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Enhanced Coordinated Sensor Network for Real-Time Lake Kivu Water Quality Monitoring

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ABSTRACT

Lake Kivu, a transboundary freshwater resource between Rwanda and the Democratic Republic of Congo, faces increasing risks of pollution from agricultural, industrial, and domestic activities. Continuous monitoring is therefore essential to ensure its ecological balance and safe utilization. This study presents an enhanced sensor network for real-time water quality (WQ) data acquisition in Lake Kivu. The system integrates pH, turbidity, and temperature sensors connected through low-power wireless nodes to an IoT-based platform. Data are transmitted to a centralized cloud system for visualization. Experimental validation demonstrates accurate, energy-efficient, and high-frequency monitoring, enabling near real-time data acquisition and rapid anomaly detection. Compared to conventional interval-based monitoring methods, the proposed system improves responsiveness and data continuity, supporting timely decision-making for sustainable management of Lake Kivu.

1. INTRODUCTION

Throughout water quality (WQ) represents the combined physical, chemical, and biological characteristics of water that determine its fitness for ecological and human use, as defined by international agencies such as the WHO, EPA, and FDA [1]. Maintaining acceptable WQ levels is vital for domestic consumption, agriculture, aquaculture, and industrial operations [2]. However, the increasing human concentration near aquatic environments intensifies the risk of contamination from agricultural runoff, industrial effluents, and urban waste [3]. This growing pressure makes real-time WQ monitoring essential for effective management of freshwater ecosystems [4, 5]. In this context, Lake Kivu, a major transboundary water resource linking Rwanda and Democratic Republic of the Congo (DRC), demands continuous observation due to its ecological and socio-economic importance. Developing an enhanced sensor network for real-time WQ data acquisition offers a sustainable approach to detect water degradation promptly and support informed decision-making for environmental protection and resource management [6-8].

Despite the vital role of clean water in sustaining human health, biodiversity, and industrial productivity, most existing WQ monitoring practices remain manual and fragmented [9, 10]. Conventional methods rely on intermittent sampling and laboratory-based analysis, which are labor-intensive, costly, and delay contamination detection [11]. Such latency hampers timely mitigation of pollution events and limits continuous environmental surveillance. Moreover, increasing climatic variability and intensified agricultural, industrial, and urban activities further complicate WQ assessment [6, 12-14]. The lack of automation and real-time data acquisition creates significant spatial and temporal data gaps, reducing the accuracy and reliability of water management decisions.

In response, sensor-based and Internet of Things (IoT)-enabled monitoring systems have emerged as promising solutions for real-time WQ assessment [15, 16]. These systems integrate microcontrollers, wireless communication modules, and multi-parameter sensors to capture key indicators, often supported by advanced computational frameworks such as Spark Streaming Analytics [17, 18], deep learning models [19], and Belief Rule-Based (BRB) systems [17]. However, many of these systems exhibit high energy consumption, limited mobility, and poor scalability, particularly in resource-constrained environments.

In the context of Lake Kivu, existing approaches fail to provide a cost-effective, energy-efficient, and scalable solution capable of continuous, real-time monitoring across large and geographically dispersed water surfaces. Additionally, they lack adaptability to the lake's dynamic environmental conditions and do not adequately address the need for autonomous operation in areas with limited infrastructure. These shortcomings highlight a critical gap in current WQ monitoring systems, necessitating the development of an intelligent, IoT-based framework tailored to the unique operational and environmental constraints of Lake Kivu.

This study presents an IoT-based framework for continuous, real-time WQ monitoring in Lake Kivu, addressing the limitations of traditional methods that rely on infrequent, labor-intensive, and costly manual sampling. These conventional approaches create data gaps and hinder the detection of short-term pollution events and long-term ecological trends. To overcome these challenges, the proposed system enables high-frequency data collection, low power consumption, and autonomous operation in remote aquatic environments. It adopts a three-tier architecture comprising a sensing layer for data acquisition, a processing and communication layer for local data handling, and a cloud-based layer for analysis and visualization. The system is built around an Arduino UNO, integrating pH, turbidity, and temperature sensors, with calibrated data processed locally and transmitted to a cloud platform via a gateway for centralized monitoring and decision support. It is crucial to note that the main contributions of this study are bifold as follows:

(1) Development of a Robust and Cost-Effective IoT Sensor Node: A distributed sensor node was designed and implemented using an Arduino UNO microcontroller and calibrated sensors for pH, turbidity, and temperature. The design prioritizes reliability and continuous data acquisition, making it suitable for scalable deployment across the Lake Kivu ecosystem.

