI Professional Pro probes, demonstrates the potential for optimizing sensor performance in aquaculture systems. Their research exemplifies how the combination of affordable components and proper calibration techniques can lead to highly accurate monitoring solutions for small-scale aquaculture farms.

Recent advancements in IoT-based aquaculture systems have integrated machine learning and quantum optimization algorithms to enhance their data processing and predictive capabilities. Baena-Navarro et al. [20] integrated IoT infrastructure with machine learning and quantum optimization techniques to improve real-time water quality prediction and management. Their system used Random Forest and Support Vector Machine (SVM) models optimized using the Quantum Approximate Optimization Algorithm (QAOA). The system achieved impressive accuracy ($R^2 = 0.999$, RMSE = 0.0998 mg/L) while reducing the training time by 50 %. This study marks a significant advancement in aquaculture monitoring by combining traditional IoT systems with advanced predictive models to enable proactive water quality management.

Moreover, Shete et al. [21] explored the use of real-time monitoring for tilapia aquaculture by integrating Arduino Uno with GSM connectivity and lab-grade sensors on a waterproof PCB. Their system achieved reliable performance with a maximum error of only 4.87 %, providing continuous monitoring of DO, pH, and temperature within the optimal ranges for tilapia farming. These advancements indicate that IoT-enabled systems are moving beyond basic data collection toward more intelligent, data-driven frameworks capable of providing actionable insights in real time.

Furthermore, Chen et al. [22] introduced an IoT-based system that addresses a critical limitation of traditional water quality monitoring, the inability of pH sensors to remain submerged, by utilizing a self-designed robotic arm to automatically execute sequential measurements, cleaning, and maintenance actions across multiple farm ponds. By wirelessly transmitting data from various sensors (temperature, pH, DO) and integrating them into a mobile monitoring platform, the system provides fish farmers with a reliable, 24-hour automated solution that helps prevent aquaculture losses and improves operational efficiency.

Further progress in intelligent aquaculture systems has focused on improving the accuracy and cost-effectiveness of dissolved oxygen (DO) monitoring. Shaghaghi et al. [23] introduced the DOxy system, an IoT-based optical DO monitoring platform that utilized a modified MAX30102 infrared pulse oximeter sensor for aquatic environments. This system uses LoRa and Wi-Fi for communication, a solar-powered unit for energy, and a cloud architecture built with Node.js and TimescaleDB. The DOxy platform achieved high accuracy ($R^2 = 0.995$, RMSE = 0.115 mg/L) while reducing operational costs by employing sustainable hardware solutions and 3D-printed waterproof casings. This development demonstrates how IoT systems can be optimized for energy efficiency, making them ideal for off-grid aquaculture.

In parallel, Kuang et al. [24] proposed a hybrid prediction model called KIG-ELM, which combined K-means clustering, an Improved Genetic Algorithm (IGA), and an Extreme Learning Machine (ELM) in an edge-computing architecture for real-time DO forecasting. Their model achieved high accuracy (MAPE = 0.0386, RMSE = 0.2591) by leveraging multiparameter inputs, such as pH, temperature, CO_2 concentration, and illumination intensity. This advanced approach to DO prediction demonstrates the effectiveness of machine learning models in enhancing the predictive capabilities of IoT-based aquaculture monitoring systems.

Unlike previous studies that mostly performed calibration or validation in a single and controlled water medium, this study explicitly introduces a multi-media calibration approach by testing the sensor across six different aquaculture water environments. This approach provides a more realistic representation of field variability and has rarely been addressed in the existing IoT–aquaculture literature. In addition to the calibration process, this study also performs a quantitative accuracy evaluation using MAE, RMSE, and percentage deviation, enabling a more rigorous assessment of sensor reliability after calibration. These two aspects—multi-media calibration and comprehensive error-based quantitative evaluation—constitute the key novelty of this research and offer practical contributions to strengthening the reliability of IoT-based dissolved oxygen monitoring systems in aquaculture.

