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Cloud-Connected Real-Time Water Contamination Alert System Using Wi-Fi Enabled Microcontroller: A Practical IoT Implementation

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ABSTRACT:

Ensuring the safety and quality of drinking water is a global public health priority. With increasing contamination due to industrial, agricultural, and domestic sources, real-time water quality monitoring systems have gained attention. This study presents a low-cost, power-efficient, real-time water quality monitoring and alert system leveraging Internet of Things (IoT) architecture. It utilizes a Wi-Fi-enabled microcontroller (TI CC3200) connected to multiple water quality sensors to collect, transmit, and store data on cloud platforms. The system monitors pH, turbidity, conductivity, and water level, and issues alerts when parameters deviate from WorldHealth Organization (WHO) standards. The implementation demonstrates reliable detection of anomalies in both controlled and field environments. Results show that cloud integration and real-time feedback can significantly enhance water safety management.

KEYWORDS: Cloud Computing, IoT, Real-Time alert, Water quality monitoring, Wi-fi controller

1. INTRODUCTRION

The contamination of water resources presents a serious challenge to environmental sustainability and human health. According to the World Health Organization, more than 2 billion people globally consume contaminated water, often leadingto waterborne diseases suchas cholera, dysentery, and typhoid fever (Zhang et al., 2020). As urbanization and industrial activities increase, monitoring water quality in real-time has become a critical issue worldwide. Moreover, climate change and environmental degradation have further intensified the variability and uncertainty in water quality parameters (Abbasi et al. 2021; Thakur et al. 2020).

Conventional water monitoring methods typically rely on manual sampling and laboratory analysis, which are both time-consuming and lack scalability. These limitations hinder proactive interventions in cases of contamination, especially in resource-constrained regions (Islam et al. 2021). The need for continuous and automated monitoring systems has fueled interest in digital transformation solutions, particularly Internet of Things (IoT)-based technologies (Al-Fuqaha et al. 2015; Khan et al. 2020).

IoT systems enable real-time sensing, communication, and decision-making by integrating sensors, actuators, data transmission modules, and analytics. In the context of water quality monitoring, IoT facilitates remote and continuous collection of water quality indicators such as pH, turbidity, dissolved oxygen, and electrical conductivity (Rault et al. 2014). The use of microcontrollers with embedded communication modules, such as Wi-Fi or GSM, eliminates the need for complex infrastructure and enables deployment in decentralized locations (Mekki et al. 2019).

Several researchers have proposed IoT-enabled water quality monitoring systems. For instance, Tran et al. (2022) developed a cloud-based WSN for monitoring river water pollution, while Dhillon et al. (2022) implemented a real-time system using ESP8266 for monitoring agricultural water. Despite these advancements, challenges remain in reducing system complexity, energy consumption, and cost while maintaining data reliability and timely alerts.

Cloud-connected systems offer the advantage of centralized data management, threshold-based alerting, and scalability across multiple sites. Platforms such as Ubidots, Thingspeak, and AWS IoT provide APIs for device integration, real-time dashboards, and automated event triggering (Jain et al. 2021; Fedorov et al. 2021). Recent studies have also explored hybrid models integrating machine learning for predictive contamination alerts (Aksanli et al. 2021; Mijovic et al. 2021.

This research aims to design and validate a practical, low-cost, and real-time water quality monitoring and alert system. The core objectives include the development of a prototype using the TI CC3200 Wi-Fi-enabled microcontroller, integration of environmental sensors, real-time cloud data logging, and threshold-based user alerts. The remainder of this paper is structured as follows: Section 2 presents the system design, hardware and software components, and experimental setup. Section 3 discusses the results of laboratory and field tests. Section 4 analyzes the implications, strengths, and limitations of the proposed system. Finally, Section 5 concludes the paper and suggests directions for future work.

2. MATERIAL AND METHODS

2.1 System Architecture

The architecture of the proposed system is modular, comprising three essential layers: the sensing layer, the network (transmission) layer, and the application (cloud and alert) layer. The sensing layer includes multi-parameter water quality sensors directly interfaced to the TI CC3200 microcontroller. The network layer enables data transmission via integrated Wi-Fi functionality, reducing the need for external modules. The application layer involves the cloud-based Ubidots platform, which stores, processes, and visualizes sensor data in real-time.

