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IoT-Driven Environmental Monitoring Model Using ThingsBoard API and MQTT

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Abstract

Environmental degradation, climate variability, and urbanization have intensified the need for intelligent and scalable environmental monitoring systems. Conventional methods of data collection often suffer from high costs, limited spatial coverage, and delayed reporting, thereby limiting their effectiveness for real-time decision-making. This paper presents an Internet of Things (IoT)-driven environmental monitoring model that integrates ThingsBoard API and the Message Queuing Telemetry Transport (MQTT) protocol to provide a cost-effective, secure, and scalable solution for real-time data acquisition, transmission, and visualization. The proposed model employs a layered architecture consisting of sensor nodes, an MQTT communication layer, and an application layer powered by ThingsBoard. Sensor nodes equipped with air quality, temperature, humidity, and water quality sensors collect environmental parameters and publish data through an MQTT broker. ThingsBoard API ingests and processes the telemetry data, enabling seamless integration with dashboards, rules engines, and external systems. The system supports role-based access control, encrypted communication, and token-based device authentication, thereby addressing security and privacy concerns. Key features of the model include real-time monitoring, historical data analysis, customizable dashboards, and threshold-based alert mechanisms. Use cases span across urban air quality management, precision agriculture, water resource monitoring, climate research, and disaster risk reduction. The framework demonstrates high scalability, allowing seamless expansion to large numbers of devices and geographically distributed deployments. This highlights both the benefits and challenges of the model. While it significantly enhances environmental data availability and policy-making through digital transformation, challenges such as sensor calibration, connectivity limitations, and long-term maintenance remain. Future directions include integrating artificial intelligence for predictive analytics, deploying edge computing for latency reduction, and leveraging blockchain for data integrity. Overall, the IoT-driven model offers a robust pathway toward sustainable, data-driven environmental management and smart city development.

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1. Introduction

The intensification of environmental challenges in the twenty-first century has placed unprecedented pressure on governments, researchers, and industries to adopt innovative solutions for sustainability (Ajayi, 2019; Ayanbode *et al.*, 2019). Climate change continues to manifest in rising global temperatures, erratic rainfall patterns, and increased frequency of extreme weather events. Air pollution from industrial emissions, vehicular traffic, and unregulated urban expansion threatens public health and exacerbates global warming (Dako *et al.*, 2019; Dare *et al.*, 2019). Deforestation further accelerates biodiversity loss and disrupts carbon cycles, while declining water quality due to agricultural runoff, chemical contamination, and poor waste management endangers both ecosystems and human populations (Babatunde *et al.*, 2019; Bankole and Lateef, 2019).

These complex challenges require monitoring approaches that can capture environmental dynamics with accuracy, timeliness, and granularity (Dako *et al.*, 2019; Essien *et al.*, 2019).

Traditional environmental monitoring systems, although well-established, face significant limitations. They are often expensive to deploy, restricted in coverage, and incapable of providing real-time insights necessary for rapid intervention (Ayanbode *et al.*, 2019; Ajayi *et al.*, 2019). Manual data collection methods are labor-intensive and prone to delays, while isolated monitoring stations provide only localized snapshots that may not adequately reflect broader conditions. To overcome these barriers, there is a growing demand for cost-effective, scalable, and automated monitoring systems capable of delivering continuous data streams to support informed decision-making (Dako *et al.*, 2019; Essien *et al.*, 2019).

The Internet of Things (IoT) has emerged as a transformative enabler in this context. By interconnecting sensors, devices, and cloud-based platforms, IoT offers a paradigm shift from static monitoring toward dynamic, intelligent, and distributed systems (Essien *et al.*, 2019; Etim *et al.*, 2019). Environmental monitoring powered by IoT leverages low-cost sensors, wireless communication, and real-time analytics to deliver actionable insights. This convergence enables not only enhanced environmental awareness but also predictive modeling and proactive management, aligning with broader sustainability and smart city initiatives (Nwokediegwu *et al.*, 2019; Onalaja *et al.*, 2019).

Among the many platforms enabling IoT applications, ThingsBoard has gained prominence as an open-source solution tailored for device management, data collection, processing, and visualization. Its modular architecture supports telemetry ingestion, rules-based event handling, and user-friendly dashboards, making it particularly suitable for large-scale deployments in heterogeneous environments. ThingsBoard also provides interoperability through APIs, enabling integration with external applications, machine learning frameworks, and enterprise systems (Etim *et al.*, 2019; Essien *et al.*, 2020).

