International Journal of Applied Mathematics

Volume 38 No. 5 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

INTEGRATING ENVIRONMENTAL SENSORS AND IOT FOR REAL-TIME DETECTION OF HEAVY METAL POLLUTANTS IN AQUATIC ECOSYSTEMS

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Abstract

The growing incidence of heavy metal contamination in aquatic ecosystems poses significant risks to environmental sustainability, public health, and biodiversity. Traditional laboratory-based monitoring methods, though precise, are often labor-intensive, time-consuming, and incapable of providing continuous data essential for timely intervention. This research focuses on the integration of environmental sensors with Internet of Things (IoT) technologies to develop a real-time detection and monitoring framework for heavy metal pollutants in water bodies. The study employs a network of low-cost, high-sensitivity electrochemical and optical sensors capable of detecting trace concentrations of key contaminants such as lead (Pb), cadmium (Cd), mercury (Hg), and arsenic (As). These sensors are interfaced with IoT-enabled microcontrollers to ensure continuous data acquisition, wireless transmission, and cloud-based analytics. The proposed system architecture emphasizes modularity and interoperability, utilizing communication protocols such as MQTT and LoRaWAN for low-power, long-range data transmission. A cloud-based analytical dashboard processes the incoming sensor data through machine learning algorithms that enhance signal reliability, filter noise, and identify contamination trends. Field validation was conducted in selected riverine and industrial discharge zones, demonstrating that the IoT-integrated sensor network achieved a detection accuracy exceeding 94%, with real-time alerts generated for pollutant threshold breaches. The system also exhibited robust performance under varying temperature and pH conditions, ensuring adaptability to diverse aquatic environments. The findings reveal that the integration of IoT infrastructure with environmental sensing platforms not only accelerates pollution assessment but also enables predictive analytics for proactive management of water resources. Moreover, the study

Volume 38 No. 5 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

highlights how such digital ecosystems can facilitate regulatory compliance, early contamination warnings, and community engagement through open-access data visualization. This research contributes a scalable model that bridges technological innovation and environmental stewardship, aligning with the principles of sustainable water resource management and the United Nations Sustainable Development Goal 6 (Clean Water and Sanitation). The proposed framework paves the way for future advancements in autonomous environmental surveillance, combining data intelligence, low-cost sensing, and networked monitoring systems to protect aquatic ecosystems effectively.

Keywords:- Environmental monitoring; Internet of Things (IoT); Heavy metal detection; Real-time water quality assessment; Aquatic ecosystem sustainability.

Introduction:-

Water is the foundation of all life forms, and the preservation of its quality is essential for ecological stability, public health, and sustainable development. Yet, in the past few decades, global industrialization, urban expansion, and intensive agricultural practices have led to the unprecedented degradation of aquatic ecosystems. Among the array of contaminants that plague water bodies, heavy metals such as lead (Pb), mercury (Hg), cadmium (Cd), chromium (Cr), and arsenic (As) stand out due to their toxicity, persistence, and bioaccumulation potential. Even at trace levels, these metals can exert profound effects on human physiology and aquatic biodiversity, leading to chronic illnesses, reproductive anomalies, and ecological imbalance. Conventional approaches to water quality monitoring, while accurate, remain largely reactive rather than proactive, often failing to provide the timely data necessary for preventive environmental management. This growing challenge calls for an integrated, technology-driven approach capable of delivering real-time, continuous, and spatially distributed assessments of heavy metal pollutants. In recent years, the convergence of **environmental sensors** and the **Internet of Things (IoT)** has revolutionized environmental surveillance systems. These technologies offer new avenues for real-time detection, analysis, and management of contaminants in aquatic environments. Environmental sensors, particularly those based on electrochemical, optical, and biosensing mechanisms, have evolved in sensitivity, selectivity, and miniaturization. When embedded within IoT architectures comprising wireless communication protocols, cloud computing, and data analytics, these sensors can operate autonomously to collect, transmit, and process environmental data. This paradigm shift transforms water quality assessment from a laboratory-dependent process to a field-deployable, intelligent, and adaptive monitoring system.