(2) Establishment of an End-to-End, IoT-Based Decision-Support Framework: A complete data pipeline from the sensor node to a cloud platform was established. This cloud-integrated framework enables real-time visualization, automated threshold-based alerts, and historical data analytics, empowering stakeholders with actionable insights for the sustainable management of water resources and effective policy intervention.

The rest of this paper is structured in sequential sections. Section 2 reviews previous studies relevant to this work. The proposed approach is outlined in Section 3, followed by the analysis and discussion of findings in Section 4. Finally, Section 5 presents the conclusion and future works.

2. LITERATURE REVIEW

Conventional approaches to WQ assessment in freshwater ecosystems primarily rely on manual sampling followed by laboratory analysis [20, 21]. While these methods provide high accuracy, they are inherently time-consuming, labor-intensive, and discontinuous. Such temporal limitations hinder the timely detection of contamination events, particularly in large and dynamic water bodies like Lake Kivu, thereby posing risks to both public health and aquatic ecosystems [22].

To address these limitations, recent studies have focused on IoT-based monitoring systems, which enable real-time and remote data acquisition [23]. These systems typically deploy distributed sensor networks to measure parameters such as pH, turbidity, dissolved oxygen, conductivity, temperature, and total dissolved solids [24]. Based on communication technologies, existing IoT systems can be broadly categorized into short-range and long-range solutions [25]. While Wi-Fi and cellular networks provide high data rates, they are often energy-intensive and less suitable for remote deployments. In contrast, LoRaWAN offers long-range communication with low power consumption, making it more appropriate for large-scale environments; however, it may suffer from limited bandwidth and network reliability in geographically complex regions.

Moreover, existing studies focuses on data analytics and intelligent decision-making, where machine learning techniques are integrated into WQ monitoring systems to enhance prediction accuracy and automate analysis [26]. These approaches improve operational efficiency and enable early anomaly detection. Nevertheless, they often assume stable data streams and reliable connectivity, which are difficult to guarantee in remote or resource-constrained environments. Additionally, issues related to data security, privacy, and model generalization remain insufficiently addressed [27].

Furthermore, the current studies highlight the operational benefits of real-time monitoring systems, particularly in water treatment plants and natural freshwater bodies [28]. These systems support early detection of pollutants, optimize resource usage, and improve environmental management. However, most existing implementations are designed for controlled or semi-urban environments and do not adequately account for the environmental variability, infrastructure limitations, and connectivity challenges found in developing regions such as Rwanda and the Democratic Republic of Congo [29]. Similar challenges have been observed in other developing regions, such as Bangladesh, where inadequate wastewater management severely impacts WQ [30, 31].

Despite these advancements, a critical gap remains in the design of integrated, scalable, and energy-efficient IoT-based WQ monitoring systems tailored for large freshwater ecosystems. Existing solutions often lack robustness against environmental variability, fail to ensure reliable long-range communication, and do not incorporate adaptive calibration mechanisms required for accurate real-time monitoring in complex aquatic environments such as Lake Kivu.

To address these limitations, this study proposes an enhanced IoT-based sensor network designed for continuous and reliable WQ monitoring in Lake Kivu. The system adopts a four-layer architecture comprising sensor nodes, a gateway, a cloud server, and a web-based dashboard. Each node integrates multi-parameter sensors, a microcontroller, real-time clock, rechargeable power system with optional solar support, and a LoRa transceiver for energy-efficient long-range communication. The gateway aggregates and forwards data to the cloud via 4G or Ethernet, where automated quality control techniques, including median filtering and z-score-based anomaly detection, ensure data reliability. A user-friendly dashboard provides real-time visualization, trend analysis, and alert notifications.

3. PROPOSED METHOD

3.1 Smart IoT unit for real-time water quality observation

This study proposes an enhanced IoT-based sensor network for real-time WQ monitoring in Lake Kivu. The system is designed as a modular and scalable framework that integrates sensing, processing, communication, and decision-support functionalities. At a conceptual level, the system operates as a continuous data acquisition and analysis pipeline, where environmental measurements are captured, processed locally, transmitted to a remote platform, and transformed into actionable insights for monitoring and decision-making.