Complementing this platform is the Message Queuing Telemetry Transport (MQTT) protocol, a lightweight publish-subscribe messaging system widely adopted in IoT deployments. MQTT is designed for constrained devices and low-bandwidth, high-latency networks, which are common in remote environmental monitoring scenarios. Its efficiency in minimizing communication overhead while maintaining reliability makes it ideal for transmitting data from distributed sensor nodes to central servers. Moreover, its scalability allows seamless expansion of sensor networks without significant infrastructural modifications (Abisoye *et al.*, 2020; Essien *et al.*, 2020). The combination of ThingsBoard and MQTT thus provides a robust foundation for building environmental monitoring solutions that are efficient, scalable, and secure.

The purpose of the proposed model is to develop a comprehensive IoT-driven environmental monitoring framework that integrates sensor devices, MQTT communication, and ThingsBoard dashboards. This model aims to collect real-time data on critical environmental parameters such as air quality, temperature, humidity, and water quality, and to process and visualize this data through customizable dashboards and automated alert systems. By leveraging the strengths of ThingsBoard and MQTT, the

framework aspires to bridge the gap between data availability and actionable decision-making, offering stakeholders—from policymakers to researchers—a scalable tool for sustainable environmental management.

2. Methodology

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology was applied to develop the IoT-driven environmental monitoring model using ThingsBoard API and MQTT. The process began with the identification of relevant studies, technical documentation, and case examples relating to IoT-based monitoring systems, middleware platforms, and real-time data streaming protocols. Sources included peer-reviewed journal articles, white papers, technical standards, and open-source project repositories. A total of 1,126 records were initially retrieved across IEEE Xplore, ACM Digital Library, SpringerLink, ScienceDirect, and grey literature databases, using search strings that combined terms such as “IoT environmental monitoring,” “ThingsBoard API,” “MQTT protocol,” and “real-time data integration.”

After importing the retrieved records into a reference management system, duplicates were removed, resulting in 892 unique studies. A two-stage screening process was then undertaken. The first stage focused on titles and abstracts to eliminate records outside the scope, such as IoT applications unrelated to environmental monitoring or implementations not utilizing MQTT-based communication. This narrowed the pool to 314 records. The second stage involved a full-text review against predefined inclusion and exclusion criteria. Studies were included if they described IoT architectures incorporating open-source middleware platforms, API integration for environmental data visualization, or MQTT as a lightweight publish-subscribe protocol for telemetry. Studies that focused only on theoretical aspects without empirical or technical validation, or that relied exclusively on proprietary closed-source platforms, were excluded. After this process, 97 studies remained for detailed synthesis.

The synthesis phase involved extracting information on system architecture, device interoperability, communication efficiency, scalability, latency, data visualization, and API integration. A standardized data extraction sheet was used to capture variables such as sensor deployment contexts, MQTT configuration parameters, ThingsBoard API functionalities, security mechanisms, and performance benchmarks. The analysis highlighted the advantages of MQTT in reducing network overhead and enabling reliable communication in constrained environments, while ThingsBoard’s API provided flexibility in visualization, rule-based processing, and integration with external applications.

To ensure robustness, quality assessment of the included studies was conducted using criteria such as clarity of system design, reproducibility of results, and applicability to real-world monitoring scenarios. Studies with incomplete descriptions of architecture or lacking validation metrics were given lower weight in the synthesis. Finally, the extracted findings were triangulated to formulate a conceptual model of IoT-driven environmental monitoring. This model demonstrates how MQTT-enabled sensors transmit telemetry to ThingsBoard, where the API handles device provisioning, data storage, visualization dashboards, and integration with external analytics engines.

The application of the PRISMA methodology thus ensured a transparent, replicable, and evidence-based approach in

constructing the IoT-driven environmental monitoring model. The systematic process not only filtered high-quality and contextually relevant studies but also integrated technical insights from diverse sources, yielding a scalable, efficient, and adaptable framework for environmental data collection, transmission, and analysis.

2.1. Conceptual Framework

The conceptual framework for an IoT-driven environmental monitoring model using ThingsBoard API and MQTT is structured around a layered system architecture and a functional flow that enables seamless data collection, transmission, analysis, and visualization (Oni *et al.*, 2018; ONYEKACHI *et al.*, 2020). The model integrates sensor networks, lightweight communication protocols, and scalable middleware to achieve real-time environmental intelligence. This section presents the core components of the system architecture—data, communication, and application layers—followed by a detailed explanation of the functional flow from data acquisition to actionable insights.

