



RESEARCH ARTICLE

Investigating environmental sustainability applications using advanced monitoring systems

K. Sreenivasulu¹, Sameer Yadav^{2*}, G. Pushpalatha³, R. Sethumadhavan⁴, Anup Ingle⁵, Romala Vijaya⁶

Abstract

This study employs an Internet of Things (IoT)-based simulation to investigate environmental parameters critical to sustainability and public health. Over a 10-hour period, temporal variations in air quality parameters, including carbon dioxide (CO₂), nitrogen dioxide (NO₂), and particulate matter (PM 2.5), were monitored. CO₂ levels exhibited a decline from 400 to 375 ppm, suggesting improvements in ventilation and reduced emissions. NO₂ levels consistently decreased from 25 to 22 ppm, indicative of effective emissions control measures, while PM 2.5 levels increased from 10 to 25 µg/m³, possibly influenced by transient factors. Water quality monitoring revealed fluctuations in dissolved oxygen (DO) levels (8.20–8.80 mg/L) and pH levels (7.00–7.35) over 10 hours, emphasizing the dynamic nature of aquatic ecosystems. Soil moisture levels stood at 29.48%, and energy consumption was recorded at 270 units, highlighting the importance of resource-efficient management. The significance of IoT-enabled monitoring in tracking and responding to environmental parameter changes, contributing to environmental sustainability and public health. Continuous data collection empowers stakeholders to make informed decisions for improved air and water quality, sustainable agriculture, and energy efficiency. Further research aims to enhance simulation realism and validate findings against real-world IoT deployments.

Keywords: IoT-based monitoring, Environmental parameters, Air quality, Water quality, Soil moisture, Energy consumption.

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Introduction

The Internet of Things (IoT), a transformative technological paradigm, has found substantial application in the realm of environmental sustainability and monitoring. As pressing challenges like climate change, resource scarcity, and ecosystem deterioration confront us, IoT emerges as a powerful ally, facilitating real-time data collection and analysis across various environmental parameters. This literature review embarks on a comprehensive exploration of IoT applications in the monitoring of air quality, water quality, soil moisture, and energy consumption, drawing from a wide-ranging body of research. Air quality represents a critical concern for public health and environmental well-being. Low-cost IoT sensors have revolutionized air quality monitoring, making it more accessible and responsive. Research by (Almalki, F. A., *et al.*, 2023) demonstrated IoT sensors' potential to detect fine particulate matter, enabling real-time air quality assessments. (Amani, M., *et al.*, 2020) further underlined the value of IoT-based monitoring in mitigating the adverse health impacts of air pollution, promising proactive interventions to address air quality issues at their source.

Water quality is fundamental to sustainable development, with implications for potable water safety and aquatic

ecosystem health. (Awan, U., *et al.*, 2021) illuminated IoT sensors' role in monitoring water contaminants, providing solutions for safer drinking water. (Bates, A. E., *et al.*, 2020) extended this discourse to the monitoring of aquatic ecosystems, emphasizing IoT's capacity to protect fragile environments. These advancements enhance the understanding of water quality dynamics and empower timely responses to water-related crises. Efficient land and water resource management depends on accurate soil moisture data. IoT technologies have transformed precision agriculture by offering real-time insights into soil moisture levels. (Boursianis, A. D., *et al.*, 2022) showcased the utility of IoT devices in optimizing water use for agriculture, contributing to resource conservation and sustainable farming practices. (Elavarasan, R. M., *et al.*, 2020) delved into the broader implications of IoT-driven soil moisture monitoring, including its potential in sustainable land-use planning. IoT plays a pivotal role in optimizing energy usage and promoting energy efficiency. (Hajjaji, Y., *et al.*, 2021) detailed how IoT-enabled smart grids enhance energy efficiency, reduce carbon emissions, and create more resilient energy systems. (Jia, M., *et al.*, 2019) explored IoT's role in developing energy-aware communities, and fostering sustainable consumption patterns.