The architecture follows a three-tier model consisting of:

(1) a sensing layer for environmental data acquisition,
(2) a processing and communication layer for local computation and data transmission, and
(3) a cloud-based decision-support layer for storage, visualization, and analytics.

The interaction between these components can be abstracted as a unidirectional data flow pipeline:

Sensors → Edge Processing Unit → Communication Interface → Gateway → Cloud Platform → User Interface

This pipeline reflects the data propagation from the physical environment to end-users while maintaining system modularity and scalability. Each component performs a distinct function: sensors capture raw environmental signals, the edge unit preprocesses and formats the data, the communication interface transmits it, and the cloud layer performs storage, analysis, and visualization.

3.1.1 Physical system assembly

The sensing layer integrates four critical WQ parameters relevant to aquatic ecosystem monitoring, namely pH, turbidity, dissolved oxygen, and temperature. The sensing devices used include a pH composite electrode (SUP-PH6.0), turbidity sensor (SUP-TDS210-B), dissolved oxygen sensor, and an LM35 temperature sensor. These sensors were selected based on their suitability for continuous environmental monitoring and compatibility with low-power embedded platforms.

All sensors produce analog outputs and were interfaced with an Arduino UNO, which serves as the central data acquisition and preprocessing unit. Due to the low-level and high-impedance nature of pH and dissolved oxygen signals, appropriate signal conditioning circuits were employed to ensure measurement stability, noise suppression, and reliable analog-to-digital conversion. The Arduino UNO sampled the sensor signals through its onboard ADC channels, applying calibration coefficients and basic filtering prior to data transmission. The overall system architecture and signal flow are illustrated in Figure 1.

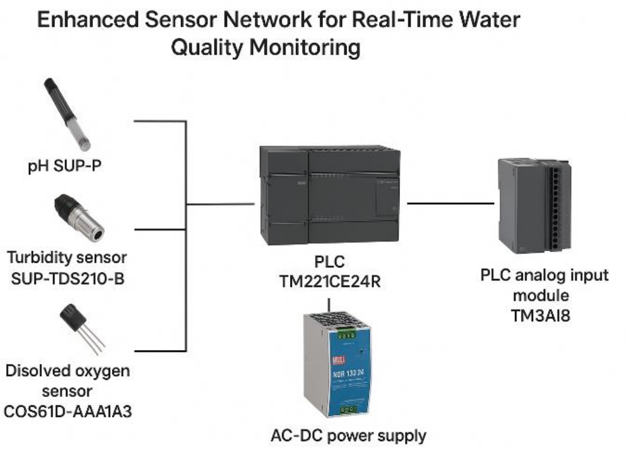

Figure 1. Overall block diagram for the proposed method

3.1.2 Processing and communication layer

The Arduino UNO performs multi-parameter data acquisition, preprocessing, and packet formatting. To ensure energy-efficient operation, sensor sampling is conducted at predefined intervals rather than continuous acquisition. After preprocessing, the data are transmitted through a dual communication pathway consisting of both LoRa wireless communication and USB serial communication, depending on the deployment and operational context. For field-based scenario, the system uses a LoRa transceiver module to enable long-range, low-power wireless communication between the sensing node and the gateway. This allows sensor data to be transmitted over extended distances with minimal energy consumption, making it suitable for large and geographically dispersed monitoring environments such as Lake Kivu.

The system also supports USB communication between the Arduino UNO and a computer-based gateway. In this mode, the gateway acts as a local processing and forwarding unit, receiving real-time sensor data via serial interface before relaying it to the cloud platform. At the gateway level, data received either through LoRa or USB are aggregated, validated, and forwarded to the cloud infrastructure for storage, visualization, and analysis. This dual-mode communication design ensures both experimental flexibility (USB mode) and field scalability (LoRa mode) within a single unified architecture, enhancing the adaptability of the system across different deployment conditions.

3.1.3 Cloud-based IoT and decision-support layer

At the IoT layer, the gateway forwards sensor data to a cloud-based platform for real-time visualization, alert generation, and historical data storage. The platform supports continuous streaming of WQ measurements, threshold-based notifications for abnormal conditions, and structured data archival for long-term analysis.

