IoT-Based Anomaly Detection for Identifying Point Sources of Water Pollution

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Abstract

This research aims to address the pressing need for improving water quality, particularly in water-stressed areas affecting a quarter of the global population. Existing water quality monitoring solutions are often expensive and inaccessible. We propose an innovative approach integrating low-cost, self-made sensors with prediction models, simulations, and satellite or webcam imagery to detect, identify, and localize pollution sources. While previous methods have shown promise, they often remain at the prototype stage without scaling up to comprehensive detection grids. Our proposed system includes a warning system to alert stakeholders and citizens of potential water threats, along with mitigation strategies. Integrating data into a centralized visualization and warning application will aid in combating pollution and safeguarding water bodies and treatment systems.

Keywords

IoT, water quality monitoring, anomaly detection, water pollution, prediction models, sensors

1. Motivation

In 2010 [1], the UN affirmed the human right to water and sanitation, ensuring access to safe, affordable water for personal and domestic use. This is supported by the Agenda 2030, which focuses on 17 sustainable development goals (SDGs) [2]. Despite these efforts, a 2021 WHO report highlights that around 2 billion people lack clean drinking water or proper sanitation [3]. Disparities in wastewater treatment contribute to water-borne diseases, causing approximately 1 million preventable deaths annually due to diarrhea alone. The goal of this research is to develop a system supporting SDGs, especially Goal 3: Good Health and Well-Being and Goal 6: Clean Water and Sanitation [2]. We aim to prevent water-borne diseases and improve water quality through a combined monitoring and warning system, implementing management and sanitation strategies in a timely manner.

2. Methodology

2.1. First Prototype

The initial prototype comprises readily available parts compatible with the Arduino platform. Its sensor suite measures temperature, pH, total dissolved solids (TDS), electrical conductivity (EC),

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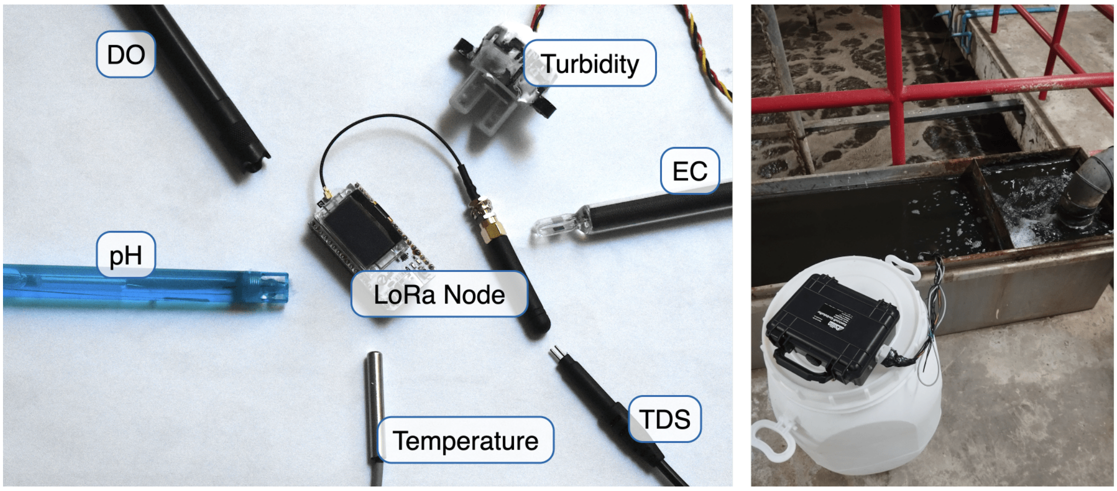

Figure 1: Left: Sensor suite and LoRa node; Right: Node at the testing site in the WWTP at the Hospital for Tropical Medicine, Bangkok, Thailand (2024 © Julia Steiwer).

dissolved oxygen (DO), and turbidity, providing insights into water quality (Fig. 1). For instance, stable temperature and pH alongside a significant decrease in DO with a simultaneous rise in EC and turbidity may indicate the presence of nutrient-rich liquid manure, potentially harmful to the environment. To evaluate its impact, additional sensors for measuring ammonia, nitrate, nitrite, and oxygen demand are necessary. However, for general water quality assessment, such as for drinking or irrigation, the current sensor suite suffices.