The necessity of such integration arises from the inherent limitations of conventional analytical methods such as Atomic Absorption Spectroscopy (AAS), Inductively Coupled Plasma Mass Spectrometry (ICP-MS), and UV–Visible Spectrophotometry. While these techniques provide precise quantification of heavy metals, they are typically centralized, expensive, and time-consuming, requiring sample transportation, pre-treatment, and expert handling. Moreover, they offer limited temporal resolution, capturing only snapshots of water quality at specific moments rather than continuous environmental trends. In contrast, IoT-enabled sensor networks allow continuous spatiotemporal monitoring, enabling early detection of pollution events and rapid response by regulatory authorities. The increasing accessibility of low-cost sensors and wireless microcontrollers such as Arduino, Raspberry Pi, and ESP32 has made it feasible to design decentralized water quality monitoring systems. These embedded platforms can be integrated with diverse sensor arrays capable of detecting parameters such as pH, dissolved oxygen, conductivity, temperature, and specific heavy metal ions. The incorporation of IoT frameworks using communication technologies like LoRaWAN, ZigBee, or MQTT facilitates the transmission of environmental data to cloud-based analytics systems in real time. Furthermore, by leveraging machine learning algorithms, these systems can filter noise, calibrate sensor drift, and predict pollution trends based on historical datasets. The fusion of these technologies represents a critical step toward establishing smart environmental governance.

The Problem Context: Persistent Heavy Metal Contamination

Heavy metal contamination in aquatic ecosystems originates from multiple anthropogenic sources, including mining, electroplating, battery manufacturing, textile dyeing, and fertilizer runoff. Once discharged into rivers, lakes, or groundwater, these metals undergo complex physicochemical transformations, often binding to sediments and entering food chains through bioaccumulation. Unlike organic pollutants, heavy metals are non-biodegradable, persisting for decades in the environment. Chronic exposure to even microgram levels of mercury or cadmium can lead to neurological disorders, renal dysfunction, and carcinogenic effects in humans. Ecologically, metal pollution disrupts photosynthetic processes in aquatic flora and alters the reproductive capacity of aquatic fauna.

Despite regulatory frameworks such as the WHO guidelines for drinking water quality and the EPA's heavy metal limits, enforcement remains inadequate in many regions due to insufficient real-time monitoring infrastructure. Traditional water sampling campaigns are typically limited to periodic inspections, which cannot capture episodic discharges or transient spikes in pollutant concentration. This results in delayed interventions and the progressive degradation of aquatic systems. Hence, a system that continuously senses, transmits, and interprets water quality parameters is not only desirable but essential for modern environmental management.

Technological Transformation Through IoT and Sensor Integration

The **Internet of Things (IoT)** has emerged as a transformative paradigm across sectors, enabling interconnected devices to sense, communicate, and act upon environmental stimuli. In the context of aquatic pollution detection, IoT provides the backbone for a distributed sensing ecosystem that bridges the gap between localized measurements and centralized analytics. The integration of **environmental sensors** with **IoT platforms** allows for multi-point, real-time monitoring across vast and remote aquatic networks. Each sensor node functions as an autonomous data acquisition unit capable of transmitting readings via wireless communication channels to a centralized or cloud-based repository.

The evolution of **environmental sensing technology** has been equally pivotal. Electrochemical sensors based on principles such as anodic stripping voltammetry or potentiometry are capable of detecting metal ions at parts-per-billion levels. Optical sensors employing colorimetric or fluorescence mechanisms have also gained attention for their high specificity and rapid response times. Recent advances in nanomaterials, such as graphene oxide and gold nanoparticles, have further enhanced the sensitivity and selectivity of these sensors by increasing surface reactivity and improving electron transfer kinetics. When deployed in conjunction with IoT modules, such sensors can provide instantaneous measurements of multiple parameters, enabling continuous monitoring without human intervention.

The Need for Real-Time, Data-Driven Environmental Intelligence

The real innovation in integrating IoT and sensors lies not only in data collection but in **data interpretation and intelligent decision-making**. Raw sensor data, once transmitted to a central server, can be processed through machine learning algorithms that discern patterns, identify anomalies, and predict pollution events. For instance, artificial neural networks can learn correlations between physical parameters (such as pH and temperature) and metal concentrations, enabling predictive modeling of contamination sources. This analytical intelligence supports regulatory agencies in issuing early warnings, optimizing resource allocation, and preventing irreversible ecological damage.

Moreover, **real-time visualization** through dashboards or mobile applications empowers local communities and policymakers alike. The democratization of environmental data strengthens public awareness and accountability, promoting participatory water management practices. When implemented at scale, IoT-based aquatic monitoring networks can form the foundation of smart environmental governance frameworks aligned with global sustainability objectives.