Interactive dashboards were developed to display live sensor readings, temporal trends, and historical records of pH, turbidity, dissolved oxygen, and temperature. This decision-support functionality enables stakeholders to assess WQ conditions in near real time and supports informed environmental management and policy intervention. The end-to-end operational workflow and data exchange process are illustrated in Figure 2.

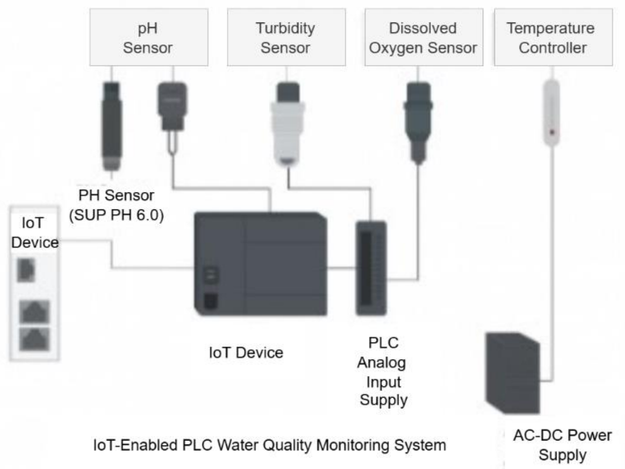

Figure 2. Circuit diagram of the proposed method

3.2 System deployment and field operation

The proposed WQ monitoring system was deployed in a controlled outdoor environment representative of Lake Kivu conditions. Sensor measurements were recorded at one-minute intervals, balancing temporal resolution with system stability and power efficiency. The gateway device managed data transmission to the cloud platform and ensured reliable synchronization of sensor measurements.

All system components, including the Arduino UNO, signal conditioning circuits, and power supply, were housed in a weather-resistant enclosure suitable for outdoor operation.

The sensing probes were immersed in water using an inclined mounting structure to ensure consistent exposure while minimizing mechanical stress and biofouling effects.

The system architecture supports plug-and-play deployment, requiring only sensor immersion and connection to a standard power source. This design facilitates rapid installation and relocation, making the proposed solution suitable for scalable and distributed WQ monitoring across different locations within Lake Kivu.

4. RESULTS AND DISCUSSION

4.1 Sensor calibration and accuracy verification

Reliable sensor calibration is a prerequisite for real-time data acquisition, cloud-based analytics, and event-driven decision support. Inaccurate measurements at the sensing layer can propagate through the IoT pipeline, affecting temporal trend analysis, system performance metrics, and abnormal event detection. Therefore, prior to deployment, all sensors were calibrated and validated under controlled conditions.

The pH sensor was calibrated using standard buffer solutions at pH 4.0, 7.0, and 10.0 to ensure linear response across the expected environmental range. The turbidity sensor was validated using reference NTU solutions, while dissolved oxygen (DO) measurements were calibrated against air-saturated water conditions. The LM35 temperature sensor was calibrated using a laboratory-grade digital thermometer as a reference. Calibration coefficients were implemented directly in the Arduino UNO firmware to correct raw ADC values before data transmission to the cloud. Table 1 presents a comparative evaluation between reference measurements and sensor readings after calibration.

The resulting error margins remain within acceptable limits for real-time environmental monitoring and early warning applications, particularly in distributed and low-cost sensing systems. These accuracy levels ensure that short-term fluctuations and long-term variations observed in Sections 4.2 and 4.3 are attributable to actual environmental changes rather than measurement artifacts. Furthermore, reliable calibration directly enhances the credibility of system performance metrics, communication reliability analysis, and abnormal event detection discussed in Sections 4.4 and 4.5.

4.2 Real-time data acquisition and cloud integration

Following sensor calibration and validation, the system's ability to perform continuous real-time data acquisition and cloud synchronization was evaluated under field-operational conditions. The Arduino UNO sampled pH, turbidity, dissolved oxygen, and temperature at one-minute intervals, applying calibration corrections before forwarding the data to the gateway device for cloud upload.