At the foundation of the architecture lies the data layer, which comprises heterogeneous sensors deployed across monitoring sites. These sensors measure critical environmental parameters such as air quality indices (particulate matter, NO₂, SO₂), temperature, relative humidity, water pH levels, carbon dioxide concentrations, and noise pollution levels. The selection of these parameters reflects global sustainability and public health priorities, as each metric provides vital information about environmental safety and quality of life. For example, air quality sensors can track urban pollution trends, while pH sensors in freshwater sources help assess ecosystem health. The sensors are typically low-power devices embedded with microcontrollers to preprocess data at the edge before forwarding it to the communication layer. This edge preprocessing minimizes bandwidth usage, filters erroneous readings, and improves the overall efficiency of the system.

The communication layer forms the backbone of reliable data transmission, and in this framework, the MQTT protocol is the primary enabler. MQTT operates on a publish-subscribe model where sensors (publishers) send telemetry data to a broker, and subscribers—including ThingsBoard—receive the relevant information. The MQTT broker manages message queues, ensures delivery, and allows decoupling between data producers and consumers. Its lightweight nature makes it particularly suitable for resource-constrained devices and low-bandwidth networks, which are common in remote environmental monitoring deployments. MQTT's quality of service levels also enable fine-tuning of reliability depending on the criticality of data, such as prioritizing alerts from CO₂ sensors in enclosed spaces over routine temperature logs (ODINAKA *et al.*, 2020; Babatunde *et al.*, 2020). By minimizing overhead and optimizing packet delivery, the communication layer ensures data integrity and timeliness.

The application layer is powered by the ThingsBoard API, which serves as the integration and management hub for sensor data. ThingsBoard provides flexible device provisioning, authentication, and role-based access control, enabling secure operations at scale. Once data is ingested, the platform supports real-time analytics, dashboard visualizations, and rule-based event processing. Through its API, ThingsBoard allows seamless connection with external

applications, machine learning pipelines, or long-term storage systems. The graphical dashboards display trends, anomalies, and spatial distributions of environmental indicators, making them accessible to stakeholders ranging from policymakers to local communities. Additionally, ThingsBoard supports automated control loops, such as activating ventilation systems in buildings when CO₂ levels exceed predefined thresholds. In this way, the application layer translates raw data into actionable insights.

The functional flow of the model operationalizes the layered architecture into a coherent process. It begins with sensor data collection, where field-deployed sensors capture environmental parameters at predefined intervals or on event triggers. This data is formatted into lightweight messages that can be easily transmitted over constrained networks. The second step involves data transmission via MQTT, where the sensors publish messages to the MQTT broker. This ensures that messages are queued and routed appropriately, while subscribers, such as the ThingsBoard platform, receive timely updates. The decoupled nature of this mechanism also allows multiple applications or analytical engines to subscribe to the same data streams without additional sensor configurations (Moruf *et al.*, 2020; Okunade *et al.*, 2020).

The third stage of the flow involves ingestion by the ThingsBoard API. Here, messages are parsed, validated, and stored within the platform's architecture. The API provides a structured mechanism to map sensor outputs into ThingsBoard's data models, allowing interoperability across heterogeneous devices. Once ingested, the fourth stage focuses on storage, processing, and real-time visualization. The platform's time-series database stores historical records, enabling long-term trend analysis and predictive modeling. Concurrently, the processing engine executes rule chains for anomaly detection, event correlation, and filtering. Visual dashboards then present data in intuitive formats, such as line graphs for temporal trends, heat maps for spatial variations, or gauge indicators for threshold monitoring.

The fifth and final stage emphasizes actionable outcomes: alerts, anomaly detection, and reporting. Threshold-based triggers or advanced machine learning models can detect unusual environmental patterns, such as sudden spikes in noise levels or abrupt declines in water quality. Alerts are automatically issued to stakeholders through multiple channels, including SMS, email, or integrated mobile applications. Reporting mechanisms further synthesize data into periodic summaries, facilitating policy formulation, compliance monitoring, and scientific research. These features close the loop by not only monitoring but also enabling proactive intervention in environmental systems.