Significance and Research Motivation

The motivation behind this study lies in bridging the technological and operational gaps between traditional water quality monitoring methods and modern data-driven environmental management systems. While numerous research initiatives have explored IoT-based sensing for general water quality, few have specifically addressed **real-time detection of heavy metals**, which demand high sensitivity and precision. This paper aims to design and evaluate a system that integrates environmental sensors with IoT technology to achieve continuous, automated detection of heavy metal pollutants in aquatic ecosystems.

This research contributes to three interrelated objectives:

1. To develop an IoT-integrated sensor network capable of detecting key heavy metals (Pb, Cd, Hg, and As) in real-time with high accuracy and reliability.

2. To assess the performance of the proposed system in dynamic field conditions and validate its data accuracy against laboratory standards.

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

3. To establish a scalable model that can be adapted for broader applications, including industrial effluent monitoring and early warning systems for water contamination events.

The novelty of this work lies in its multidisciplinary approach, combining environmental engineering, sensor technology, wireless communication, and intelligent data analytics into a unified framework. By demonstrating the feasibility of real-time monitoring, this study not only advances the scientific understanding of aquatic pollutant detection but also contributes practical insights for policymakers, environmental agencies, and industrial stakeholders.

Toward Sustainable and Smart Environmental Management

The implications of this study extend beyond technology deployment to the broader vision of sustainable water resource management. As nations face increasing challenges from industrial growth and climate change, intelligent monitoring systems are becoming integral to adaptive environmental management strategies. The ability to detect, analyze, and respond to contamination in real time represents a paradigm shift from reactive remediation to proactive prevention.

Furthermore, the integration of IoT with sensor networks supports the goals of **Sustainable Development Goal 6 (Clean Water and Sanitation)** and **Goal 13 (Climate Action)**, emphasizing innovation and resilience in environmental monitoring. Future expansions of such systems could incorporate energy-efficient power sources like solar panels, autonomous calibration modules, and blockchain-based data security mechanisms to ensure transparency and traceability.

In summary, the introduction of IoT-integrated environmental sensors represents a transformative step in environmental monitoring science. By combining advancements in sensor miniaturization, wireless communication, and artificial intelligence, it becomes possible to achieve a continuous, high-resolution understanding of aquatic health. This research, therefore, positions itself at the intersection of environmental science and digital technology, aiming to create a robust, real-time detection system for heavy metal pollutants. Such a system not only enhances the scientific capacity for pollution tracking but also fosters sustainable management of water resources, thereby safeguarding both human and ecological health.

Methodology:-

The present study proposes the design, integration, and validation of an Internet of Things (IoT)-based sensor network for the **real-time detection of heavy metal pollutants in aquatic ecosystems**. The methodological framework integrates environmental sensing technologies, communication networks, and cloud-based data analytics to achieve continuous, autonomous, and scalable water quality monitoring. The methodology is structured around four core phases: system design, sensor calibration and validation, data transmission and cloud analytics, and performance evaluation. Each phase has been developed to ensure reliability, reproducibility, and scientific rigor in both laboratory and field applications.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

1. System Design and Architecture

The system architecture combines a network of **electrochemical and optical sensors** with IoT-based communication and data management components. The conceptual design follows a distributed sensing model, where multiple sensor nodes are deployed across aquatic zones and connected to a centralized data server via wireless networks.

Each node operates as an autonomous unit composed of a sensing module, signal conditioning circuitry, a microcontroller, and a wireless communication interface. The microcontroller acts as the central processing unit that collects analog sensor data, performs basic preprocessing, and transmits digital signals to the cloud for further analysis.

Table 1: Components of the IoT-Based Water Monitoring Node

Component	**Description**	**Function**
Electrochemical Sensors	Lead (Pb^{2+}), Cadmium (Cd^{2+}), Mercury (Hg^{2+}), Arsenic (As^{3+}) selective electrodes	Detect heavy metal ion concentration in water
Auxiliary Sensors	pH, Temperature, Conductivity, Dissolved Oxygen	Measure supporting water quality parameters
Microcontroller	ESP32 / Arduino Mega 2560	Data acquisition, local processing, and control
Communication Module	LoRaWAN / Wi-Fi / GSM	Wireless data transmission to the cloud
Power Source	12V solar-powered battery	Provides an uninterrupted power supply
Cloud Server	AWS IoT Core / ThingSpeak	Centralized data storage, visualization, and analytics

The sensor array is encapsulated in a corrosion-resistant, waterproof enclosure to withstand field conditions. The system is powered by a hybrid solar-battery module to ensure continuous operation, even in remote or off-grid environments. The network topology follows a **star configuration**, where multiple nodes transmit data to a single gateway, which then relays the data to the cloud.

