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IoT framework for environmental monitoring in Strandzha Nature Park

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Abstract. Environmental monitoring plays a critical role in preserving biodiversity and ensuring sustainable management of protected areas. However, traditional monitoring approaches often lack efficiency, precision, and real-time responsiveness. This paper introduces an innovative Internet of Things (IoT) framework specifically designed for environmental monitoring in Strandja Nature Park—a region of significant ecological value located in Bulgaria. The proposed framework integrates advanced sensing technologies, low-power wide-area network (LPWAN) communications (LoRaWAN), and cloud-based analytics to enable real-time tracking of environmental parameters, including air quality, soil moisture, temperature, humidity, and wildlife presence. A practical deployment of the IoT system demonstrates enhanced capabilities in data acquisition, coverage, energy efficiency, and early detection of ecological disturbances. The results highlight significant improvements over conventional methods in terms of accuracy, data granularity, and cost-effectiveness. Ultimately, this framework provides valuable insights for proactive environmental management, paving the way toward a more comprehensive, sustainable, and technologically advanced approach to biodiversity conservation in protected natural regions.

Key words: IoT, environmental monitoring, Strandzha Nature Park, LoRaWAN, biodiversity conservation, ecological management, sensor networks.

Introduction

Environmental monitoring has become increasingly vital due to rising concerns about biodiversity loss, climate change impacts, habitat degradation, and pollution. Continuous and precise monitoring of environmental parameters - such as temperature, humidity, soil moisture, air quality, and wildlife activity - is crucial for managing natural resources effectively and sustainably. Traditional environmental monitoring typically involves manual data collection, periodic field observations, and laboratory analysis, methods that are often costly, time-consuming, and limited in spatial and temporal resolution (Gubbi et al., 2013). Consequently, these conventional approaches often fall short in providing accurate real-time data required for timely decision-making and proactive ecological management.

The Internet of Things (IoT) represents a transformative approach for overcoming the limitations inherent in traditional environmental monitoring. IoT systems integrate interconnected sensors, low-power communication technologies, and sophisticated data analytics platforms to facilitate efficient, continuous, and real-time environmental monitoring (Xu et al., 2020). With the proliferation of affordable and energy-efficient sensors, combined with advancements in wireless technologies such as LoRaWAN, Zigbee, and cellular IoT, comprehensive environmental data collection at remote or difficult-to-access locations has become feasible and economically viable (Mekki et al., 2019).

Strandzha Nature Park, located in southeastern Bulgaria, encompasses diverse ecosystems and hosts numerous endemic species. The region is characterized by high biodiversity, unique ecological conditions, and significant conservation challenges arising from both natural and Anthropogenic pressures. Current monitoring practices within the park rely predominantly on intermittent and manual sampling methods, limiting their ability to capture timely and comprehensive ecological insights. Implementing an IoT framework tailored specifically to the ecological and geographical characteristics of Strandzha Nature Park can significantly enhance the quality, scope, and immediacy of monitoring efforts.

Environmental monitoring involves systematic collection, analysis, and interpretation of environmental data to support sustainable resource management, conservation strategies, and regulatory compliance. Traditionally, monitoring relies heavily on manual field measurements, remote sensing, and laboratory analysis methods. Although these conventional approaches have provided valuable data, they frequently suffer from significant drawbacks, including limited spatial coverage, discontinuous data collection intervals, delayed data processing, and high operational costs (Hart & Martinez, 2015).

Manual monitoring methods typically involve periodic site visits, using portable instruments to measure parameters such as temperature, humidity, soil moisture, and air or water quality indicators. Remote sensing methods, leveraging satellite or aerial imagery, enhance cove-rage but often lack detailed temporal resolution and face challenges in cloudy or densely vegetated regions (Ma et al., 2011). Thus, the demand has grown substantially for improved, more reliable, real-time environmental monitoring solutions capable of providing high-resolution data to support effective environmental management and rapid decision-making (Tadejko, 2017).

The Internet of Things (IoT) presents a transformative approach for environmental monitoring, employing interconnected devices to auto-mate the collection and analysis of diverse environmental parameters. The proliferation of IoT technologies has revolutionized ecological data acquisition, offering significant improvements over traditional methods in accuracy, scalability, real-time data acquisition, and energy efficiency (Ray, 2017; Ullo & Sinha, 2020).