METHODS

Location and Scope of Study

This research was conducted at the IoT Laboratory of the Vocational School, IPB University, located at Jl. Kumbang No.14, RT.02/RW.06, Babakan Sub-district, Bogor Tengah District, Bogor City, West Java 16128. The research activities were conducted over four months, from March to June 2025. Water quality measurements were performed directly at several aquaculture water sites, including catfish ponds, red-eye fish, black tilapia, gourami, catfish, and ornamental fish aquariums for comparison.

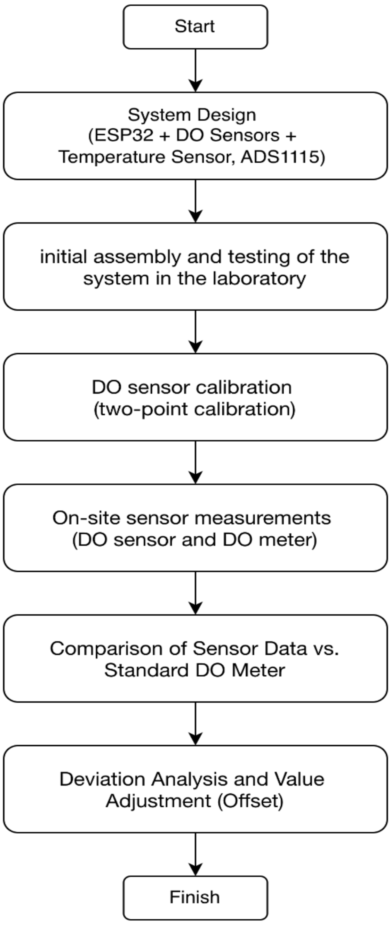

FIGURE 1. Research Diagram.

Methods

This study aimed to develop and evaluate an Internet of Things (IoT)-based dissolved oxygen (DO) monitoring system for various aquatic media. To achieve this objective, a series of stages were conducted. The stages of this study are presented in the flowchart shown in FIGURE 1.

The first stage is system design, which includes selecting and integrating key components such as the ESP32-S3-WROOM-1 microcontroller, SEN0237 Dissolved Oxygen (DO) sensor, DS18B20 temperature sensor, and ADS1115 external ADC module. The system was designed to build a DO monitoring device that could measure and transmit data efficiently. Next, the assembly and initial testing of the system in the laboratory was performed to ensure that all components functioned properly and that the system could read and display data from the sensors stably. The next stage was the calibration of the DO sensor using the two-point calibration method, which involves calibrating at two reference points: the oxygen saturation point (aerated water) and the zero-oxygen point (water treated with a sodium sulfite solution). This calibration is necessary to make the sensor readings more accurate and in accordance with measurement standards. Subsequently, direct field measurements were conducted by comparing the readings from the custom-built DO sensor with those of a standard DO meter. Measurements were taken across various water types to evaluate the performance of the system under real conditions. The measurement data from both devices were then used to compare the sensor values with the standard DO meter, which was analyzed to determine the difference or deviation between the two devices. If a significant deviation is found, correction analysis and value adjustment (offset) are performed to improve the accuracy of the system readings. This offset was calculated based on the average difference between the sensor values and the standard during testing. These stages were conducted systematically to ensure that the developed DO monitoring system had good performance in terms of data accuracy and stability and was suitable for real-time water quality monitoring applications.

Dissolved Oxygen Sensor Calibration Process

The calibration comparison method used in this study was the comparative method. This method is used to compare one object with another [25]. Therefore, in this study, we compared the measurement results of dissolved oxygen (DO) levels from a calibrated DO sensor and a standard DO meter. Measurements were conducted directly in the types of aquatic media without using separate water samples. The DO and temperature sensors were immersed simultaneously in the specific aquatic medium, followed by the immersion of the standard DO meter. Measurement values were recorded once the readings from both devices showed stable conditions to ensure the accuracy and validity of the obtained data. The sensor value adjustment procedure was performed by simultaneously recording the DO level measurements from both the sensor and DO meter in the same type of water medium. If there were differences between the DO sensor readings and the standard DO meter, adjustments were made using software corrections. In this context, the software refers to the program code written using the Arduino IDE and executed on the ESP32-S3 microcontroller. Corrections were made by adding certain functions or formulas to the code, such as modifying the reading voltage on CAL1_V and CAL2_V based on the differences in readings compared with the reference device. This step aimed to improve the accuracy of the dissolved oxygen data recorded by the system. The DO sensor calibration process was performed using a two-point calibration method with reference solutions and under different temperature conditions. The reference solution used in the calibration process was clean water (tap water or mineral water) left open to reach natural oxygen saturation at 24°C and 18°C. The calibration steps are as follows:

1. Preparation of Electrolyte Solution

The electrolyte solution was prepared by mixing 20 g of sodium hydroxide (NaOH) or caustic soda with 100 mL of distilled water. The solution was stirred until NaOH was completely dissolved, and a homogeneous mixture was obtained. The solution was then left to stand for approximately 3 min to allow the temperature to decrease and prevent it from being excessively hot. This solution was used as the electrochemical medium in the DO sensor probe to support the detection of the dissolved oxygen.

2. Filling the Electrolyte Solution into the Sensor Probe

The DO probe sensor was opened, and two to three drops of NaOH solution were added to the internal chamber of the probe. Subsequently, the probe was carefully reattached to the sensor's body. Any remaining solution that may drip through the gap between the probe and the sensor should be cleaned with a dry cloth or clean tissue to prevent interference with the sensor-reading process.

3. Calibration Media Preparation

Two 350 ml glasses were prepared as calibration media, each filled with 100 ml of clean water (tap water or mineral water) that had been stabilized at 24°C and 18°C. The water was left uncovered in open air for several minutes to allow its oxygen content to approach saturation (natural saturation by air).

4. First Point Calibration (24°C)

The DO sensor filled with the electrolyte solution was placed in glass A, which contained water at 24°C. The sensor was left fully submerged until the entire probe was immersed in the solution. The solution was allowed to sit for approximately 1 min until the readings stabilized. The sensor was then removed and placed horizontally on the surface of the table, with the tip of the probe exposed to the surrounding air without direct exposure to a fan or an air conditioner. This process was repeated thrice to obtain consistent results. The voltage and temperature values that appeared as the first reference points (glass A) were recorded.

5.Second Point Calibration (18°C)

The same steps were repeated using glass B, which contained water at 18°C. The sensor was immersed in water until it stabilized, removed, and exposed to air. As with the first point, the reading was performed three times. The temperature and voltage values under these conditions were recorded as the reference for the second point (glass B).

The two recorded calibration voltages ($CAL1_V$ at $CAL1_T$ and $CAL2_V$ at $CAL2_T$) were used to estimate the saturation voltage at any measurement temperature T by linear interpolation:

$$V_{sat}(T) = CAL1_V + \frac{(T - CAL1_T)(CAL2_V - CAL1_V)}{(CAL2_T - CAL1_T)}. \tag{1}$$

The dissolved oxygen concentration was then obtained by scaling the measured voltage $V(T)$ with the oxygen saturation concentration $DO_{sat}(T)$:

$$DO(T) = \frac{V(T)}{V_{sat}(T)} \times DO_{sat}(T), \tag{2}$$

where $DO_{sat}(T)$ follows the temperature-based saturation reference used in the sensor library.

RESULTS AND DISCUSSIONS

Hardware Implementation and System Assembly

In the design of the developed water quality monitoring system, a combination of hardware was used, consisting of the ESP32-S3-WROOM-1 microcontroller, the Dissolved Oxygen (DO) sensor SEN0237, the DS18B20 temperature sensor, and the external ADC Module ADS1115. The ADS1115 module was used to improve the accuracy of the analog signal readings from the DO sensor, considering that the internal ADC on the ESP32-S3 has limitations in terms of stability and precision, particularly at low voltages. With a resolution of 16 bits, the ADS1115 allows for more precise and reliable data acquisition of dissolved oxygen levels. The equipment used is listed in TABLE 1, and a circuit schematic is shown in FIGURE 2.