The conceptual framework demonstrates the synergy between a layered system architecture and a structured functional flow. The data layer ensures comprehensive environmental sensing, the communication layer guarantees efficient transmission through MQTT, and the application layer leverages the ThingsBoard API for analytics and visualization (Ilufoye *et al.*, 2020; Essien *et al.*, 2020). The functional flow operationalizes these layers into a dynamic cycle of collection, transmission, ingestion, storage, visualization, and action. By integrating edge-level sensing with cloud-level intelligence, the model provides a scalable, efficient, and adaptive solution for environmental monitoring, with direct implications for sustainability, urban planning, and public health.

2.2. Features of the Model

The IoT-driven environmental monitoring model that integrates ThingsBoard API and the MQTT protocol is designed to provide an efficient, reliable, and scalable framework for tracking diverse environmental parameters. Its features are oriented toward enabling real-time insights, analytical depth, and usability across multiple contexts (EYINADE *et al.*, 2020; Bankole *et al.*, 2020). By combining real-time monitoring, advanced analytics, scalability, interoperability, and user-centric dashboards, the model establishes a comprehensive digital ecosystem for environmental intelligence.

One of the primary features of the model is its capacity for real-time monitoring. Environmental sensors deployed across multiple sites continuously collect data on variables such as temperature, humidity, air quality, noise levels, and water quality. Through the MQTT publish–subscribe protocol, this data is transmitted with minimal latency to the ThingsBoard platform, where it is processed and visualized. Real-time monitoring ensures that stakeholders, such as municipal authorities or agricultural managers, can access live data streams through dashboards, enabling immediate awareness of environmental conditions. For example, in urban air quality management, continuous tracking of particulate matter (PM_{2.5} and PM₁₀) provides insights into daily fluctuations caused by traffic congestion or industrial activity, supporting timely interventions like traffic rerouting or pollution control measures.

Beyond real-time visualization, the model incorporates data analytics capabilities that add significant value to raw sensor readings. ThingsBoard enables historical trend analysis, allowing users to examine long-term changes in environmental conditions. For instance, the platform can display weekly or seasonal temperature variations, enabling climate researchers to detect anomalies and establish correlations with external events. This temporal perspective is essential for identifying patterns such as gradual increases in pollution or water quality degradation over time.

The analytics component also supports threshold-based alerts. Customizable rules can be set in line with regulatory or health guidelines—for example, alerting users when PM_{2.5} levels exceed World Health Organization (WHO) standards. These alerts can be configured to trigger notifications via SMS, email, or automated system actions, ensuring rapid response to potentially harmful conditions. In agriculture, similar threshold mechanisms could be applied to soil moisture monitoring, triggering irrigation systems when values fall below predefined limits (Ilufoye *et al.*, 2020; Lateefat and Bankole, 2020). By enabling both descriptive and prescriptive analytics, the model transforms data into actionable intelligence.

Scalability is a critical feature of the proposed model, reflecting its ability to support large-scale, distributed deployments. Environmental challenges are seldom confined to a single location; effective monitoring often requires wide geographic coverage. The combination of MQTT and ThingsBoard is inherently scalable, enabling the integration of thousands of devices without significant infrastructure strain. MQTT's lightweight communication design minimizes bandwidth consumption, making it suitable for networks with constrained resources, such as rural monitoring stations or remote research sites.

At the application layer, ThingsBoard is built to handle high

volumes of telemetry data, with options for clustered deployments that enhance performance and reliability. This scalability ensures that the framework can evolve from pilot projects with a handful of sensors to nationwide environmental monitoring systems. Furthermore, distributed deployments allow stakeholders to capture local variations while still contributing to centralized, aggregated datasets, thereby improving environmental modeling and policy formulation.

The model emphasizes interoperability, a crucial requirement for integrating diverse devices and systems. ThingsBoard offers REST and MQTT APIs, enabling seamless connectivity with third-party platforms, enterprise applications, and advanced analytics engines. This interoperability ensures that environmental data can be embedded into broader digital ecosystems, such as smart city management systems, public health monitoring platforms, or climate research databases (Dimitrov *et al.*, 2017; Kouroubali and Katehakis, 2019).

For example, air quality data from the model could be integrated into transportation systems to inform dynamic traffic control or linked with hospital databases to correlate pollution spikes with respiratory illness cases. By adhering to open standards and supporting multiple protocols, the model avoids vendor lock-in and enhances long-term adaptability to evolving technological landscapes (Dako *et al.*, 2020; Essien *et al.*, 2020).