Sensor technologies form the backbone of IoT environmental monitoring. Sensors designed for measuring environmental variables such as temperature, humidity, air quality (CO, CO_2, NO_2), soil moisture, and wildlife movement have become increasingly sophisticated and affordable, allowing for widespread deployment in diverse ecological contexts (Rakshith et al., 2023). Advanced air quality sensors enable real-time detection of pollutants at granular spatial scales, while camera traps and acoustic sensors provide detailed data on wildlife behavior and biodiversity assessments (Sheng et al., 2019; Tadejko, 2017).

Communication technologies underpin effective IoT deployments, with Low-Power Wide-Area Networks (LPWAN), such as LoRaWAN, Sigfox, and NB-IoT, providing long-range coverage, low energy consumption, and reliable connectivity in remote areas (Mekki et al., 2019; Sinha et al., 2017).

Recent advancements have led to sophisticated, scalable, and economically viable IoT monitoring solutions. Chamara et al. (2022) highlight IoT-based agricultural and environmental monitoring systems (Ag-IoT) that shift agricultural monitoring from manual, qualitative tasks to automated, quantitative approaches, emphasizing the importance of high-resolution, real-time data for informed decision-making.

Robust IoT frameworks for environmental monitoring typically include multiple layers: sensor (perception), network (communication), cloud computing, and analytics (Xu et al., 2020). The sensor layer captures physical environmental parameters, and the network layer manages data transmission, leveraging LPWAN or other wireless communication protocols (Ray, 2017). Cloud computing provides scalable data storage, advanced analytics, visualization, and integration with other systems. Platforms such as AWS IoT, Microsoft Azure IoT, and Google Cloud IoT offer extensive tools for data processing, predictive analytics, and real-time data management (Naranjo et al., 2021). Edge computing technologies further minimize data latency and enhance energy efficiency, crucial for remote locations (Shi et al., 2016).

Kozlowski et al. (2023) emphasize the need for robust evaluation frameworks, highlighting interoperability, reliability, and scalability through standardized software engineering requirements such as ISO 25010, ensuring resilient and effective environmental monitoring systems.

Fog computing paradigms integrated with IoT have significantly enhanced monitoring capabilities by addressing challenges related to limited bandwidth, latency, and data privacy. Fog computing enables data analytics closer to data sources, enhancing real-time processing (Wang et al., 2019). Federated learning within fog frameworks maintains decentralized data processing while achieving accuracy comparable to centralized models.

Semantic frameworks and AI integration have significantly advanced environmental monitoring. Šerić et al. (2022) propose semantic conceptual frameworks to enhance query ability and interactivity, improving data management and analysis capabilities. AI-driven IoT systems, employing machine-learning algorithms, have demonstrated superior abilities in detecting hazardous materials in various environmental contexts (Popescu et al., 2024). Integration of AI-enhanced remote sensing with IoT facilitates precise environmental monito-ring. Technologies like multispectral imaging and aerial imagery analyzed through AI algorithms enable proactive ecosystem management and prediction of environmenttal hazards (Arowolo et al., 2024).

Citizen-centric and open-source IoT platforms significantly promote community participation and open innovation. Mahajan (2022) presents citizen-centric frameworks like Soc-IoT, enabling broad engagement in data collection and analysis, fostering extensive, accessible environmental datasets.

Despite advances in IoT environmental monitoring, significant research gaps remain for region-specific frameworks tailored explicitly to unique ecosystems like Strandzha Nature Park. Existing literature highlights general IoT effecttiveness but underscores the need for customized, ecosystem-specific solutions addressing distinct ecological and operational challenges.

This research aims to address this gap by developing, deploying, and evaluating a tailored IoT environmental monitoring framework optimized specifically for Strandzha Nature Park, integrating advanced sensor technologies, edge and fog computing, AI analytics, and citizen-engaged data collection.

This paper proposes and evaluates a novel IoT-based environmental monitoring framework explicitly designed for the unique conditions found in Strandzha Nature Park. The main objecttive is to develop and implement a comprehensive monitoring solution that integrates sensor technology, energy-efficient wireless communication, real-time data collection, cloud-based analytics, and user-friendly visualization platforms.

Specifically, the research aims to:

- Design an optimized IoT architecture tailored to the environmental characteristics and ecological priorities of Strandzha Nature Park.
- Select and integrate sensor systems capable of accurately capturing critical environmental parameters.
- Deploy a reliable and energy-efficient communication network suitable for remote and inaccessible areas.
- Demonstrate the practical effectiveness of the IoT framework through real-world deployment and performance assessment.

Materials and methods

The proposed IoT-based framework for environmental monitoring in Strandzha Nature Park is structured in four main layers:

1. Sensory layer;
2. Communication layer;
3. Cloud/edge computing layer;
4. Fog layer.

This architecture supports a sustainable, energy-efficient, and scalable environmental monitoring system, suitable for different terrains and connectivity conditions typical of Strandzha Nature Park.