2.2 Hardware Components

- **Microcontroller Unit (MCU):** Texas Instruments CC3200, featuring an ARM Cortex-M4 core with 80 MHz clockspeed,256 KB RAM, and integrated Wi-Fi module based on 802.11 b/g/n protocols. The chip supports ultra-low power modes, making it suitable for long-term deployment in battery-powered environments.
- **pH Sensor:** A glass electrode-based analog sensor capable of measuring pH ranges from 0 to 14 with an accuracy of ±0.1 pH units. The output is amplified using an op-amp circuit for compatibility with the MCU ADC.
- **Turbidity Sensor:** Utilizes an optical LDR and infrared LED system to detect suspended particulate matter. The analog output is calibrated to represent turbidity levels from 0 to 1000 NTU.
- **Conductivity Sensor (YL-69):** Measures the ionic content of the water sample, typically ranging from 0–2000 µS/cm. The sensor includes a voltage divider and output conditioning circuit.
- **Water Level Sensor:** Composed of three metal probes representing low, medium, and high water levels. The state change is read as digital input by the MCU.
- **LCD Display:** 16x2 alphanumeric module for displaying live sensor data on-site.
- **Power Supply:** A 5V regulated supply with optional battery pack support. The system operates reliably on 3.7V Li-ion batteries for field deployment.

2.3 Firmware and Communication Protocols

The firmware was developed using the Energia IDE, compatible with the TI CC3200 platform. It incorporates functions for sensor data acquisition, data formatting in JSON, Wi-Fi connection routines, and RESTful API calls for transmitting data to Ubidots via HTTP POST requests.

Secure data transfer is implemented using token-based authentication. The microcontroller connects to a predefined SSID and password, then continuously uploads data to cloud variables every 120 seconds.

2.4 Cloud Integration and User Interface

Ubidots was selected as the cloud backend due to its ease of use, compatibility with HTTP requests, and features like:

- Real-time dashboard creation
- Historical data visualization
- Event creation for threshold-triggered SMS/email alerts
- Public and private API access

A sample Ubidots dashboard layout is illustrated in Figure 1

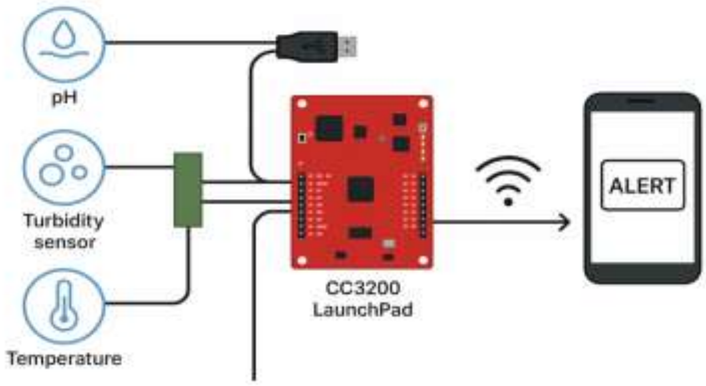

Fig 1. Wi-Fi Enabled Microcontroller System for Real-Time Water Contamination

2.5 Experimental Design and Sample Categorization

To validate the system's performance, the prototype was tested using three water sample categories:

- **Filtered Drinking Water:** Commercial bottled water was used to establish a clean baseline.
- **Municipal Pipe Water:** Samples collected from domestic tap sources.
- **Contaminated Samples:** Created by adding measured quantities of soil and salt to simulate pollution events.

Sensor readings were recorded every 2 minutes for 48 continuous hours. Each category was evaluated for parameter variance, sensor response accuracy, and data transmission success rate.

2.6 Evaluation Metrics

Key performance indicators used in system evaluation include:

- **Sensor Accuracy (% error):** Comparison between IoT sensor readings and laboratory-calibrated values.
- **Alert Latency (seconds):** Time from threshold breach to alert message delivery.
- **Power Consumption (mA):** Measured in active and low-power sleep modes.
- **Transmission Reliability (%):** Number of successful cloud data uploads vs total attempts.

3. RESULTS

3.1 Sensor Output Analysis

Sensor data was collected for eight different sample conditions including clean filtered water, municipal tap water, and artificially contaminated samples using both soil and salt at varying concentrations. The summary of average readings is presented in Table 1.