Finally, the model prioritizes user-centric dashboards that transform complex data streams into intuitive, decision-ready insights. ThingsBoard provides customizable dashboards that can display real-time charts, historical graphs, geographical maps, and key performance indicators (KPIs). These dashboards are adaptable to different user needs: policymakers may prefer high-level summaries with color-coded indicators, while researchers may require detailed temporal graphs for in-depth analysis.

The dashboards also enhance accessibility by allowing role-based views. For instance, a municipal environmental agency might configure dashboards for field officers with simplified data relevant to their tasks, while senior officials could access aggregated metrics for policy evaluation. Geographic Information System (GIS) integration further enhances decision-making by mapping sensor data spatially, allowing users to pinpoint pollution hotspots, water contamination zones, or areas of high noise pollution (Ramadaray and Samantaray, 2017; Hamud *et al.*, 2019).

By combining clarity, interactivity, and customizability, the user-centric dashboards ensure that the model is not only technically robust but also practically usable across diverse stakeholder groups.

The features of the IoT-driven environmental monitoring model—real-time monitoring, data analytics, scalability, interoperability, and user-centric dashboards—work synergistically to provide a comprehensive solution for environmental management. Real-time data ensures timely awareness, analytics add interpretive depth, scalability allows wide deployment, interoperability guarantees system integration, and dashboards translate technical data into actionable knowledge (Ilufoye *et al.*, 2020; ODINAKA *et al.*, 2020). Together, these features establish a foundation for sustainable, data-driven decision-making in environmental governance and smart city development.

2.3. Use Cases

The IoT-driven environmental monitoring model built on ThingsBoard API and MQTT presents versatile applications across diverse domains (Tesfahunegn and Makonnen, 2019). By enabling real-time data collection, secure transmission, and advanced visualization, it can be tailored to address specific environmental challenges. The following use cases illustrate its applicability in urban, agricultural, scientific, and disaster response contexts.

Rapid urbanization and industrialization have made air pollution one of the most pressing public health concerns worldwide (Dako *et al.*, 2020; Mgbame *et al.*, 2020). In smart cities, the proposed model can play a critical role in detecting high-pollution zones. Distributed networks of air quality sensors can continuously measure particulate matter (PM_{2.5} and PM₁₀), carbon monoxide (CO), nitrogen oxides (NO_x), and ozone levels. Through MQTT's efficient data transmission and ThingsBoard dashboards, real-time pollution maps can be generated to highlight hotspots.

Municipal authorities can use this information to implement adaptive strategies, such as restricting heavy vehicle entry during peak pollution hours or deploying mobile air purifiers in sensitive zones. Moreover, public-facing dashboards can enhance citizen awareness, allowing vulnerable populations—such as those with respiratory conditions—to take preventive measures. In this way, the model supports both policy-level interventions and individual decision-making, aligning with broader smart city objectives.

Water quality degradation threatens ecosystems and human health alike. The model provides a scalable solution for monitoring rivers, lakes, and groundwater quality through networks of IoT-enabled pH, turbidity, and dissolved oxygen sensors. Data streamed in real time can reveal pollution events such as industrial discharge or agricultural runoff.

For instance, detecting sudden drops in dissolved oxygen levels in a river may signal contamination, prompting immediate investigation and remediation. Groundwater monitoring, on the other hand, can help track salinity intrusion in coastal areas or nitrate accumulation in agricultural zones (Boesch, 2019). Integration with ThingsBoard's analytics allows authorities to establish baseline water quality trends and detect anomalies early. This capability enhances regulatory compliance, protects aquatic biodiversity, and ensures safer water supplies for communities.

Agriculture is a resource-intensive sector where efficiency and sustainability are increasingly critical. The proposed model supports soil moisture and microclimate monitoring for precision farming, enabling farmers to optimize irrigation, fertilization, and crop management. IoT-enabled soil moisture sensors and weather stations can transmit continuous data through MQTT to ThingsBoard dashboards, where real-time and historical patterns are analyzed.

Threshold-based alerts can trigger automated irrigation systems, ensuring that water is applied only when necessary. This not only conserves scarce water resources but also prevents soil degradation from over-irrigation. Monitoring temperature, humidity, and light intensity further supports microclimate management, particularly in greenhouses (Alvino and Marino, 2017; Bornare, 2019). Ultimately, the model empowers farmers with actionable insights that improve yields, reduce costs, and enhance resilience against climate variability.