TABLE 1. Tools used

No	Tools/Materials used	Functions
1	Microcontroller ESP32-S3-WROOM-1-N16R8	The ESP32 is used as the brain of the system, collecting data from the DO sensor, processing it, and sending the results to the display.
2	Dissolved Oxygen (DO) sensor SEN0237	The DO sensor is used to measure the dissolved oxygen content in water in real-time, which is a key indicator of water quality.
3	Temperature sensor DS18B20	A temperature sensor is used to measure the water temperature, which is necessary to compensate the DO sensor readings for greater accuracy.
4	ADS1115	ADS1115 is used to convert analog signals from sensors (such as DO sensors) into digital signals so they can be read by the ESP32 microcontroller.

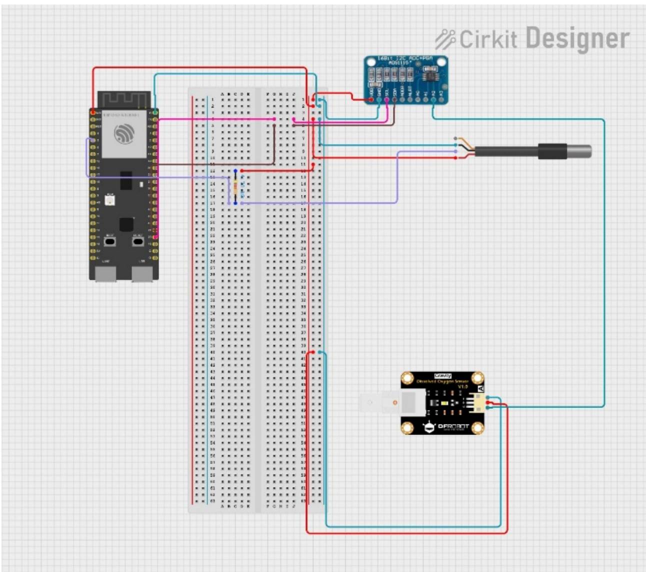

FIGURE 2. Circuit Schematic

The DO sensor was connected to channel A2 on the ADS1115, which functioned as an analog input line. This channel converts the analog voltage signal from the DO sensor into digital data, which are then sent to the microcontroller via the I2C communication protocol. The selection of channel A2 was based on the efficient use of space on the breadboard and expansion flexibility if the system was developed to support additional sensors in the future. Communication between the ADS1115 module and ESP32-S3 was performed through the I2C lines, namely, the Serial Data Line (SDA) and Serial Clock Line (SCL). The SDA pin on the ADS1115 was connected to pin 21 on the ESP32-S3, whereas the SCL pin was connected to pin 20, in accordance with the common I2C communication conventions. The SDA line serves as a bidirectional data transfer channel between the master (ESP32) and slave (ADS1115), whereas the SCL line is used to synchronize the data transmission. The DS18B20 temperature sensor was connected directly to pin 5 on the ESP32-S3 because this sensor uses a 1-Wire communication protocol, which allows digital data transmission using only a single data pin. All system components, including the DO sensor, ADS1115, and temperature sensor, received power from the 3.3V and GND pins on the ESP32-S3, allowing the system to operate with a stable and consistent voltage. With a system design capable of reading temperature and dissolved oxygen levels in an integrated and precise manner, this device greatly supports the analysis of water quality in various types of aquatic environments, including fish farming ponds and ornamental fish aquariums, in accordance with the main focus of this study.

Field Data Collection Procedure

Each measurement was taken once at each location point, specifically on six types of different water media: catfish pond, panon beureum, black tilapia, gourami, catfish, and ornamental fish aquariums. The sensor was left in place until the readings for DO and temperature stabilized at 25 °C, with a stabilization time ranging from 2 to 3 min. Subsequently, the data were recorded manually from both the sensors and the standard DO meter. To maintain data consistency, the entire measurement process was conducted in a controlled environment, ensuring that the sensor position remained unchanged during data collection, there was no water flow disturbance or excessive fish activity, and the ambient temperature remained stable. This is important for minimizing external variables that could affect the accuracy of sensor readings.