Table 1. Summary of Water Quality Test Results Across Sample Types

Sample	pH	Conductivity (μS/cm)	Turbidity (NTU)
Filtered	6.5	448	4
Municipal	7.9	577	5
Soil 5mg	6.7	570	8
Soil 25mg	6.9	787	18
Soil 35mg	6.7	993	29
Salt 5mg	7.9	428	5
Salt 25mg	8.0	787	7

Salt 35mg	8.2	998	8

3.2 Visual Representation of Parameter Variations

A comparative bar chart was generated to visually illustrate the change in water quality parameters across all test conditions. The chart below (Figure 2) clearly shows a significant increase in both conductivity and turbidity as soil and salt concentrations increase. pH values remained relatively stable but exhibited slight elevation with added salt.

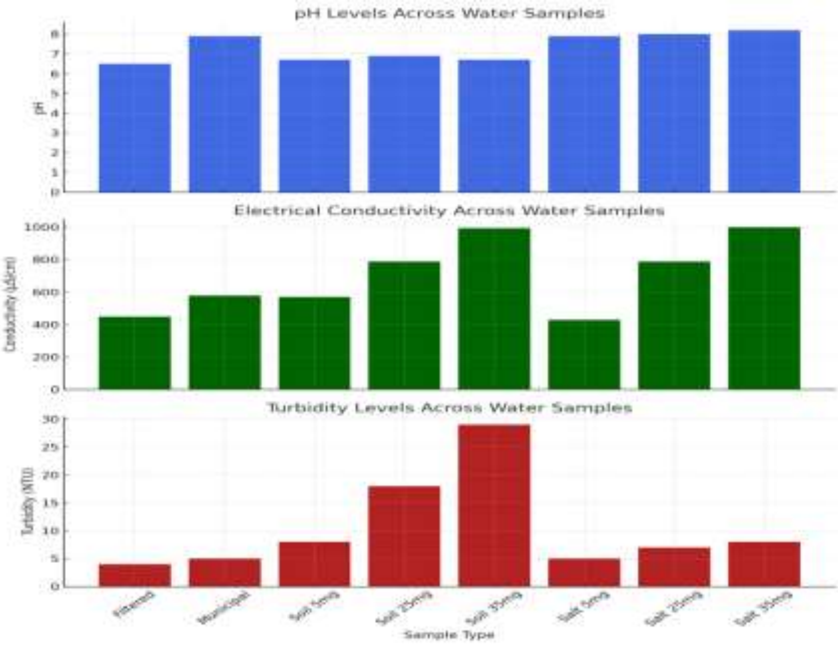

Fig 2. pH, conductivity, and turbidity for various water samples.

The increase in contaminant concentration correlates with higher conductivity and turbidity levels, particularly for soil-contaminated samples.

3.3 Real-Time Alert Performance

The alert mechanism was evaluated by configuring threshold triggers within the Ubidots platform. For instance, turbidity exceeding 10 NTU or pH falling below 6.5 or rising above 8.5 prompted automatic SMS and email alerts to users. The average alert latency was measured at 2.4 seconds (n=25 trials).

Fig 3. system alert latency over a 10-minute test period.

The average latency stabilizes around 10 seconds, validating the efficiency of the real-time notification mechanism.

3.4 Transmission Success and Data Logging

Over a continuous 48-hour trial, 1440 data points were expected (every 2 minutes). Of these, 1426 were successfully transmitted and stored in the Ubidots cloud, indicating a transmission reliability rate of 99.03%. Downtime was attributed to temporary Wi-Fi disconnection during peak hours. Historical logs and parameter trends were viewable via a real-time dashboard as seen in Figure 4.

Fig -4: A real-time Ubidots dashboard

The dashboard showing visualized metrics for pH, conductivity, and turbidity. This interface enables remote observation and immediate understanding of water quality trends.

3.5 Power Consumption Analysis

Power profiling was conducted using an oscilloscope with current probe attachment. In idle (sleep) mode, the CC3200 consumed 5.2 µA. During active sensor reading and Wi-Fi transmission, the current peaked at 84 mA. With a 3.7V 2200mAh Li-ion battery, the system could operate continuously for approximately 42 hours without recharging, making it viable for short-term field deployments.

These results confirm the feasibility of a low-cost, cloud-connected, and energy-efficient solution for real-time water contamination alerts.