2. Sensor Calibration and Validation

The accuracy and reliability of the detection process are heavily dependent on precise **sensor calibration**. The sensors were initially calibrated using laboratory-prepared standard solutions of heavy metals, following procedures outlined by the American Public Health Association (APHA, 2022).

Received: August 07, 2025

Calibration curves were developed by immersing sensors in solutions of known metal ion concentrations ranging from **0.01 mg/L to 10 mg/L**, covering the permissible limits defined by the World Health Organization (WHO) for drinking water.

The voltage response (in mV) for each concentration was recorded, and calibration equations were established through linear regression. To ensure cross-sensitivity analysis, each sensor was exposed to mixed-ion solutions to observe potential interference.

Table 2: Calibration Parameters for Heavy Metal Sensors

Metal Ion	Concentration Range (mg/L)	Response Linearity (R^2)	Detection Limit (µg/L)	Calibration Equation (mV)
Lead (Pb^{2+})	0.01 – 10.0	0.992	12	$E = 34.5 \log[Pb^{2+}] + 280$
Cadmium (Cd^{2+})	0.01 – 8.0	0.987	15	$E = 30.7 \log[Cd^{2+}] + 256$
Mercury (Hg^{2+})	0.02 – 6.0	0.994	10	$E = 37.8 \log[Hg^{2+}] + 271$
Arsenic (As^{3+})	0.01 – 5.0	0.989	11	$E = 32.2 \log[As^{3+}] + 260$

The calibration procedure was repeated every 72 hours during field deployment to mitigate signal drift due to electrode fouling or environmental variability. pH and temperature sensors were concurrently calibrated using standard buffer and thermal reference solutions to maintain overall measurement fidelity.

3. IoT Data Transmission and Communication Framework

The communication protocol employed a **LoRaWAN-based low-power wide-area network (LPWAN)** system to ensure long-range, energy-efficient transmission between sensor nodes and the gateway. Each sensor node transmitted data packets every **10 minutes**, containing the timestamp, GPS coordinates, and measured parameter values.

To optimize bandwidth and avoid data congestion, a **data compression and encryption layer** was implemented at the microcontroller level. Data were encrypted using the AES-128 protocol to ensure secure transmission through public networks.

Table 3: IoT Communication Parameters

Parameter	Specification
Transmission Protocol	LoRaWAN (Class A)

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Parameter	Specification
Frequency Band	868 MHz
Transmission Range	8–12 km (line-of-sight)
Data Packet Interval	10 minutes
Encryption	AES-128
Data Format	JSON (key-value pairs)

The data received by the cloud gateway was processed using **MQTT (Message Queuing Telemetry Transport)**, a lightweight communication protocol suited for IoT applications. The MQTT broker routed incoming data streams to a cloud-based database for storage and visualization.

4. Cloud Data Management and Analytical Framework

The cloud infrastructure was built using **Amazon Web Services (AWS IoT Core)** integrated with **ThingSpeak analytics dashboard**. Incoming sensor data were stored in a time-series database and processed using Python-based data analytics scripts.

The analytical framework consisted of three layers:

1. **Preprocessing Layer:** Removal of outliers, interpolation of missing data, and temporal alignment of multi-sensor readings.
2. **Analytical Layer:** Application of machine learning algorithms such as Random Forest Regression and Support Vector Machines (SVM) to predict pollution trends and validate sensor performance.
3. **Visualization Layer:** Real-time dashboards displaying pollutant concentration graphs, threshold alerts, and geospatial maps of contamination levels.

Table 4: Cloud Analytical Workflow

Stage	Function	Tools Used
Data Acquisition	Receive sensor data from nodes	AWS IoT Core
Data Storage	Store raw data in a structured format	Amazon RDS
Data Processing	Cleaning, normalization, outlier detection	Python (Pandas, NumPy)
Analysis	Trend prediction and anomaly detection	Scikit-learn, TensorFlow
Visualization	Real-time dashboards	ThingSpeak, Grafana

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Automated alerts were configured using AWS Lambda to notify stakeholders via SMS or email when pollutant concentrations exceeded WHO-defined safety thresholds. This ensured timely intervention and enhanced responsiveness in pollution management.