Measurement results of oxygen levels

Dissolved oxygen levels were measured in six types of water media using a calibrated DO sensor and compared with those measured using a standard DO meter. TABLE 2 shows the results of the dissolved oxygen measurements in various types of pond and aquarium water. From the results provided, it can be seen that there is consistency between the values measured by the DO sensor and the DO meter across six types of water media. In five of these water media, namely patin fish pond water, panon beureum fish pond water, black nila fish pond water, gourami fish pond water, and catfish pond water, the difference and percentage deviation between the DO sensor and the DO meter were zero, indicating that the sensor operated accurately and precisely after calibration. However, there was an exception in the lele fish pond water medium. The value obtained from the DO sensor was only 0.05 mg/L, whereas the DO meter showed a value of 0.7 mg/L. The difference between these two values was 0.65 mg/L, resulting in a deviation of 92.86%. This is because catfish pond water is murkier and likely contains more particles, which can affect the sensor performance.

FIGURE 3 presents a comparison of dissolved oxygen (DO) values between the calibrated sensor and the standard DO meter across the six water types. In general, the DO sensor readings were consistent with those of the reference instrument. However, in catfish pond water, there was a significant deviation in the results. This is suspected to be caused by the high concentration of suspended particles or organic matter in the water, which can affect the performance of the DO sensor both optically and electrochemically, especially if it has not fully stabilized after calibration.

TABLE 2. Comparison of DO Sensor Values and Standard DO Meter

No	Types of Water Media	DO sensor	DO Meter	Differ-ence	% Deviation
1	Water from the catfish pond	1,4	1,4	0	0
2	Water from the panon beureum fish pond	3,3	3,3	0	0
3	Water from the black tilapia fish pond	4,1	4,1	0	0
4	Water from the gourami fish pond	3,5	3,5	0	0
5	Water from the lele fish pond	0,05	0,7	0.65	92.86
6	Water for ornamental fish aquariums	3,4	3,4	0	0

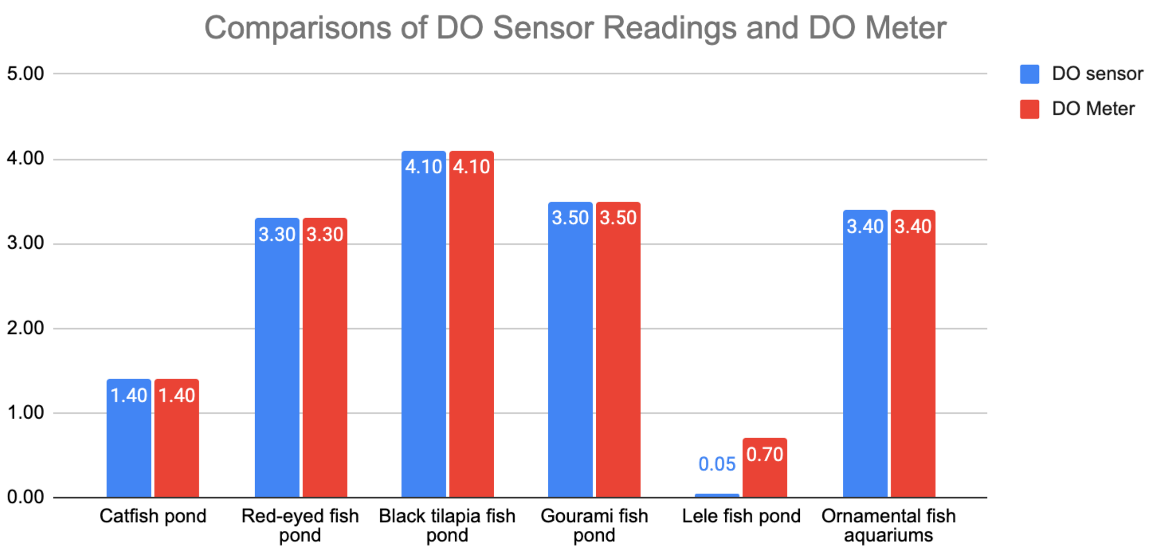

FIGURE 3. Comparison of DO sensor readings and DO meter.