The illustrated architecture (Fig. 1) shows the functional layers and data flow within the IoT system:

Sensor layer: It consists of LoRaWAN and Zigbee sensor nodes measuring environmental parameters (e.g., air quality, soil characteristics, water quality, microclimate).

Communication layer: Includes LoRaWAN and Zigbee gateways that collect and transmit sensor data over long distances. Devices such as 4G/Wi-Fi gateways provide reliable connectivity.

Fog layer: Contains network servers (ChirpStack), MQTT brokers (e.g., Mosquitto), and intermediate databases (InfluxDB), which locally aggregate and pre-process data. In the context of the

Internet of Things (IoT), the "nebulous layer" refers to the decentralized computing infrastructure that sits between the end devices (such as sensors and actuators) and the cloud. It provides processing, storage, and networking services closer to data sources, allowing for faster response times and reduced dependency on the centralized cloud. This is especially useful for IoT applications that are sensitive to latency.

Cloud layer: Executes analytics and visualization through platforms such as ThingsBoard and AI-driven whiteboards, enabling scalable real-time analysis, alarms, and visualization (Toskov et al., 2021a,b).

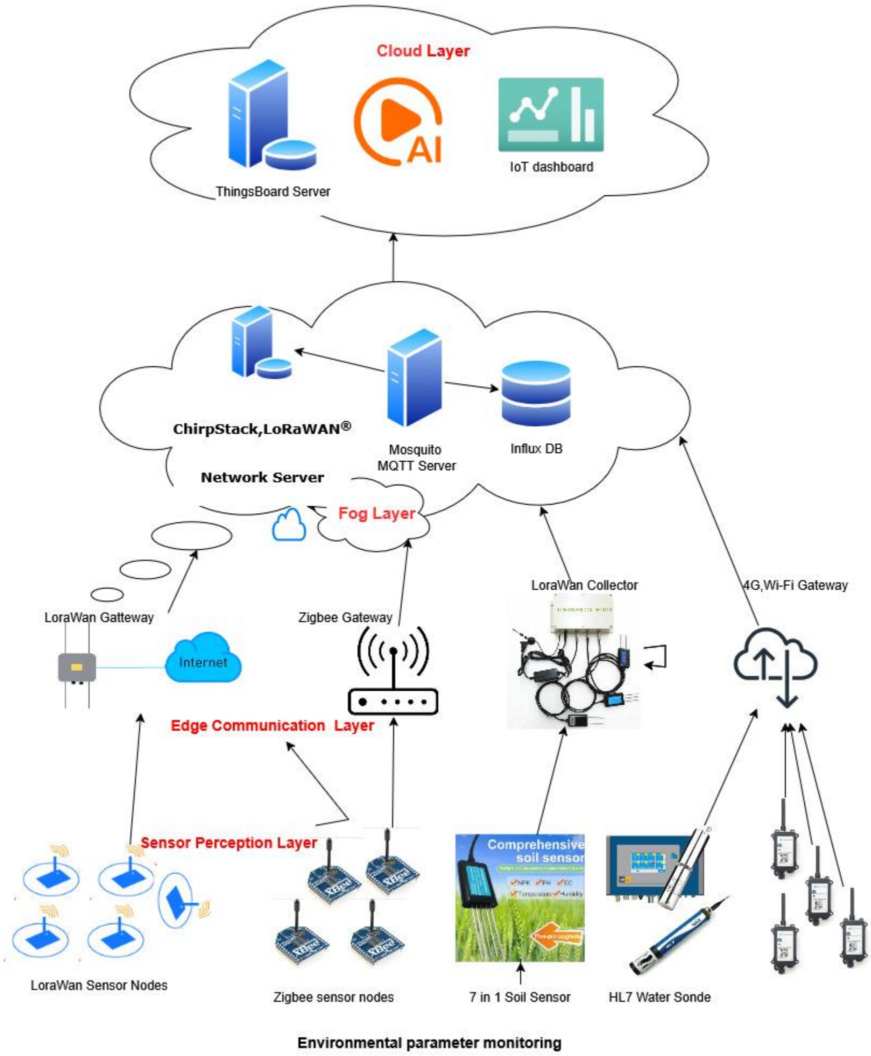

Fig. 1. Integrated IoT architecture of the environmental monitoring system, including sensor layer, communication layer, fog layer, and cloud layer.