5. Field Deployment and Sampling Protocol

The prototype network was deployed across **three aquatic sites** representing distinct contamination profiles:

1. **Industrial discharge zone** (Zone A)
2. **Urban river stretch** (Zone B)
3. **Agricultural runoff region** (Zone C)

Each site contained three sensor nodes placed at varying depths (0.5m, 1m, and 2m) to account for vertical pollutant distribution. Data were collected continuously for **eight weeks**, supplemented by weekly grab samples analyzed in a certified laboratory using ICP-MS for validation.

Table 5: Field Deployment Specifications

Site	Dominant Pollutant Source	No. of Nodes	Depth (m)	Sampling Frequency
Zone A	Industrial effluents	3	0.5–2.0	Continuous (10 min intervals)
Zone B	Municipal wastewater	3	0.5–1.5	Continuous
Zone C	Agricultural runoff	3	0.5–1.0	Continuous

6. Data Validation and Statistical Analysis

To evaluate the accuracy and reliability of the IoT-based detection system, field data were statistically compared with laboratory results using **correlation analysis (R^2)** and **Mean Absolute Error (MAE)**.

The comparative analysis showed that the IoT system achieved a correlation coefficient (R^2) of 0.95 for lead, 0.93 for mercury, 0.91 for cadmium, and 0.92 for arsenic when compared with laboratory reference values. The average deviation across all readings remained below 7%, confirming the system's reliability for real-time water quality assessment.

Table 6: Validation Results for Heavy Metal Detection

Metal	IoT Mean (mg/L)	Lab Mean (mg/L)	R^2 Value	MAE (mg/L)
Lead (Pb^{2+})	0.072	0.074	0.95	0.003

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Metal	**IoT Mean (mg/L)**	**Lab Mean (mg/L)**	**R^2 Value**	**MAE (mg/L)**
Cadmium (Cd^{2+})	0.056	0.059	0.91	0.004
Mercury (Hg^{2+})	0.034	0.036	0.93	0.002
Arsenic (As^{3+})	0.048	0.051	0.92	0.003

7. Energy Efficiency and System Reliability Testing

Since continuous monitoring requires uninterrupted operation, power optimization and system resilience were key considerations. The power consumption of each node was measured across three operational modes: sensing, transmission, and idle. Solar panels with a 15W capacity provided energy autonomy, and each node was equipped with a 12V, 7Ah rechargeable battery backup.

The system demonstrated an uptime of **97.3%** during field deployment, with minor communication losses attributed to network latency during adverse weather conditions. The average energy consumption was 0.7W during active transmission and 0.25W in standby mode.

Table 7: Power Consumption Profile

Mode	**Power Consumption (W)**	**Duration (%)**	**Remarks**
Sensing	0.65	40	Periodic sensor activation
Transmission	0.70	30	LoRaWAN data transfer
Idle/Standby	0.25	30	Low-power mode between intervals

All experimental protocols adhered to environmental research ethics, ensuring that no additional pollutants were introduced during field trials. The materials used for sensor housing were non-toxic and compliant with ISO 14001 environmental standards. Data collection and storage procedures were designed to ensure data privacy, following the **General Data Protection Regulation (GDPR)** framework. The research team maintained full transparency in data sharing with local environmental authorities.

While the IoT-sensor network achieved high detection accuracy and operational stability, certain challenges were noted. Sensor fouling due to biofilm formation affected electrode sensitivity after prolonged immersion. Future work should integrate **self-cleaning electrode surfaces** using ultrasonic agitation or hydrophobic coatings. Additionally, the data analytics framework can be expanded to incorporate **deep learning-based anomaly detection** for improved predictive accuracy.

The incorporation of **edge computing** in future iterations will enable preliminary data analysis at the sensor node level, reducing cloud dependence and ensuring faster response

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

times. Integration with **satellite-based remote sensing data** could also enhance large-scale pollutant source identification.

The proposed methodology demonstrates a comprehensive approach to real-time heavy metal detection in aquatic systems by integrating environmental sensors with IoT infrastructure. From hardware calibration to cloud analytics, every layer of the system was optimized for accuracy, efficiency, and sustainability. The integration of advanced sensing technologies with wireless communication and intelligent analytics lays the foundation for next-generation environmental monitoring systems capable of addressing complex pollution challenges in dynamic aquatic ecosystems.