Measurement error analysis

Error analysis was conducted using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and percentage deviation. The MAE was calculated by:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, \tag{3}$$

where y_i is the measurement value of the standard device (DO meter), $\hat{y}_i$ is the measurement value of the DO sensor and n is the total number of measurements.

The MAE measures the average of all absolute differences between the sensor readings and the reference device. A smaller MAE indicates that the sensor produces data closer to the actual value. Based on the data in TABLE 2, the MAE was 0.1083 mg/L. An MAE value of 0.1083 mg/L indicates that the average error of the sensor compared to the reference value was quite low and remained within the tolerance limits for field-scale water quality monitoring.

The Root Mean Square Error (RMSE) was used to calculate the average of the squared errors, which gives a greater penalty for extreme differences. The RMSE is more sensitive to large errors than the MAE. The formula for RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}. \tag{4}$$

The RMSE was 0.2654 mg/L. This indicates that although most readings are highly accurate, one data point (catfish pond) contributes a large error. However, overall, this error was acceptable for the water quality monitoring system.

The percentage of the average deviation was calculated to determine the extent of the relative deviation that occurred in each measurement compared to the standard value. To determine the relative deviation from the reference value, the percentage deviation is calculated as follows:

$$\text{Deviation}(\%) = \frac{|y_i - \hat{y}_i|}{y_i} \times 100\%. \tag{5}$$

The percentage deviation was calculated for each data point. The average deviation was 15.48%. This value was quite high. However, this was influenced by a single outlier in the lele fish pond. The other five points showed a deviation of 0%, indicating that the sensor readings were consistent with those of the reference instrument after calibration. Based on the results of the MAE, RMSE, and deviation calculations, it can be concluded that the DO sensor calibration process significantly improved the accuracy of the readings. The sensor showed a high level of agreement with the standard instrument in almost all water media types. The relatively small error values further strengthen the validity of using the sensor in IoT systems for aquaculture water quality monitoring. However, the presence of a single high-error point in the lele fish pond water indicates the need to pay attention to extreme environmental factors.

Increased accuracy and stability of reading

The measurement results showed that the calibrated DO sensor could produce data with a high level of accuracy. This is indicated by a Mean Absolute Error (MAE) value of 0.1083 mg/L and a Root Mean Square Error (RMSE) value of 0.2654 mg/L, which reflect a very low deviation compared to the standard DO meter. In addition, five of the six types of water media showed readings identical to those of the reference device, indicating consistent sensor performance across various aquaculture water environments. In contrast, the reading process also demonstrated good stability, with the sensor reaching a stable value within 2–3 min at each measurement point. A stable value in this context refers to when the dissolved oxygen (DO) readings from the sensor show very little or almost constant fluctuation, that is, no more than ±0.01 mg/L within a certain time span. This indicates that the sensor achieved electrochemical stability and can be relied upon for data acquisition. These results show that two-point calibration not only improves accuracy but also provides system stability when used repeatedly in different types of water media.

Challenges in the calibration process in the field

The calibration process of Dissolved Oxygen (DO) sensors in the field faces several challenges that can affect the accuracy of the results. One of the main challenges is the environmental conditions, which cannot be fully controlled, such as ambient temperature fluctuations, high humidity, and the presence of airflow from fans or natural wind, all of which can disrupt the process of reaching oxygen saturation when the sensor is exposed to the air. When performing two-point calibration, maintaining the reference water temperature at a constant value (for example, 24°C and 18°C) is an important step to ensure data accuracy. To consistently achieve these temperatures, temperature conditioning devices, such as water baths or portable coolers, are required, particularly in locations with high ambient temperatures. The quality of the reference water used can also be a source of uncertainty, as tap or mineral water may contain contaminants or have varying levels of dissolved oxygen. Therefore, special attention is required to maintain consistent and accurate calibration procedures, including the use of temperature control devices, routine application of sensor-cleaning protocols, and adequate planning of the time required for each measurement stage.