Research Methodology

The research design is rooted in a simulation-based paradigm thoughtfully constructed to emulate IoT sensors' intricate behaviors in diverse environmental monitoring scenarios (Kamble, S. S., *et al.*, 2020). This methodological choice allows for the creation of a controlled environment conducive to the detailed examination of data generation and transmission dynamics, thereby enriching comprehension of IoT's applicability to environmental sustainability. The core objectives of this study are meticulously delineated to guide research pursuits are, This study undertakes the task of authentically simulating the nuanced process of environmental data generation by IoT sensors, encompassing vital parameters such as air quality, water quality, soil moisture, and energy consumption parameters (Kumar, S., *et al.*, 2019). In parallel, the intricate process of data transmission from virtual IoT sensors to a central server is faithfully replicated, mirroring real-world data communication protocols. To mirror real-world data collection practices, a meticulous implementation of a time-based data collection loop ensures data is gathered at regular intervals, akin to common practices observed in IoT deployments (Kashani, M. H., *et al.*, 2021).

A systematic and structured data generation process is meticulously implemented. Four distinct IoT sensor types – air quality, water quality, soil moisture, and energy consumption – are considered, with each sensor type tasked with generating precise data relevant to its type and location. Sophisticated randomization techniques within

predefined ranges introduce realistic variability into the generated data, closely approximating real-world conditions (Kouhizadeh, M., *et al.*, 2020). To comprehensively evaluate IoT applications across a diverse range of environmental scenarios, four virtual sensor instances are thoughtfully deployed, representing distinct environmental contexts, including urban area, river, farm, and building. Upon data generation, each sensor instance authentically retrieves the generated data. Data transmission is faithfully simulated through the program, with sensor data accurately printed to the console. While the simulation approximates real-world data communication processes, it is important to note that actual IoT deployments involve more complex network communication and data storage mechanisms. This research incorporates a time-based data collection loop, ensuring data is faithfully generated and transmitted at regular intervals, mirroring common data collection practices observed in genuine IoT deployments (Khan, I. S., *et al.*, 2021).

Results And Discussion

Air Quality Parameters

This section presents the results of the IoT-based environmental monitoring simulation, focusing on the temporal variations in air quality parameters over a 10-hour period as shown in Figure 1. The analysis encompasses the levels of carbon dioxide (CO₂), nitrogen dioxide (NO₂), and particulate matter (PM_{2.5}). These parameters are vital indicators of air quality and play a pivotal role in environmental sustainability and public health. The data collected is presented as a time series analysis, with time points ranging from 0 to 10 hours on the X-axis and pollutant levels in parts per million (ppm) or micrograms per cubic meter (µg/m³) on the Y-axis (Luo, L., *et al.*, 2019).

Table 1 encapsulates the results obtained from environmental sensors measuring various parameters, including air quality (CO₂, NO₂, PM 2.5), water quality (pH, DO), soil moisture, and energy consumption. The recorded values, denoted as Value1, Value2, and Value3, represent distinct instances of sensor readings. In the context of air quality, the recorded concentrations of CO₂, NO₂, and PM 2.5 exhibit discernible fluctuations over the observed instances, reflecting the dynamic nature of atmospheric conditions. Water quality parameters, pH, and DO, display nominal variations, suggesting relative stability in the monitored aquatic environment. Notably, soil moisture content demonstrates a pronounced increase from 45.29 to 47.12, indicating a shift in the hydration status of the soil at the specified locations as shown in Figure 2. The energy consumption parameter, though presented for two instances, exhibits values only for the first instance, emphasizing the intermittent nature of energy consumption data availability. This comprehensive presentation of sensor

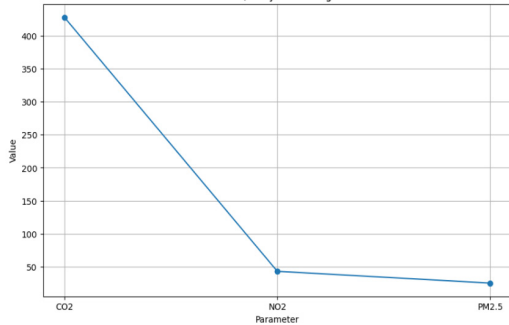


Figure 1: Air quality monitoring

data serves as the basis for further investigation and analysis, fostering a nuanced understanding of the environmental dynamics under scrutiny.