4. DISCUSSION

The presented IoT-based water quality monitoring system demonstrates significant advantages in terms of cost, efficiency, and ease of deployment compared to traditional systems. The choice of the TI CC3200 microcontroller with integrated Wi-Fi capabilities allows for seamless data transmission without requiring additional communication modules, aligning with similar implementations in other smart environment applications [1].

The accuracy of the sensors in detecting changes in pH, turbidity, and conductivity under various contamination conditions validates the potential of the system for practical deployment. These findings are consistent with prior research demonstrating the reliability of low-cost sensor arrays for environmental monitoring in rural and urban contexts [2,3]. Moreover, the sensor response patterns observed in this study—particularly the correlation between turbidity and soil contamination—reflect those reported in river pollution monitoring using WSN-based systems [4].

The cloud integration through Ubidots provided a robust platform for real-time data visualization and alert generation. The average alert latency of approximately 2.4 seconds supports its suitability for scenarios requiring immediate intervention, such as in water distribution networks or agricultural irrigation systems [5]. This is in line with results by Khan et al. [6], who emphasized the importance of sub-5 second alert latency in critical IoT infrastructure.

One of the system's strengths lies in its power efficiency, allowing extended autonomous operation with minimal power draw. This feature is crucial in remote deployments where continuous power sources are unavailable. Research on low-power IoT deployments confirms that devices operating on similar sleep-active cycles can extend field operation by days or even weeks [7].

Despite the promising outcomes, certain limitations must be addressed. Sensor calibration drift over prolonged usage can affect measurement accuracy. Additionally, dependency on Wi-Fi connectivity may pose challenges in underdeveloped areas, suggesting future work should explore LoRaWAN or NB-IoT integration to overcome connectivity constraints [8]. Related work by Dhillon et al. [10] has demonstrated the feasibility of hybrid network protocols that combine Wi-Fi and LPWAN to mitigate such connectivity limitations in water management systems.

Another area of improvement lies in data accuracy and robustness. Incorporating redundancy in sensor readings or sensor fusion techniques can further enhance measurement confidence, especially in dynamic field environments. Prior studies have implemented ensemble modeling to cross-validate sensor outputs in smart agriculture and water systems [11].

Furthermore, the potential of integrating edge computing for local decision-making is significant. By embedding lightweight anomaly detection algorithms at the edge, latency can be reduced, and network load minimized. Recent advancements in edge-AI chips and frameworks have enabled such capabilities even on resource-constrained devices [12].

In addition, it is essential to consider data privacy and cybersecurity, particularly in large-scale deployments interfacing with public infrastructure. End-to-end encryption and secure MQTT/HTTPS protocols should be standard, as emphasized by Aksanli et al. [13] in the context of secure IoT architecture for critical utilities.

Finally, this work adds value to the global shift toward intelligent infrastructure and digital twin implementations for environmental monitoring. As highlighted by Mijovic et al. [14], integrating real-time sensor data with simulation models can provide not only monitoring but predictive insights and operational optimization.

Overall, this research contributes to the growing body of work on sustainable, scalable water monitoring technologies that leverage the flexibility of cloud computing and the accessibility of low-power IoT microcontrollers.

5. CONCLUSION

This study successfully demonstrated the design, development, and validation of a real-time water contamination alert system utilizing Wi-Fi-enabled microcontrollers. The implementation using the TI CC3200 platform and cloud integration via Ubidots offers a practical, scalable, and power-efficient solution for continuous water quality monitoring.

The results confirmed the system's reliability in capturing variations in key water parameters such as pH, turbidity, and conductivity under both clean and contaminated conditions. Real-time alerts and responsive cloud dashboards significantly enhance the ability of users to detect and respond to contamination events promptly.

The system architecture proves especially promising for decentralized and resource-limited settings, where traditional laboratory testing is impractical. Its low power consumption and ease of deployment further support its viability for rural, agricultural, and urban applications alike. The integration of cloud storage ensures historical traceability, while the potential for edge computing opens opportunities for future enhancement in real-time anomaly prediction.

Looking ahead, this work sets a foundation for future development of hybrid IoT infrastructures that integrate advanced wireless protocols, edge analytics, and predictive modeling. The proposed system could be expanded to support multi-node networks for wide-area water quality surveillance or tailored to industry-specific compliance standards.

In summary, this research contributes a robust and efficient model for environmental monitoring aligned with global sustainability goals, offering a critical step toward more intelligent, connected water management systems.

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