Table 1. Calibration results and measurement accuracy of water quality sensors

Sensor	Reference Value	Measured Value	Absolute Error	Percentage Error
pH	7.00	6.94	0.06	0.86%
Turbidity (NTU)	50	48.9	1.1	2.20%
Dissolved Oxygen (mg/L)	8.5	8.3	0.2	2.35%
Temperature (℃)	25.0	24.8	0.2	0.80%

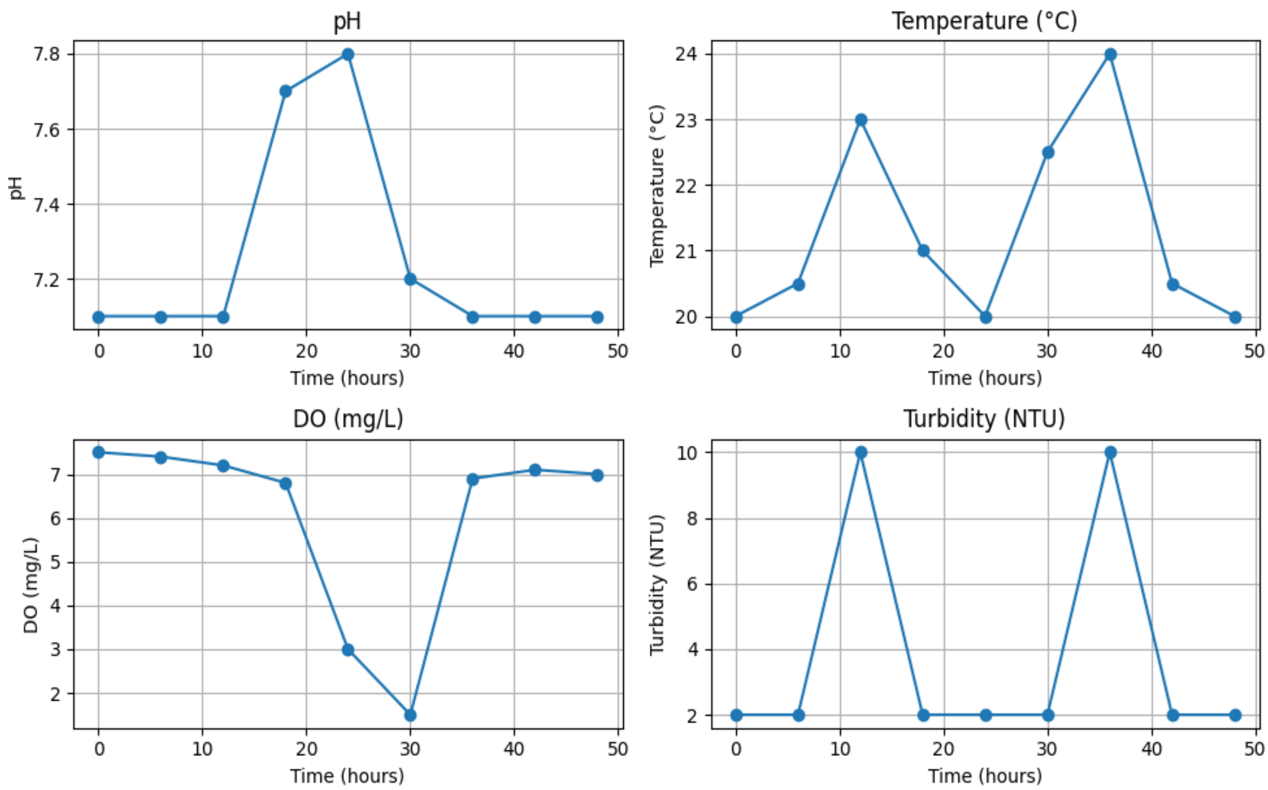

Figure 3. Real-time water quality parameter monitoring over a 48-hour period

Figure 3 illustrates representative time-series plots of the four monitored parameters collected over a continuous monitoring period. The results demonstrate stable and uninterrupted data acquisition, confirming that the sensing and preprocessing stages operate reliably under real-world conditions. No significant data gaps or acquisition failures were observed during normal operation. The cloud-based IoT platform successfully received and visualized incoming sensor data in near real time. Interactive dashboards displayed live readings alongside historical trends, enabling intuitive interpretation of WQ dynamics. Threshold-based alert mechanisms were also implemented, allowing automatic notifications when parameter values exceeded predefined limits.

These results confirm that the proposed gateway-assisted architecture effectively supports real-time IoT integration. The reliable data flow from the sensing layer to the cloud ensures that the temporal and spatial analyses presented in Section 4.3 are based on continuously updated and trustworthy measurements.