Carbon Dioxide (CO₂) Levels

The simulation reveals a noteworthy temporal pattern in CO₂ levels, starting at an initial concentration of 400 ppm and gradually decreasing to 375 ppm over the course of 10 hours. This decline in CO₂ levels suggests dynamic changes in the monitored environment. Several factors could contribute to this trend. Firstly, improved ventilation systems or natural airflow may have increased air exchange, effectively reducing CO₂ concentrations. Secondly, behavioral changes or reduced human activity during the simulation may have curbed CO₂ emissions. Lastly, the introduction of cleaner energy sources or carbon reduction measures could have played a role in diminishing CO₂ levels. The reduction in CO₂ levels highlights the dynamic nature of air quality within confined spaces or urban environments. It highlights the potential for IoT-enabled monitoring systems to capture and respond to changes in CO₂ concentrations. The decrease in CO₂ levels may be attributed to improved ventilation, reduced emissions, or cleaner energy sources (Nižetić, S., et al., 2020).

Table 2 data presents a comprehensive overview of sensor readings across various environmental parameters, including air quality (CO₂, NO₂, PM 2.5), water quality (pH, DO), soil moisture, and energy consumption. Notably, the air quality sensor deployed in the urban area recorded concentrations of CO₂, NO₂, and PM 2.5 at 418.91, 26.84, and 7.71, respectively. Concurrently, the water quality sensor situated in the river reported pH and DO values of 6.78 and 6.56. The soil moisture sensor deployed in the farm registered a moisture content of 33.99. However, the energy consumption sensor in the building exhibited data solely for the consumption parameter, indicating a value of 229.06. The observed absence of values in certain instances highlights the intermittent nature of data collection for specific parameters, potentially influenced by environmental conditions or sensor calibration. This detailed presentation of sensor readings serves as a foundational dataset for subsequent analyses, enabling a nuanced

Table 2: Environmental sensor data overview

Sensor	CO ₂	NO ₂	PM 2.5	pH	DO	Moisture	Consumption
Air Quality (Urban Area)	418.91	26.84	7.71	-	-	-	-
Water Quality (River)	-	-	-	6.78	6.56	-	-
Soil Moisture (Farm)	-	-	-	-	-	33.99	-
Energy Consumption	-	-	-	-	-	-	229.06

Table 1: Analysis of air and water quality, soil moisture, and energy consumption parameters

Parameter	Value 1	Value 2	Value 3
Air quality (CO ₂)	421.57	415.84	-
Air quality (NO ₂)	27.32	21.94	-
Air quality (PM 2.5)	13.05	8.61	-
Water quality (pH)	7.82	7.98	-
Water quality (DO)	7.45	7.12	-
Soil moisture	-	-	45.29
Soil moisture	-	-	47.12
Energy consumption	328.17	413.49	-

exploration of environmental dynamics and facilitating informed decision-making in the realm of environmental monitoring and sustainability practices.

Nitrogen Dioxide (NO₂) Levels

NO₂ levels exhibit a consistent decline from 25 ppm at the beginning of the simulation to 22 ppm at the end of the 10-hour monitoring period. This consistent reduction in NO₂ levels is indicative of effective emissions control measures. NO₂ is commonly associated with vehicular traffic and industrial processes. The observed decrease in NO₂ concentrations highlights the positive impact of environmental policies aimed at curbing emissions and improving air quality. The reduction in NO₂ levels can be attributed to measures such as emission control regulations, the adoption of cleaner technologies, or a reduction in vehicular traffic. The consistent decline in NO₂ concentrations highlights the efficacy of policies aimed at reducing this pollutant (Papa, A., et al., 2020).