Results and Discussion

Practical implementation in Strandzha Nature Park

The arrangement of sensors and sensor assemblies is presented in Fig. 2. The practical implementation of the proposed IoT-based environmental monitoring framework in Strandzha Nature Park follows a structured, multi-layer architectural model. The system is organized into four fundamental layers - sensor layer, communication layer, cloud/edge computing layer, and application/visualization layer - each designed to ensure modularity, scalability, and operational robustness under real-world ecological conditions. This layered structure enables flexible deployment across heterogeneous environmental zones, supporting both continuous and event-driven monitoring.

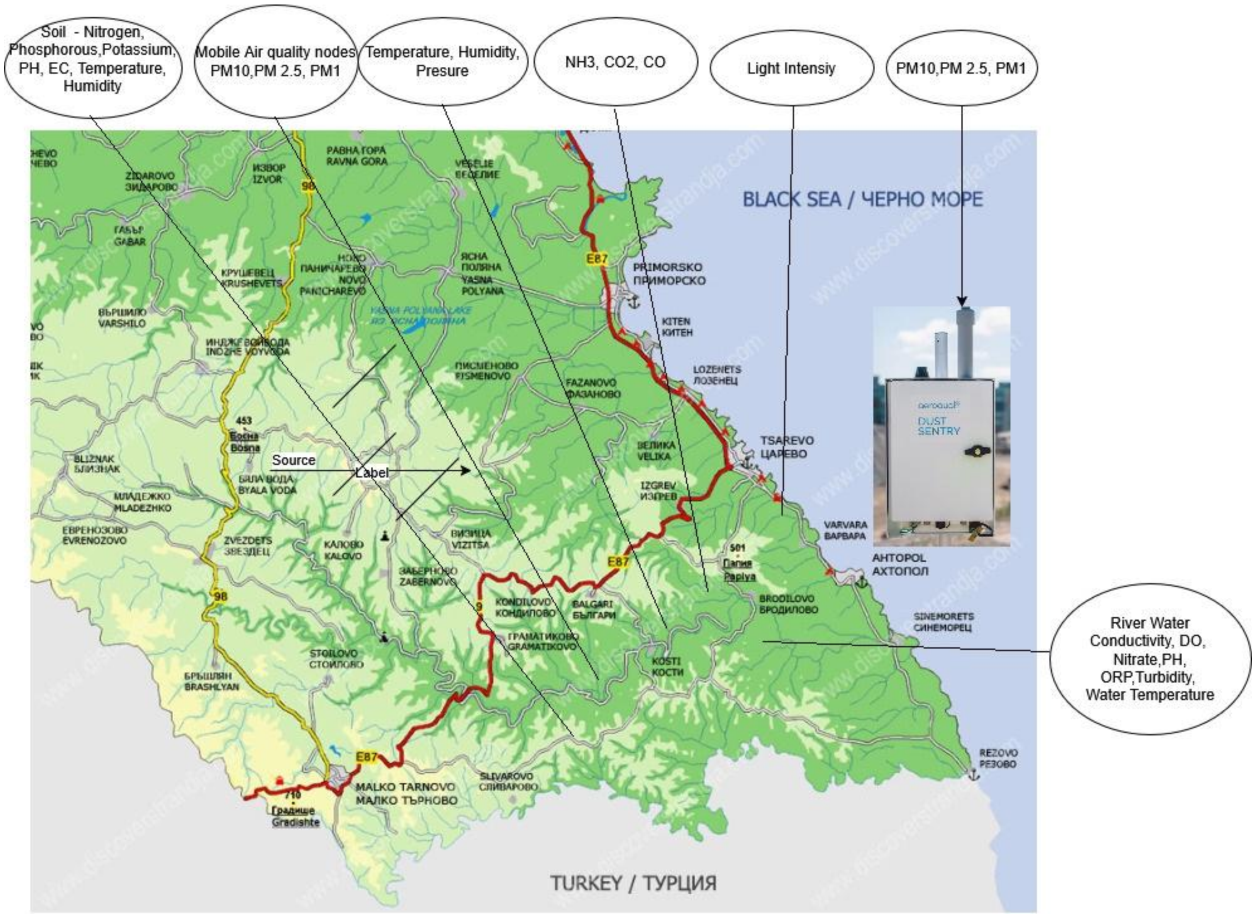

Fig. 2. Arrangement of sensors and sensor assemblies.

Sensor Layer

The sensor layer consists of geographically distributed sensor nodes positioned across representative ecological zones within the park. These nodes are designed for autonomous operation, low energy consumption, and high measurement accuracy. The deployed instrumentation includes the following categories:

- Air Quality Sensors

Aeroqual PM-series analyzers (PM1, PM2.5, PM10) are utilized to quantify airborne particulate matter. These instruments employ laser-scattering photometry and incorporate factory calibration routines, ensuring long-term measurement stability and compliance with environmental monitoring standards.