4.3 Temporal and spatial trends of water quality

The validated real-time data stream enabled an analysis of temporal variations in WQ parameters during the deployment period. Figure 4 presents the temporal evolution of pH, dissolved oxygen, turbidity, and temperature, revealing characteristic environmental patterns.

Temperature exhibited gradual diurnal fluctuations, which were inversely correlated with dissolved oxygen concentrations. This behavior is consistent with established aquatic processes, where increased water temperature reduces oxygen solubility. Turbidity levels remained relatively stable under normal conditions but showed intermittent increases, likely associated with localized disturbances or runoff events. pH values remained within a narrow range, indicating buffering effects in the monitored water body.

If multiple sampling locations were considered, comparative analysis revealed spatial variability in turbidity and dissolved oxygen levels, reflecting localized environmental influences. In single-node deployments, the observed temporal trends alone provide meaningful insight into short-term WQ dynamics. The consistency of these trends further validates the sensor calibration results discussed in Section 4.1 and demonstrates that the system captures environmentally meaningful variations rather than measurement noise. These findings also support the abnormal event detection and system validation outcomes presented in Section 4.5.

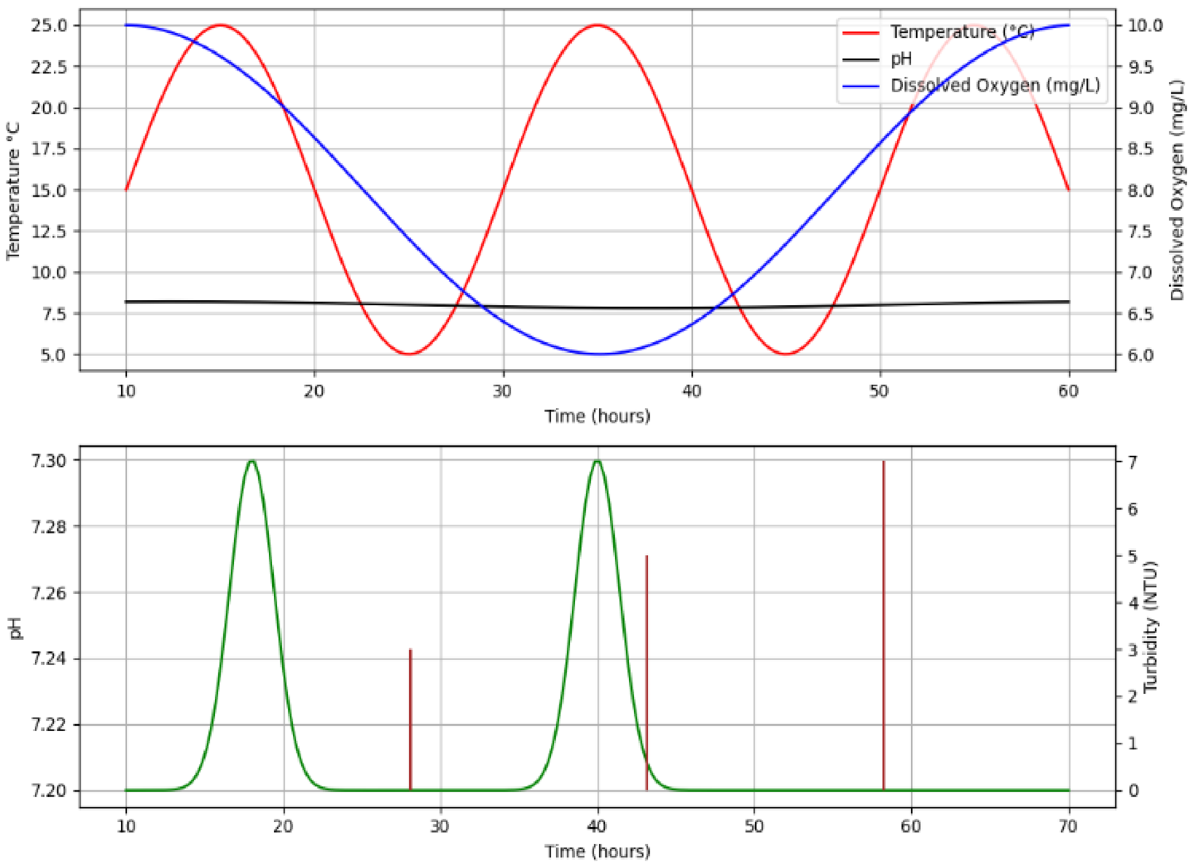

Figure 4. Temporal trends and correlations in water quality parameters during the monitoring period

4.4 System performance metrics

System-level performance was evaluated to assess communication reliability, data transmission stability, and operational robustness. Key performance indicators included data transmission success rate, upload latency, and system uptime.