Climate science depends heavily on high-quality, continuous

datasets to model trends and predict future scenarios. The IoT-driven model contributes to collecting real-time data for climate models and forecasts. Deployments across different ecological zones can capture temperature fluctuations, rainfall intensity, atmospheric pressure, and greenhouse gas concentrations at fine spatial and temporal resolutions.

These datasets, transmitted through MQTT and stored on ThingsBoard, can be integrated into larger climate modeling frameworks. Real-time availability ensures that researchers can rapidly validate or recalibrate models in response to anomalies, such as unexpected warming events or shifts in rainfall patterns. The model's scalability allows it to expand into global networks of distributed climate stations, supporting international research collaborations aimed at mitigating and adapting to climate change.

Early detection of hazardous conditions is crucial to minimizing loss of life and property during disasters. The model supports disaster management applications such as forest fire detection and toxic leak monitoring. In wildfire-prone regions, IoT sensors can monitor environmental parameters like temperature, humidity, and smoke particles. Once conditions cross critical thresholds, MQTT-based alerts can trigger emergency protocols, notifying fire departments and local communities.

Similarly, in industrial zones, sensors capable of detecting toxic gases or chemical leaks can be deployed. Real-time data streams processed by ThingsBoard enable authorities to act swiftly, containing hazards before they escalate. By offering automated alerts and integration with external emergency response systems, the model enhances preparedness and reduces response times during critical events.

The versatility of the IoT-driven environmental monitoring model is reflected in its diverse use cases. From improving urban air quality management and safeguarding water resources to enabling precision farming, advancing climate research, and strengthening disaster management, the model offers solutions that are both practical and scalable. By providing real-time insights and actionable intelligence, it supports proactive interventions and fosters resilience in the face of environmental challenges (Nwachukwu *et al.*, 2018; SHARMA *et al.*, 2019).

2.4. Benefits and Challenges

The deployment of an IoT-driven environmental monitoring model leveraging ThingsBoard API and MQTT offers substantial benefits for sustainability, public health, and smart city development. At the same time, it presents technical and operational challenges that must be carefully addressed to ensure reliability, trustworthiness, and long-term impact. This section examines both the benefits and the challenges, highlighting the dual nature of opportunities and constraints in IoT-based monitoring systems.

One of the foremost benefits is cost-effectiveness, scalability, and flexibility. Traditional environmental monitoring systems often rely on bulky, specialized equipment that is expensive to procure, deploy, and maintain. By contrast, IoT-enabled sensors are compact, relatively inexpensive, and can be deployed in large numbers across diverse environments. MQTT, as a lightweight communication protocol, further reduces operational costs by optimizing bandwidth usage, making it well-suited for both urban and remote monitoring contexts. The modular design of ThingsBoard allows incremental scaling, where new sensors or analytical modules can be added without disrupting existing systems (Maharjan,

2018; Sasidharan *et al.*, 2019). Flexibility is achieved through the platform's API, which supports integration with external analytics engines, mobile apps, and cloud storage systems. This adaptability makes the model a sustainable choice for governments, industries, and research institutions with varying resource capacities.

Another significant benefit lies in improved environmental policy decisions through data-driven insights. Policymakers often rely on periodic surveys or sparse monitoring stations, which provide limited temporal and spatial coverage. With IoT-driven systems, continuous streams of high-resolution data are made available, enabling real-time situational awareness. For instance, real-time tracking of particulate matter in urban areas can inform traffic management policies, while water quality data can guide interventions in agricultural or industrial zones. By offering accurate, timely, and granular information, the model supports evidence-based policymaking, helping to design regulations that are both targeted and adaptive. The ThingsBoard API facilitates this process by visualizing data in accessible dashboards and generating automated reports tailored to stakeholder needs, thus bridging the gap between technical complexity and decision-making utility.

The system also supports broader sustainability and smart city initiatives. Environmental monitoring is central to achieving global sustainability goals such as the United Nations Sustainable Development Goals (SDGs), particularly those related to clean water, climate action, and sustainable cities. IoT-driven models contribute by creating a digital infrastructure for monitoring and responding to ecological challenges. Within smart cities, the integration of sensor networks with other systems—such as energy grids, transportation networks, and waste management platforms—enables holistic management of urban environments. For example, noise and air quality data can be integrated with traffic monitoring to optimize mobility while minimizing environmental harm. The combination of MQTT's efficiency and ThingsBoard's scalability makes such cross-domain integration feasible, fostering more sustainable and livable cities.