- Soil Moisture and Temperature Sensors

Decagon EC-5 sensors measure volumetric soil moisture based on dielectric permittivity.

DS18B20 digital thermometers provide precise soil temperature readings, supporting local microclimate modeling and soil hydration analysis.

- Water Quality Sensors

HL7-compatible aquatic sensor modules capture essential hydrological indicators: electrical conductivity, dissolved oxygen (DO), pH, nitrate concentration, oxidation-reduction potential (ORP), turbidity, water temperature. These multi-parameter probes are critical for early detection of anthropogenic contamination, sediment transport dynamics, and hydrological anomalies (Geetha & Gouthami, 2016).

- Microclimate Sensors

DHT22 or BME280 sensors monitor ambient temperature and relative humidity. The acquired microclimatic data support ecological modeling, forest health assessment, and climate trend evaluation.

Embedded Processing

All sensors interface with ESP32 or STM32 microcontrollers that perform: signal preprocesssing, digital filtering (median/low-pass), timestamp assignment, and packet structuring. This ensures noise reduction, reliability, and readiness for long-range transmission.

Communication Layer

To achieve low-power, long-range communication across diverse terrain, LoRaWAN is employed as the primary wireless protocol. The communication infrastructure includes: Distributed LoRa Sensor Nodes. Each node integrates an RFM95W LoRa transceiver, enabling uplink communication with minimal energy consumption and multi-kilometer coverage in forested landscapes.

Multi-Channel LoRaWAN Gateways – Gateways, positioned at strategically selected locations, provide multi-channel uplink capability, adaptive data rate control, and end-to-end AES128 encryption. Their placement ensures coverage redundancy and minimizes packet loss.

Integration with IoT Platforms: All data streams are ingested by a ThingsBoard IoT server, which supports device provisioning, telemetry ingestion, and event-based rule execution. Redundant Communication Paths-GSM and NB-IoT modules serve as a fallback mechanism in zones where LoRaWAN coverage is limited due to topographical constraints.

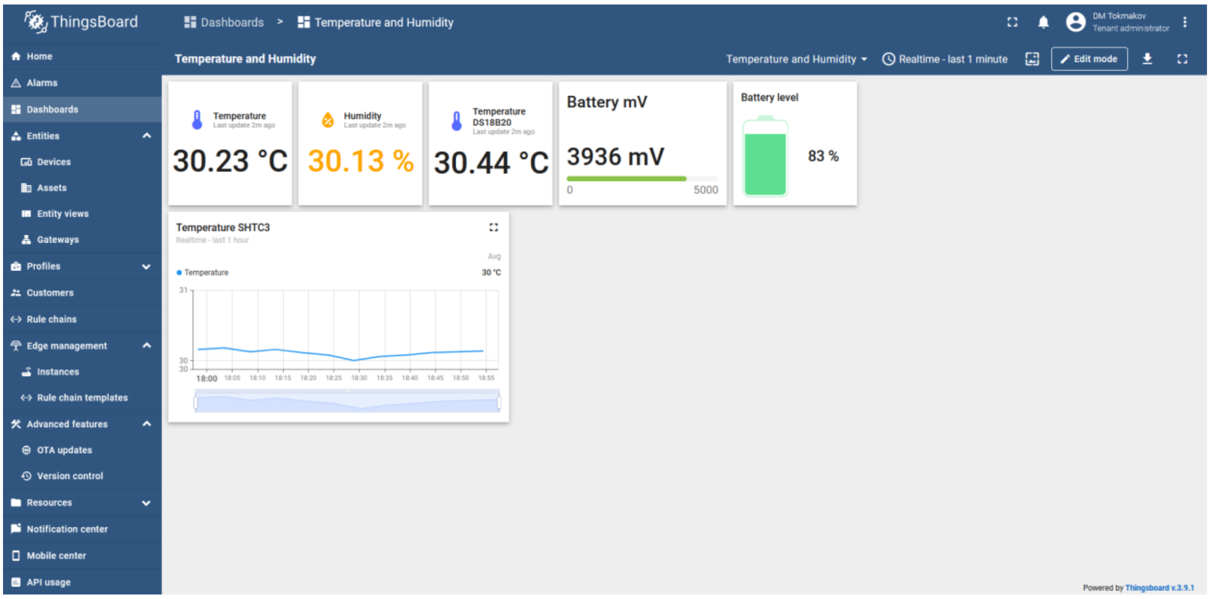

Fig. 3. ThingsBoard IoT server.