Implications of the results on the long-term performance of the IoT system

The calibration results, which demonstrate a high level of accuracy and stability in the DO sensor readings, provide a strong foundation for developing a reliable IoT-based water quality monitoring system for long-term use in the future. Consistent sensor readings across various types of water media indicate that this system has the potential to be implemented in sustainable fish farming, both on a small scale, such as in aquariums, and on a larger scale, such as in commercial ponds. With proper and regular calibration, the developed IoT system can serve as an early detection tool for declining water quality, enabling fish farmers to take corrective action. This can directly improve cultivation productivity, reduce the risk of fish mortality, and decrease the need for frequent water changes. Additionally, the stability of the sensor readings demonstrated in this test serves as an indicator that the system can be integrated with wireless communication modules and cloud-based data storage, allowing for trend analysis and data-driven decision-making in real time in the future

Discussion

The evaluation results showed that the calibrated DO sensor produced readings that closely matched the reference values obtained using the standard DO meter. This study is also one of the few that evaluates dissolved oxygen sensor performance across multiple real aquaculture water media, which strengthens the generalizability of the calibration results. A Mean Absolute Error (MAE) of 0.1083 mg/L and a Root Mean Square Error (RMSE) of 0.2654 mg/L indicate that the measurement errors of the sensor fall within a very low and acceptable range for practical water quality monitoring. Meanwhile, the average percentage deviation of 15.48% emerged due to one anomalous data point, whereas five of the other six types of water media showed a deviation of 0%, reinforcing the stability of the sensor readings after calibration. The highest deviation was recorded in catfish pond water, which is suspected to be caused by the water's tendency to be turbid and rich in suspended particles and organic materials. These factors can affect the readings of DO sensors, especially those that work optically or electrochemically, owing to interference with the sensor signal response or deterioration in the quality of data transmission from the sensor to the microcontroller. These findings indicate that even though the sensor was calibrated, extreme environments can still influence its performance, particularly if biofouling or dirt accumulation is not controlled.

Compared with previous studies, these results show significant progress in the field. Rahman et al. (2020) noted that IoT systems without calibration produced deviations of more than 0.5 mg/L [9]. Michelucci et al. (2019) emphasized the importance of the long-term stability of optical DO sensors and the need for regular recalibration [11]. This study supports these findings and provides empirical evidence that the proper application of two-point calibration can significantly improve system accuracy, even in heterogeneous aquaculture water environments. These findings have important implications for developing IoT systems in the aquaculture sector. With higher sensor accuracy, the system can provide reliable data to support decision-making, such as scheduling water changes, adjusting feed, or early identification of water quality deterioration in aquaculture. Therefore, periodic calibration not only enhances the technical performance of the sensor but also supports operational sustainability and efficiency in aquaculture settings. However, this study had some limitations. Testing was conducted on only six types of water media and did not include extreme conditions such as high temperature, high salinity, or specific pollutants. Therefore, further studies are recommended to evaluate the sensor performance under a wider variety of field conditions and to integrate automatic or software-based calibration mechanisms to support the efficiency and ease of use of long-term IoT systems.

CONCLUSION

Based on the test results, the applied two-point calibration improved the accuracy of the Dissolved Oxygen (DO) sensor readings, as indicated by the low MAE and RMSE values and minimal deviation from the reference instrument. To maintain the consistency and reliability of the data over the long term, calibration must be performed regularly, particularly when the system is used in aquatic environments with varying characteristics. With the achieved accuracy and stability of the readings, the calibrated DO sensor is considered suitable for integration into IoT systems to support real-time water quality monitoring in aquaculture applications. Nevertheless, the high deviation observed in the lele pond medium indicates that additional cleaning/anti-fouling control and repeated measurements are necessary in highly turbid environments.

This study used one stabilized field measurement per water medium (n = 6), which limits the statistical generalization across time and operating conditions. Future work will include repeated measurements in each medium, evaluation under more extreme conditions (e.g., higher temperature or salinity), and the integration of automated/assisted calibration routines for long-term deployments.

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