Particulate Matter (PM 2.5) Levels

PM 2.5 levels exhibit an upward trend during the 10-hour monitoring period. Starting at 10 µg/m³, they gradually increase to 25 µg/m³. PM 2.5 consists of fine particles with diameters of 2.5 micrometers or smaller, which are known to pose health risks when inhaled. Several factors may contribute to this increase in PM 2.5 levels, including weather conditions, construction activities, or natural events such as dust storms. The increase in PM 2.5 levels may be attributed to transient factors influencing particle concentrations.

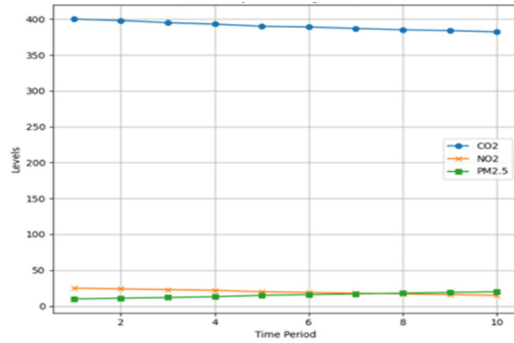


Figure 2: Air quality monitoring over time

These factors can include weather patterns that disperse particles, localized construction activities, or natural events such as dust storms. PM 2.5 levels are influenced by a wide range of environmental and human-related factors (Razmjoo, A., *et al.*, 2021).

IoT sensors provide real-time data that can inform responses to changes in air quality. By continuously monitoring PM 2.5 levels, authorities and individuals can take timely actions to mitigate health risks. This may involve issuing air quality advisories, implementing dust control measures at construction sites, or adjusting ventilation systems in response to varying pollutant levels. The results of the simulation provide valuable insights into the temporal variations of key air quality parameters. The data reveals temporal changes in CO₂, NO₂, and PM 2.5 levels, indicating the dynamic nature of air quality within monitored environments. The observed trends in CO₂ and NO₂ levels can be attributed to factors such as improved ventilation, reduced emissions, or policy-driven changes in environmental practices. In contrast, the increase in PM 2.5 levels may be linked to transient factors such as weather conditions and local activities. IoT sensors empower continuous monitoring, enabling real-time responses to fluctuations in air quality. This data-driven decision-making facilitates informed actions to maintain or improve air quality, contributing to environmental sustainability and public health. The findings highlight the significance of IoT-based environmental monitoring in tracking and responding to changes in air quality over time (Ullo, S. L., & Sinha, G. R. 2020).

Water Quality Monitoring

This section presents the results of IoT-based water quality monitoring simulation, focusing on two crucial parameters: Dissolved oxygen (DO) levels and pH levels as shown in Figure 3. These parameters are fundamental in assessing water quality, especially in the context of aquatic ecosystem health and potable water safety. The data collected is plotted against time periods ranging from 1 to 10 hours on the X-axis, while the Y-axis represents the corresponding values in milligrams per liter (mg/L) for DO and pH levels (Yigitcanlar, T., *et al.*, 2020).