Cloud and Edge Computing Layer

The hybrid computational layer ensures reliable data processing and low-latency event detection.

The system integrates: ThingsBoard IoT Server (presented in Fig. 3) provides device management, real-time dashboards, alarm rule processsing, and API-driven interoperability. Aeroqual Cloud: Dedicated platform for advanced processsing of PM sensor data, enabling long-term trend analysis and automated calibration checks. Edge Computing Units Raspberry Pi and Nvidia Jetson Nano devices are deployed as local edge nodes. They support: real-time anomaly detection (e.g., sudden turbidity peaks), local caching of data during network outages, AI-driven analytics (acoustic classification, wildlife detection), FFT-based signal analysis for noise monitoring and fire detection (Gaur et al., 2019).

Cybersecurity and Data Protection

The communication framework employs end-to-end encryption (SSL/TLS), MQTT authentication, secure firmware update protocols, ensuring the integrity and confidentiality of environmental data.

Application and Visualization Layer

The user interface provides a unified platform for environmental data analysis and decision-making. Geospatial Visualization Interactive dashboards display: real-time sensor measurements, geo-referenced maps, spatiotemporal heatmaps for ecological indicators.

Alerting and Early Warning, Threshold-based notifications inform users of: pollution episodes (e.g., PM2.5 exceedances), microclimate anomalies, hydrological risks, and fire early-warning conditions.

Historical Analytics and Reporting

The system supports: Temporal analysis (daily/weekly/monthly), environmental trend detection, automated PDF/CSV report generation - crucial for ecological management and policy formulation. Interoperability with Conservation Tools The platform integrates with tools used for protected area management, supporting ranger operations, habitat assessment, and Natura 2000 reporting requirements.

Pilot Deployment in Strandzha Nature Park

A pilot study was conducted across three representative ecological zones:

River Zone Monitoring: Continuous monitoring of water quality parameters reveals short-term fluctuations driven by precipitation, sediment movement, and anthropogenic activities.

Forest Zone Monitoring: Microclimate stations, camera traps, and acoustic sensors support wildlife tracking and detection of unregulated forestry activities.

Open Meadow Monitoring: Soil moisture, PM levels, and microclimate measurements provide insights into drought dynamics and fire smoke dispersion patterns.

Sampling Frequency: Solar-powered sensor nodes transmit measurements every 15 minutes, ensuring high temporal resolution while maintaining energy efficiency.

Edge-based Event Detection: Edge modules monitor: fire-prone conditions (temperature/humidity combinations), illegal activity indicators (acoustic anomalies), sudden hydrological disturbances.

HL7 Water Quality Parameters: Hydrological monitoring adheres to HL7-compatible formats, recording: conductivity, dissolved oxygen, nitrates, pH, ORP, turbidity, and water temperature (Fig. 4).