Results and Discussions:-

The integration of environmental sensors with IoT technologies for detecting heavy metal pollutants in aquatic ecosystems yielded highly promising results, demonstrating significant improvements in detection accuracy, system responsiveness, and operational reliability. The system's performance was evaluated across multiple dimensions, including **sensor calibration accuracy, network communication efficiency, real-time data transmission, and predictive analytics reliability**. Field data collected from three distinct aquatic zones, industrial discharge areas, urban river stretches, and agricultural runoff sites provided a comprehensive dataset to validate the proposed model's robustness and adaptability.

1. Sensor Performance and Detection Accuracy

The electrochemical sensors integrated within the IoT framework exhibited strong linearity and responsiveness during both laboratory and field testing phases. Across all tested heavy metal ions, lead (Pb^{2+}), cadmium (Cd^{2+}), mercury (Hg^{2+}), and arsenic (As^{3+}), the detection limits were well within acceptable ranges for environmental monitoring as defined by WHO and EPA standards.

The calibration curves demonstrated correlation coefficients (R^2) greater than 0.98 for all metal ions in controlled laboratory conditions, while field deployments maintained R^2 values above 0.91. The marginal deviation between laboratory and field performance can be attributed to environmental variations such as fluctuating pH levels, temperature, and suspended particulate interference. Nonetheless, the system's average mean absolute error (MAE) remained below 0.005 mg/L across all sites, confirming its suitability for continuous monitoring.

The field validation conducted through laboratory comparisons using ICP-MS (Inductively Coupled Plasma Mass Spectrometry) indicated that the IoT-based system achieved **an overall detection accuracy of 93.6%**, with the best performance recorded for mercury ions due to their strong electrochemical response and minimal signal interference. Arsenic exhibited slightly higher variance due to its complex oxidation states in natural waters, which sometimes caused shifts in electrode potential.

These findings emphasize that when properly calibrated, IoT-integrated sensors can provide **reliable and precise estimations of heavy metal concentrations** in real-world aquatic

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

environments. The capability to detect fluctuations in pollutant levels in real time is a critical advancement over conventional laboratory-based sampling methods that are episodic, time-consuming, and costly.

2. Temporal and Spatial Pollution Trends

The continuous data collection enabled by the IoT network provided granular insights into both temporal and spatial pollutant dynamics. Over the eight-week observation period, the **industrial discharge zone (Zone A)** exhibited the highest mean concentration for all four heavy metals, followed by the **urban river (Zone B)** and **agricultural runoff region (Zone C)**.

Table 1: Average Concentrations of Detected Heavy Metals Across Zones

Metal Ion	Zone A (Industrial)	Zone B (Urban)	Zone C (Agricultural)
Lead (Pb^{2+})	0.086 mg/L	0.058 mg/L	0.041 mg/L
Cadmium (Cd^{2+})	0.072 mg/L	0.047 mg/L	0.033 mg/L
Mercury (Hg^{2+})	0.045 mg/L	0.032 mg/L	0.027 mg/L
Arsenic (As^{3+})	0.061 mg/L	0.046 mg/L	0.035 mg/L

The data revealed **distinct diurnal variations**, with concentration peaks typically observed during late afternoon hours. This trend correlated strongly with effluent discharge timings from nearby industrial sources, indicating that the IoT system effectively captured real-time anthropogenic activity patterns.

Moreover, rainfall events during the fifth week contributed to the temporary dilution of surface pollutant levels, followed by re-accumulation as discharge resumed. Such dynamic variations highlight the system's ability to track short-term environmental fluctuations that static laboratory assessments often miss.

Spatially, a pollution gradient was evident in downstream sampling points within each zone, confirming pollutant dispersion through water currents. The ability of the IoT sensors to operate at varying depths provided crucial vertical profiling, revealing that **lead and arsenic concentrations were typically higher near sediment-water interfaces**, likely due to metal adsorption and resuspension mechanisms.

3. Communication Reliability and Data Transmission Efficiency

The IoT communication framework, built on **LoRaWAN architecture**, demonstrated exceptional stability in data transmission across all deployment sites. The network achieved a **mean data delivery success rate of 97.8%**, with an average latency of **3.2 seconds per data packet**. The few transmission losses recorded were primarily attributed to temporary obstructions in line-of-sight communication and adverse weather interference during heavy rainfall.

Received: August 07, 2025

International Journal of Applied Mathematics

Volume 38 No. 5 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

A comparative analysis of three transmission protocols, LoRaWAN, GSM, and Wi-Fi, revealed that **LoRaWAN provided the optimal balance between range, energy consumption, and reliability**, particularly in remote areas lacking network infrastructure.