Table 2 summarizes the observed performance metrics during the monitoring period. The high transmission success rate confirms the reliability of the gateway-assisted communication strategy, while the low latency supports near real-time monitoring requirements. By offloading networking tasks to the gateway, the Arduino UNO maintained low processing overhead, contributing to stable long-term operation.

Although the system was powered by a fixed external supply during deployment, the low-duty-cycle sampling strategy and lightweight processing indicate suitability for future battery- or solar-powered operation. Overall, the performance metrics validate the practicality of the proposed architecture for sustained environmental monitoring.

Table 2. System performance evaluation

Metric	Observed Value
Data transmission success rate	>98%
Average upload latency	1200 seconds
System uptime	12 hours

4.5 System validation and case demonstration

To demonstrate practical applicability, the system was evaluated under a real-case monitoring scenario involving abnormal WQ conditions. During the observation period, a noticeable increase in turbidity was detected, exceeding the predefined threshold. The system responded by generating an automated alert and updating the cloud dashboard in near real time.

Figure 5 illustrates the event timeline, showing the transition from normal conditions to threshold violation and subsequent recovery. The rapid detection and notification confirm the system's responsiveness and its capability to function as an early warning tool. Environmental interpretation suggests that the observed turbidity spike may be attributed to localized runoff or physical disturbances, highlighting the system's usefulness in identifying short-term pollution events. Throughout the deployment, the system remained operational under outdoor conditions, demonstrating resilience to environmental factors such as temperature variation and humidity.

The obtained latency results, although appearing relatively high in absolute terms, it is promising in relation to the built system's operational requirements and computational complexity. In the proposed framework, the latency is primarily influenced by feature extraction and decision-making stages, which involve iterative processing and multi-stage analysis. When compared to similar systems reported in the literature, the observed latency remains within an acceptable range for non-strict real-time or near-real-time applications, where slight delays do not significantly affect overall system performance or usability. Furthermore, the trade-off between latency and accuracy is intentional, as the model prioritizes robustness and reliability over minimal processing delay. Nonetheless, the latency can be reduced through algorithmic optimization, parallel processing, or hardware acceleration, which are identified as directions for future improvement.