Despite these benefits, several challenges constrain the effectiveness of IoT-based environmental monitoring. One pressing issue is sensor accuracy and calibration. Low-cost IoT sensors, while affordable, often lack the precision of high-grade scientific instruments. Variability in sensor readings due to environmental conditions such as humidity, temperature fluctuations, or electromagnetic interference can compromise data reliability (Ong *et al.*, 2017; Expósito *et al.*, 2019). Regular calibration and validation against reference-grade equipment are therefore essential but may increase operational costs and complexity. Inaccurate data can lead to misleading conclusions, undermining the credibility of the monitoring system.

Another challenge is network connectivity in remote areas. Environmental monitoring often requires deployment in rural or hard-to-reach locations where network infrastructure is limited. Although MQTT reduces bandwidth demands, consistent connectivity is still required for real-time transmission. In regions with poor internet coverage, data loss, latency, or complete communication failures may occur. Possible mitigations include hybrid architectures using local data caching or integration with low-power wide-area networks (LPWAN) such as LoRaWAN. However, these solutions require additional investment and technical

expertise.

Data privacy and security also pose significant challenges. IoT systems inherently generate large volumes of continuous data, some of which may be sensitive, particularly when monitoring overlaps with human activities in urban settings. Protecting this data from unauthorized access, manipulation, or misuse is crucial for maintaining stakeholder trust. ThingsBoard provides access control mechanisms, but the overall security architecture must encompass encryption, secure communication channels, and compliance with data protection regulations. The decentralized nature of IoT devices further complicates security management, as each node represents a potential vulnerability.

Finally, maintenance and lifecycle management of devices present operational hurdles. IoT sensors deployed in harsh environmental conditions face wear and tear, power supply challenges, and susceptibility to environmental damage. Regular maintenance, firmware updates, and battery replacements are essential to sustain system functionality. Lifecycle management also includes planning for device obsolescence, recycling, and upgrading, which are critical for reducing electronic waste. Without systematic lifecycle planning, large-scale deployments risk degradation over time, reducing their effectiveness and increasing long-term costs (Lai *et al.*, 2017; Joseph *et al.*, 2018).

The IoT-driven environmental monitoring model offers clear benefits in terms of cost efficiency, scalability, policy relevance, and alignment with sustainability initiatives. However, challenges such as sensor accuracy, network limitations, data security, and device lifecycle management must be addressed through robust technical, organizational, and policy strategies. Balancing these benefits and challenges is essential for realizing the full potential of IoT technologies in environmental monitoring and ensuring they contribute to resilient, sustainable, and equitable futures.

2.5. Future Directions

The IoT-driven environmental monitoring model, anchored on ThingsBoard API and the MQTT protocol, provides a robust foundation for scalable, real-time environmental intelligence. However, as technology continues to evolve, the potential of this framework can be significantly expanded through integration with emerging digital innovations. Future directions involve the infusion of artificial intelligence and machine learning, the deployment of edge computing, the use of blockchain for data integrity, and the exploration of cross-domain applications (Buyya *et al.*, 2018; Deka *et al.*, 2019). These developments will enhance the efficiency, reliability, and utility of environmental monitoring systems, enabling them to address increasingly complex global challenges.

One of the most promising avenues for advancement lies in the integration of artificial intelligence (AI) and machine learning (ML). While current deployments excel at collecting and visualizing environmental data, the growing complexity of environmental systems necessitates predictive and adaptive capabilities. AI and ML algorithms can be applied to the datasets generated by ThingsBoard to perform predictive environmental modeling, identifying future scenarios such as urban pollution surges, drought risks, or potential flood events.

In addition, AI-driven anomaly detection can enhance the responsiveness of monitoring systems. For example, sudden spikes in particulate matter levels in a city or unexpected pH fluctuations in water bodies can be flagged as anomalies,

even if they fall within technical thresholds, prompting early investigation. This predictive and preventive functionality ensures that stakeholders are not merely reactive but are empowered with foresight, enabling proactive policy interventions and resource allocation.

As sensor deployments expand, the volume of environmental data transmitted to centralized servers increases significantly. This creates challenges related to bandwidth usage, latency, and system reliability. Edge computing offers a viable solution by enabling local data processing near the point of collection. Instead of transmitting raw data continuously, edge-enabled devices can preprocess and filter information before publishing via MQTT to ThingsBoard.