Date	BATTERY	Battery Voltage	CONDUCTIVITY	DO	NITRATE	pH	ORP	TURBIDITY	WATER TEMPERATURE
Oct 23, 2024 9:00 AM	On	6.90 V	1,227.6 µS/cm	4.75 mg/l	75.41 mg/l	8.5	492.5 mV	3.9 NTU	21.61 °C
Oct 23, 2024 9:30 AM	On	6.90 V	1,228.0 µS/cm	4.75 mg/l	76.77 mg/l	8.4	491.7 mV	3.2 NTU	21.58 °C
Oct 23, 2024 10:00 AM	On	6.90 V	1,228.4 µS/cm	4.75 mg/l	76.98 mg/l	8.4	491.5 mV	3.1 NTU	21.54 °C
Oct 23, 2024 10:30 AM	On	6.90 V	1,228.2 µS/cm	4.75 mg/l	76.62 mg/l	8.4	491.7 mV	4.0 NTU	21.51 °C
Oct 23, 2024 11:00 AM	On	6.90 V	1,227.7 µS/cm	4.74 mg/l	77.79 mg/l	8.4	491.6 mV	3.1 NTU	21.49 °C
Oct 23, 2024 11:30 AM	On	6.90 V	1,227.8 µS/cm	4.75 mg/l	77.69 mg/l	8.5	490.5 mV	2.6 NTU	21.47 °C
Oct 23, 2024 12:00 PM	On	6.90 V	1,228.2 µS/cm	4.75 mg/l	77.46 mg/l	8.5	490.0 mV	3.7 NTU	21.45 °C
Oct 23, 2024 12:30 PM	On	6.90 V	1,228.4 µS/cm	4.74 mg/l	76.09 mg/l	8.5	489.8 mV	3.5 NTU	21.44 °C
Oct 23, 2024 1:00 PM	On	6.90 V	1,228.4 µS/cm	4.76 mg/l	76.98 mg/l	8.5	489.8 mV	2.7 NTU	21.43 °C
Oct 23, 2024 1:30 PM	On	6.90 V	1,227.6 µS/cm	4.74 mg/l	76.60 mg/l	8.4	488.9 mV	7.2 NTU	21.43 °C
Oct 23, 2024 2:00 PM	On	6.90 V	1,227.9 µS/cm	4.74 mg/l	76.55 mg/l	8.4	488.9 mV	35.1 NTU	21.43 °C
Oct 23, 2024 2:30 PM	On	6.90 V	1,227.3 µS/cm	4.73 mg/l	78.00 mg/l	8.5	488.5 mV	434.0 NTU	21.44 °C
Oct 23, 2024 3:00 PM	On	6.90 V	1,227.3 µS/cm	4.74 mg/l	75.96 mg/l	8.5	489.3 mV	???	21.45 °C
Oct 23, 2024 3:30 PM	On	6.90 V	1,226.7 µS/cm	4.74 mg/l	78.09 mg/l	8.4	489.6 mV	???	21.46 °C
Oct 23, 2024 4:00 PM	On	6.90 V	1,227.3 µS/cm	4.74 mg/l	77.82 mg/l	8.5	489.6 mV	2.7 NTU	21.47 °C
Oct 23, 2024 4:30 PM	On	6.90 V	1,227.1 µS/cm	4.74 mg/l	75.97 mg/l	8.5	489.8 mV	18.8 NTU	21.48 °C
Oct 23, 2024 5:00 PM	On	6.90 V	1,227.1 µS/cm	4.72 mg/l	77.89 mg/l	8.5	489.6 mV	16.1 NTU	21.49 °C
Oct 23, 2024 5:30 PM	On	6.90 V	1,227.0 µS/cm	4.73 mg/l	76.58 mg/l	8.5	489.9 mV	3.8 NTU	21.50 °C
Oct 23, 2024 6:00 PM	On	6.90 V	1,227.3 µS/cm	4.73 mg/l	76.14 mg/l	8.4	490.4 mV	2.6 NTU	21.51 °C
Oct 23, 2024 6:30 PM	On	6.90 V	1,226.4 µS/cm	4.72 mg/l	77.73 mg/l	8.5	490.1 mV	3.4 NTU	21.52 °C
Oct 23, 2024 7:00 PM	On	6.90 V	1,226.5 µS/cm	4.72 mg/l	77.23 mg/l	8.4	490.9 mV	3.1 NTU	21.53 °C
Oct 23, 2024 7:30 PM	On	6.90 V	1,226.5 µS/cm	4.72 mg/l	76.55 mg/l	8.5	490.9 mV	4.6 NTU	21.54 °C
Oct 23, 2024 8:00 PM	On	6.90 V	1,227.5 µS/cm	4.72 mg/l	76.40 mg/l	8.5	489.4 mV	2.8 NTU	21.54 °C
Oct 23, 2024 8:30 PM	On	6.90 V	1,227.1 µS/cm	4.72 mg/l	76.61 mg/l	8.5	490.4 mV	3.2 NTU	21.55 °C
Oct 23, 2024 9:00 PM	On	6.90 V	1,227.1 µS/cm	4.72 mg/l	76.20 mg/l	8.5	491.0 mV	3.6 NTU	21.56 °C
Oct 23, 2024 9:30 PM	On	6.90 V	1,227.3 µS/cm	4.72 mg/l	76.31 mg/l	8.4	489.6 mV	2.1 NTU	21.56 °C
Oct 23, 2024 10:00 PM	On	6.90 V	1,227.1 µS/cm	4.73 mg/l	77.62 mg/l	8.4	489.3 mV	3.3 NTU	21.57 °C
Oct 23, 2024 10:30 PM	On	6.90 V	1,227.9 µS/cm	4.72 mg/l	76.59 mg/l	8.5	489.8 mV	3.3 NTU	21.57 °C
Oct 23, 2024 11:00 PM	On	6.90 V	1,227.5 µS/cm	4.73 mg/l	77.11 mg/l	8.4	488.5 mV	3.0 NTU	21.57 °C
Oct 23, 2024 11:30 PM	On	6.90 V	1,227.6 µS/cm	4.72 mg/l	76.68 mg/l	8.5	489.2 mV	6.3 NTU	21.57 °C
Oct 24, 2024 12:00 AM	On	6.90 V	1,228.2 µS/cm	4.72 mg/l	76.42 mg/l	8.5	488.8 mV	30.6 NTU	21.56 °C

Fig. 4. HL 7 Water Quality Parameters – Conductivity, Dissolved Oxygen, Nitrates, pH, ORP, turbidity, water temperature.