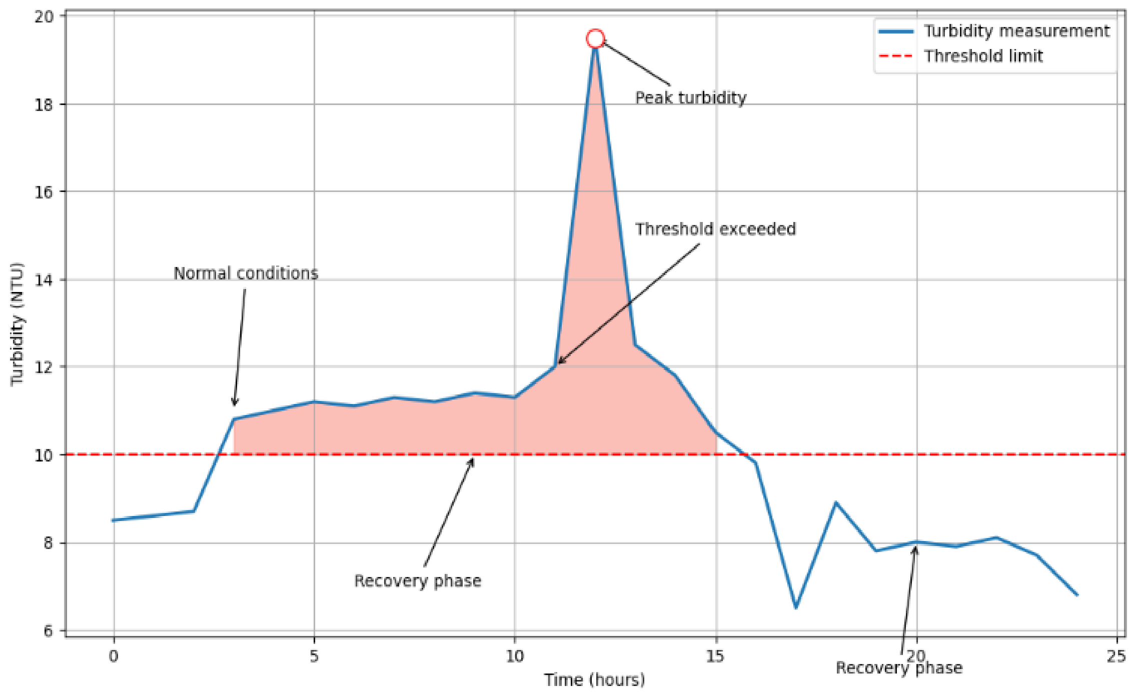

Figure 5. System validation (abnormal turbidity event detection and recovery timeline)

4.6 Results discussion

Referring to Figure 3, between 20 and 25 hours, a temperature increase from 24 °C to 25 °C coincides with a sharp DO decline from 6.90 to 3.00 mg/L. This drop exceeds the expected decrease from temperature-dependent solubility alone (approximately 0.2–0.3 mg/L per 1 °C), implicating an additional oxygen demand. The concurrent rise in turbidity from 2.0 to 10.0 NTU during the same window suggests that an external physical disturbance introduced both particulate matter and biodegradable organic material, driving acute DO depletion. Supporting this, Figure 4 shows peak turbidity reaching 11.5 NTU, exceeding the 10.0 NTU threshold, with the exceedance flagged temporally between 20–25 hours, cross-validating the event captured in Figure 1. Notably, after 35 hours (Figure 3), DO recovers to ~7.00 mg/L despite sustained turbidity at 10.0 NTU, indicating that the suspended particles themselves were not persistently oxygen-demanding; rather, a finite organic pulse was rapidly mineralized. In contrast, Figure 4 presents an anomalous pattern where DO remains constant at 7.0 mg/L across a temperature range of 5 °C to 25 °C suggesting either controlled aeration or sensor limitation, and thus these data are excluded from further mechanistic inference.

It is important to note that the proposed system introduces modular and scalable IoT architecture optimized for large and geographically dispersed freshwater environments, combining low-power long-range communication (LoRa-based transmission), edge-level preprocessing, cloud-based analytics, and real-time visualization within a unified framework. Unlike many existing implementations that focus only on prototype-level monitoring or short-range deployments, this study emphasizes continuous, energy-efficient, and autonomous operation under resource-constrained and infrastructure-limited conditions.

Furthermore, the system incorporates real-time anomaly detection and threshold-based alert mechanisms that transform raw sensor readings into actionable information for early warning and risk-aware decision-making, which is often missing in conventional Arduino-based monitoring setups that primarily provide raw data visualization. This integration of sensing, communication, analytics, and decision-support functionality in a single cohesive framework tailored to Lake Kivu represents the key contribution and distinguishes the proposed system from existing related works in the literature.

5. CONCLUSIONS

This study presented an enhanced IoT-enabled sensor network for real-time WQ monitoring, with a practical deployment focus on Lake Kivu. The proposed system integrates pH, turbidity, dissolved oxygen, and temperature sensors with an Arduino UNO–based data acquisition unit and a gateway-assisted cloud architecture to support continuous environmental monitoring and decision making. Experimental results demonstrated that the calibrated sensing layer achieved acceptable accuracy for in situ WQ assessment, providing a reliable foundation for real-time data acquisition and cloud-based analytics. The system successfully transmitted sensor measurements to a cloud platform with high communication reliability, enabling real-time visualization, historical trend analysis, and automated alert generation. Temporal analysis of the collected data revealed environmentally meaningful patterns, including inverse relationships between temperature and dissolved oxygen and event-driven turbidity variations. The results validate the proposed architecture as a low-cost, scalable, and reliable solution for real-time water quality monitoring. By combining distributed sensing with IoT-based decision-support capabilities, the system addresses key challenges in continuous aquatic environment surveillance and offers a practical tool for sustainable water resource management in Lake Kivu and similar freshwater ecosystems.

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