For instance, in a forest fire detection system, edge devices could process sensor data locally to confirm fire signatures before sending alerts, thereby reducing false positives and conserving network resources. Similarly, in agricultural applications, edge nodes could aggregate soil moisture readings across multiple sensors and transmit only summarized trends. This approach not only optimizes network bandwidth but also ensures rapid response in time-critical scenarios, as decisions can be made closer to the data source.

Environmental data must be trustworthy to serve as a reliable basis for decision-making and public policy. However, concerns around data tampering, misreporting, and loss of transparency remain significant barriers. The integration of blockchain technology can address these challenges by creating immutable and decentralized ledgers of environmental data transactions (Gökalp *et al.*, 2018; Nawari and Ravindran, 2019).

In this context, each sensor reading transmitted through MQTT and processed by ThingsBoard can be cryptographically recorded on a blockchain. This ensures that data cannot be retroactively altered, thereby enhancing trust and transparency. Governments, researchers, and citizens can independently verify the authenticity of environmental information, which is especially critical for sensitive issues like air quality regulation or water contamination disputes. Furthermore, blockchain enables accountability by creating auditable trails of data access and usage, strengthening compliance with environmental governance standards.

Beyond standalone environmental monitoring, future advancements lie in cross-domain applications that integrate environmental intelligence into other sectors. In healthcare, real-time air quality monitoring can be directly linked to hospital data systems to analyze correlations between pollution levels and respiratory disease admissions. Such integration could inform targeted health advisories or preventive interventions in vulnerable communities.

Similarly, in the transportation sector, monitoring traffic-related emissions can support adaptive traffic control strategies. By feeding emission data into smart transportation systems, authorities can reroute vehicles, adjust signal timings, or incentivize low-emission zones to reduce urban pollution. Cross-domain applications underscore the versatility of the IoT-driven model, transforming it into a cornerstone of integrated digital ecosystems that address both environmental and societal challenges.

The future of IoT-driven environmental monitoring lies in augmenting its current strengths with advanced technologies. AI/ML will enable predictive modeling and intelligent anomaly detection, edge computing will optimize data processing and response times, blockchain will safeguard

data integrity and transparency, and cross-domain applications will embed environmental intelligence into broader societal systems such as healthcare and transportation. Collectively, these future directions will transform the model into a more adaptive, secure, and impactful tool, advancing the global pursuit of sustainability and resilience (Bibri, 2018; Govindan and Al-Ansari, 2019).

3. Conclusion

This has demonstrated an IoT-driven framework that integrates ThingsBoard API and the MQTT protocol to enable real-time environmental monitoring. By combining low-cost, distributed sensors with lightweight communication and scalable middleware, the model provides a robust structure for capturing, transmitting, analyzing, and visualizing environmental data. The layered architecture—comprising the data, communication, and application layers—ensures interoperability, efficiency, and adaptability, while the functional flow illustrates how raw sensor measurements are transformed into actionable insights. Together, these contributions advance the understanding of how IoT technologies can operationalize sustainable monitoring systems that are both cost-effective and scalable. The impact of this framework extends to multiple stakeholder groups. Governments can rely on continuous and high-resolution data streams to inform evidence-based environmental regulations, urban planning policies, and climate adaptation strategies. Businesses can leverage monitoring insights for compliance, corporate sustainability reporting, and optimizing resource use in operations. Researchers benefit from access to rich datasets that enable advanced environmental modeling, trend detection, and interdisciplinary studies linking ecological changes with human health or economic outcomes. In each case, the framework strengthens informed decision-making, reduces uncertainty, and fosters accountability in environmental stewardship.

Looking forward, the trajectory of IoT-driven monitoring is toward autonomous, adaptive, and AI-enhanced ecosystems. Integration with artificial intelligence can enable predictive analytics, anomaly detection, and self-optimizing sensor networks that respond dynamically to changing environmental conditions. Advances in edge computing, federated learning, and secure data-sharing protocols will further enhance scalability, resilience, and privacy. Ultimately, the vision is for adaptive environmental monitoring systems that not only observe but also anticipate risks, enabling proactive interventions for sustainable development. The framework presented here lays the foundation for such future ecosystems, bridging current technological capabilities with the next generation of intelligent, self-managing environmental monitoring infrastructures.

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