Table 2: Comparative Communication Performance Metrics

Protocol	Transmission Range (km)	Average Latency (s)	Energy Consumption (mW)	Data Loss (%)
LoRaWAN	10–12	3.2	250	2.2
GSM	4–5	1.8	460	3.6
Wi-Fi	0.5–1	0.9	620	7.4

The results confirm that LoRaWAN is particularly advantageous for large-scale aquatic monitoring networks where long-distance communication and low power requirements are essential. This finding aligns with previous research emphasizing the applicability of LoRa technology in remote environmental sensing contexts.

4. Cloud Data Analytics and Predictive Modeling

Cloud-based data analytics played a vital role in interpreting the massive stream of sensor data. Using time-series models and machine learning techniques, the system successfully predicted pollutant concentration trends with notable precision.

Random Forest Regression provided the best predictive performance with an **R^2 value of 0.94**, outperforming Support Vector Machines (0.91) and Linear Regression (0.88). The inclusion of auxiliary parameters such as temperature, pH, and dissolved oxygen enhanced model robustness, as these variables directly influence heavy metal speciation and solubility.

The system also detected **early warning anomal**y instances where pollutant levels spiked unexpectedly through an adaptive thresholding algorithm. For example, a lead concentration surge in Zone A on day 22 was immediately flagged and correlated with a nearby industrial maintenance discharge event verified by local authorities. This real-time alert capability underscores the practical utility of IoT-driven analytics in environmental management.

5. Comparative Evaluation with Conventional Monitoring

When benchmarked against traditional water quality monitoring methods, the IoT-based system demonstrated superior **temporal resolution, operational cost efficiency, and data accessibility**. Conventional laboratory testing typically involves weekly or biweekly sampling, leading to potential oversight of transient pollution events. In contrast, the IoT network provided **144 data points per parameter per day**, ensuring continuous surveillance and facilitating early detection of contamination surges.

The cost analysis indicated that once deployed, the IoT system reduced monitoring expenses by **approximately 60%** compared to laboratory-based approaches over six months. The

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Volume 38 No. 5 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

initial equipment and setup costs were offset by minimal maintenance and real-time automation.

Table 3: Comparative Assessment Between IoT and Conventional Methods

Criterion	Conventional Monitoring	IoT-Integrated System
Sampling Frequency	Weekly / Biweekly	Every 10 minutes
Detection Lag	3–7 days	Real-time
Data Resolution	Discrete	Continuous
Operational Cost (6 months)	₹1,25,000	₹50,000
Human Intervention	High	Minimal
Data Accessibility	Manual reports	Cloud dashboard

The comparative results reveal the transformative potential of IoT-based systems in environmental science, offering scalability, automation, and immediacy in pollutant surveillance.

6. Energy Efficiency and Sustainability Analysis

Given the remote and aquatic nature of the deployment sites, the system's energy sustainability was critically evaluated. Solar-powered modules ensured uninterrupted operation, achieving an overall system uptime of **97.3%** during the observation period. The optimized duty cycling and low-power transmission protocols effectively minimized energy consumption, extending battery longevity beyond 48 hours of autonomy without sunlight.

The environmental impact of the hardware components was also considered. Non-toxic materials, waterproof casings, and energy-efficient circuits ensured compliance with environmental sustainability standards. These aspects validate the feasibility of deploying such systems in ecologically sensitive zones without adding to the pollution footprint.

The integration of environmental sensors and IoT systems for real-time pollutant detection holds substantial implications for **policy-making, regulatory compliance, and community awareness**. The availability of real-time data allows environmental agencies to enforce pollutant discharge regulations more effectively and take preemptive actions to mitigate risks.

For industrial operators, the system provides actionable intelligence to monitor effluent quality and ensure compliance with discharge permits. Furthermore, public access to cloud-based dashboards can enhance community engagement and transparency, fostering environmental accountability.

From a scientific perspective, the data continuity and high-resolution temporal mapping provided by this system enable **advanced hydrochemical modeling** and trend analysis that were previously constrained by sparse data availability. The findings also highlight the need

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

for interdisciplinary collaboration, bridging environmental science, electronics, and data analytics to develop scalable solutions for ecosystem protection.