The data collected is transmitted via the LoRaWAN protocol for its low power consumption and extended transmission ranges, suitable for urban and rural areas. These data packets are sent to TheThingsNetwork, using a webhook to present real-time data on ThingSpeak both visually and numerically. To ensure remote usability, particularly in rural areas, minimizing node battery usage is crucial. Currently, two methods are employed to extend system lifespan when operating on battery power. Firstly, the entire system enters deep sleep mode when inactive, achieved by utilizing a voltage converter with an internal MOSFET to reduce deep sleep energy consumption to around 20 μA. Secondly, a solar panel, connected to a Sunny Buddy solar voltage controller, serves as an energy harvesting solution, powering the development board and sensors while also recharging the battery, significantly increasing system longevity.

2.2. Planned Developments

Expanding the sensor suite is necessary to detect and localize pollution events, as well as classify pollutants. However, commercial sensors for detecting pollutants like chemical oxygen demand, ammonia, or *E. coli.* are often costly. To make monitoring affordable, low-cost sensors or self-made solutions are essential. For instance, [4] utilized a color sensor to detect Coliform bacteria based on their Gram-staining properties, providing results after a 24-hour setting time, while [5] employed an immunoagglutination-based detection protocol for bacteria, yielding results within 10 minutes. [6] detected trace metals using modified IDE-type microwave sensors. Our project will integrate a microbial fuel cell from [7] for microbe detection and potential power harvesting. To establish a comprehensive sensor grid for monitoring water quality in bodies of water and wastewater treatment plants, we will integrate sensors for environmental and meteorological factors, including rainfall, temperature, solar irradiance, and flow measurement, to adapt sampling rates accordingly.

For parameters without direct sensor measurements or affordable sensors, prediction models and simulations are valuable. These models can predict factors like bacterial presence based on laboratory analysis and real-time environmental data. They can also be integrated into anomaly detection systems to alert stakeholders of critical thresholds being crossed. For instance, [8] predicted schistosomiasis based on temperature, pH, and solar irradiance, while [9] developed a model using historic and real-time sensor data to predict Coliform bacteria presence and calculate the water quality index (WQI). [10] utilized an Elman neural network (ENN) to predict flocculant dosage in drinking water purification using DO, OC, pH, temperature, and turbidity measurements. Combining detection models with sensors can address illegal waste discharge, as demonstrated in [11], while [12] showed that pH and EC measurements alone can detect pollutants like sulfuric acid (H_2SO_4) and sodium hydroxide (NaOH); we aim to develop a system capable of real-time pollution detection, identification, and localization using similar methods.

To enhance our understanding of surface parameters at a high spatial resolution, we plan to incorporate satellite imagery and webcams into our system. Satellite images, although sometimes challenging to obtain, provide valuable data on surface temperature and large-scale phenomena like harmful algal blooms (HABs) or oil spills. Conversely, webcams offer a more limited spatial coverage but are a cost-effective alternative with higher data availability and temporal resolution, providing valuable insights at monitoring stations.

Finally, our goal is to establish a warning system capable of alerting stakeholders and citizens to potential water threats such as bacterial contamination or HABs, along with providing mitigation and prevention strategies. This system will feature graphs displaying parameter trends over time, real-time and averaged values, Water Quality Index (WQI), monitoring site locations, detected point sources, and event notifications. To handle large data volumes from various sources reliably, we intend to transition from LoRaWAN with TTN to MQTT.

3. Relevance and Novelty

Given that a quarter of the global population resides in water-stressed areas lacking clean water and adequate wastewater treatment, improving water quality is imperative for human and environmental well-being. Existing water quality monitoring solutions are often costly and inaccessible to those most affected by pollution. Our approach, integrating low-cost, selfmade sensors with prediction models, simulations, and satellite or webcam imagery, offers a novel method for detecting, identifying, and localizing pollution sources. While some previous methods have shown promise, most remain at the prototype stage without scaling up to comprehensive detection grids, essential for understanding pollution events. Integrating our data into a centralized visualization and warning application would aid in combating pollution and preventing its spread in water bodies and treatment systems.

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