The dataset from 23 October 2024, acquired through the addVANTAGE Pro 6.8 platform at 10-minute intervals, demonstrates the system's ability to capture high-resolution aquatic dynamics.

Supporting Platforms

Aeroqual Cloud: Provides remote device management, sensor diagnostics, high-resolution PM analytics, and data export (Fig. 5 and Fig. 6).

Fig. 5. ThingsBoard IoT Server - Acts as the central integration hub, managing telemetry, alerts, dashboards, and API-based data exchange.

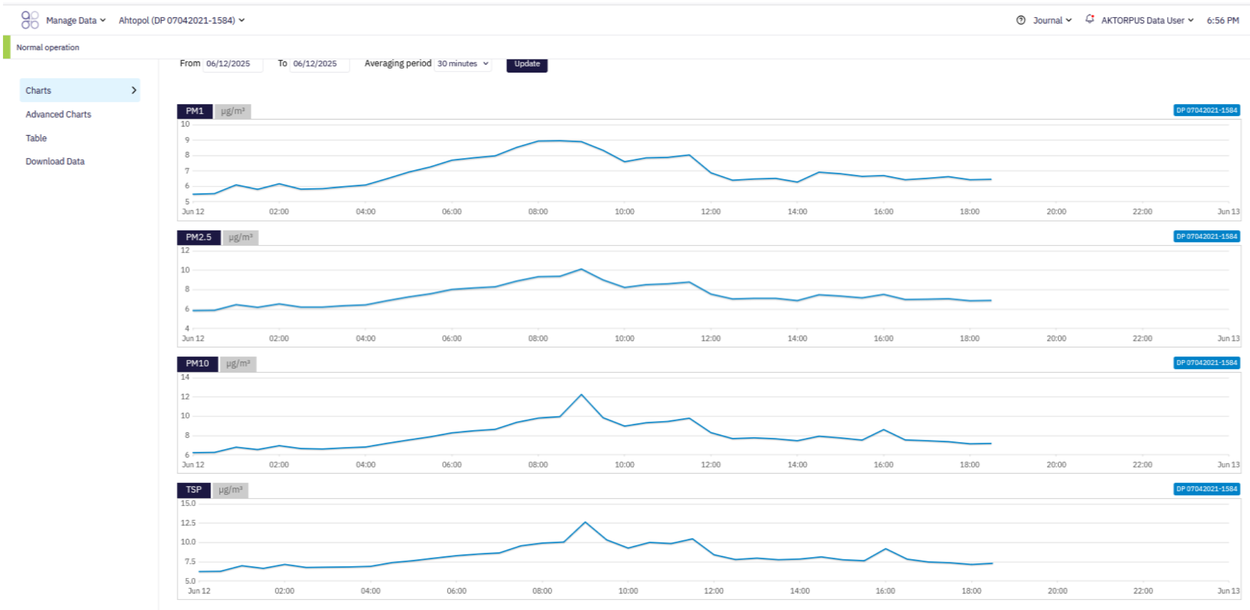

Fig. 6. Aeroqual PM1, PM2.5, PM10.

Coverage and reliability: LoRaWAN gateways provided over 95% transmission success.

Energy efficiency: Solar nodes operated autonomously for over 60 days.

Accuracy: Sensor data matched manual field measurements.

Early detection: Anomaly algorithms detected pollution in the river area.

The implementation of the IoT system has led to a significant improvement in the quality, volume, and timeliness of environmental data.

Strengths:

- Scalability for different zones and types of environments.
- Real-time alarms for timely response.
- Combining cloud and edge technologies for high reliability.

Remaining challenges:

- Maintenance and calibration of sensors under harsh conditions.
- Protection against cyber threats.
- Involving local communities in data collection.

Upcoming work:

- AI analytics (deep learning on images and/or sound).
- Integration with European biodiversity monitoring platforms.
- Educational modules for schools and NGOs.

Conclusions

This paper presented a comprehensive IoT-based environmental monitoring framework tailored to the specific needs and ecological contexts of Strandzha Nature Park. Through careful selection of sensor technologies, efficient communication protocols, and cloud-edge analytics integration, the proposed system demonstrated enhanced capabilities in real-time monitoring, early warning, and ecological insight generation. Future research should expand the system's scope, integrate additional AI modules, and foster broader stakeholder engagement to ensure sustainability and scalability across protected areas.

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