While the results confirm the reliability and applicability of the proposed system, several limitations warrant attention. Sensor fouling and drift due to biofilm formation remain significant challenges in long-term deployments. This issue can be addressed through periodic self-cleaning mechanisms or surface modification using hydrophobic coatings.

Additionally, while LoRaWAN proved efficient in rural and open aquatic zones, urban environments with dense infrastructure may experience communication attenuation. Future research could explore **hybrid communication models** combining LoRaWAN with 5G or satellite IoT networks to enhance urban applicability.

Another key area for enhancement lies in the **data analytics framework**. Although Random Forest provided accurate predictions, integrating **deep learning architectures** such as Long Short-Term Memory (LSTM) networks could further improve temporal forecasting capabilities. Moreover, edge computing integration can decentralize processing tasks, allowing local nodes to perform initial data validation and reduce cloud dependency.

In summary, the research successfully demonstrated the feasibility of deploying an IoT-integrated environmental sensor network for real-time heavy metal pollutant detection. The results conclusively indicate that such systems can achieve:

- Over **93% detection accuracy** across multiple metal ions.
- **97.8% communication reliability** with minimal energy consumption.
- Continuous, automated, and cost-effective operation with minimal maintenance.
- High predictive accuracy for trend forecasting and anomaly detection.
- Practical applicability in both rural and industrial aquatic environments.

These findings collectively illustrate that **IoT-enabled sensing technologies can revolutionize aquatic ecosystem monitoring**, transforming environmental management from a reactive to a proactive paradigm.

Conclusion:-

The integration of environmental sensors with Internet of Things (IoT) frameworks has emerged as a transformative advancement in the field of aquatic ecosystem monitoring and management. The present study demonstrated that an IoT-enabled sensor network can effectively bridge the gap between traditional laboratory-based testing and the urgent need for real-time, continuous surveillance of heavy metal contamination. Through systematic experimentation and field validation, the results established that such intelligent systems can accurately detect, classify, and communicate pollutant data in near real time, enabling timely intervention and decision-making. This technological synergy between sensor science and digital communication marks a pivotal shift from reactive environmental assessment to proactive ecological governance.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The performance analysis revealed that electrochemical and optical sensors, when appropriately calibrated and integrated within an IoT architecture, deliver reliable accuracy and consistency even in fluctuating environmental conditions. By leveraging low-power communication protocols such as LoRaWAN, the system achieved efficient data transmission with minimal latency, ensuring uninterrupted monitoring across diverse aquatic environments. The inclusion of cloud-based analytics and machine learning algorithms further enhanced the capability of the system to recognize contamination trends, predict pollutant fluctuations, and trigger alerts before threshold breaches occurred. This feature not only supports early warning mechanisms but also strengthens compliance monitoring for industries and regulatory authorities. The study's findings underline a significant paradigm shift in environmental surveillance from periodic sampling and laboratory dependence to autonomous, sensor-driven intelligence. The IoT-based model demonstrates scalability, cost-effectiveness, and adaptability, making it a practical solution for both developed and resource-constrained regions. Furthermore, the integration of predictive modeling and data visualization tools facilitates transparent and informed environmental governance. Such platforms empower policymakers, industries, and communities to collaborate in maintaining water quality standards, mitigating pollution sources, and preserving ecological health.

However, the research also identifies certain limitations that must be addressed for large-scale implementation. Sensor drift due to long-term submersion, biofouling effects, and environmental interference may impact long-duration accuracy. Likewise, ensuring cybersecurity and data integrity in wireless transmission remains critical as the volume of environmental data continues to expand. Future work should explore self-calibrating sensors, bio-resistant materials, and hybrid communication systems combining LoRaWAN, 5G, and satellite networks to enhance robustness and global scalability. Moreover, integrating edge computing can significantly reduce cloud dependency, allowing localized data analysis and faster response times. In conclusion, the study validates that IoT-integrated environmental sensing offers a sustainable, intelligent, and highly responsive alternative to conventional water quality monitoring systems. Its ability to provide real-time pollutant insights and predictive analytics represents a significant contribution to the broader objective of environmental protection and sustainable resource management. By advancing technological innovation in ecological monitoring, this approach supports the global pursuit of cleaner water systems, healthier ecosystems, and informed stewardship of natural resources, thereby aligning with international sustainability frameworks such as the UN Sustainable Development Goals (SDG 6 and SDG 13). The outcomes of this research reinforce that the future of environmental monitoring lies in the convergence of data-driven intelligence, sensor innovation, and responsible technological application.

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Received: August 07, 2025