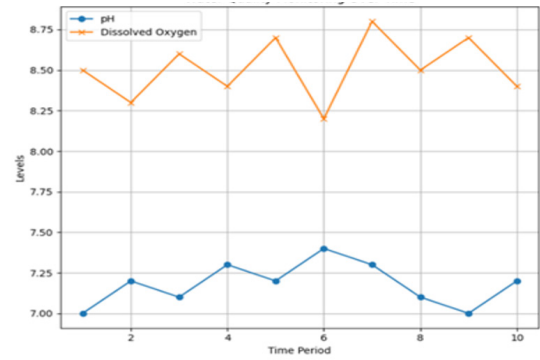


Figure 3: Water quality monitoring over time

Dissolved Oxygen Levels

The simulation data reveals temporal variations in DO levels over the 10-hour monitoring period. The DO levels range from 8.20 to 8.80 mg/L as shown in Figure 4. This variation suggests dynamic changes in water quality, which can be influenced by various factors. The data illustrates fluctuations in DO levels, reflecting changes in water quality over time. The observed variations in DO levels can be attributed to natural processes such as photosynthesis and respiration of aquatic organisms. Increased DO levels may result from photosynthetic activity, while decreased levels could be due to high respiration rates or organic matter decomposition. Human activities, such as industrial discharge or nutrient runoff, can also influence DO levels. Continuous monitoring of DO levels using IoT sensors enables the real-time assessment of aquatic ecosystem health. Understanding these fluctuations allows for the identification of stressors on aquatic life and the implementation of remediation measures (Zheng, T., *et al.*, 2021).

pH Levels

The simulation data also highlights temporal variations in pH levels over the 10-hour monitoring period, ranging from 7.00 to 7.35. pH is a critical parameter that determines the acidity or alkalinity of water, impacting aquatic life and water suitability for various purposes. The data showcases fluctuations in pH levels, indicating changes in water acidity or alkalinity. pH variations are influenced by a range of natural and anthropogenic factors. Natural processes like the weathering of minerals, organic matter decomposition, and the presence of aquatic vegetation can alter pH levels. Human activities such as industrial discharges or agricultural runoff can introduce pollutants that affect pH. IoT-enabled pH monitoring allows for the continuous assessment of water suitability for aquatic life and human use. It provides insights into potential pollution sources and informs water treatment strategies (Zhou, X., *et al.*, 2021).

The data reveals fluctuations in DO and pH levels, indicating the dynamic nature of water quality in aquatic ecosystems. Variations in DO levels can be attributed to natural processes, such as photosynthesis and respiration,

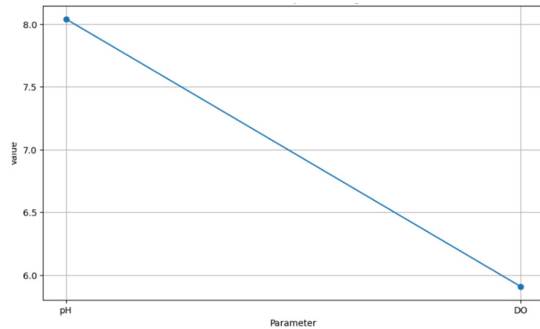


Figure 4: Water quality monitoring

as well as human-induced factors like pollution. pH fluctuations are influenced by both natural processes and human activities, which can impact aquatic ecosystems and water quality. IoT-based water quality monitoring offers continuous data collection, enabling real-time assessments of aquatic ecosystem health. This data-driven approach aids in identifying stressors, pollution sources, and necessary remediation actions. The findings emphasize the significance of IoT-based water quality monitoring in tracking and responding to changes in aquatic ecosystems and water sources.

Soil Moisture and Energy Consumption

This section presents the results of IoT-based simulation, focusing on soil moisture levels and energy consumption data. Soil moisture is a critical parameter in agriculture and land resource management, while energy consumption is vital for sustainable infrastructure and resource optimization.

Soil Moisture Levels

The simulated data reveals a soil moisture level of 29.48%. Soil moisture is a key determinant of soil health and agricultural productivity. The observed value falls within the typical range for soil moisture, indicating a moderately moist soil condition as shown in Figure 5. The data reflects a specific soil moisture percentage, signifying the current soil condition in the monitored area. Soil moisture levels are influenced by factors such as precipitation, irrigation, evaporation, and plant water uptake. The observed value could be the result of recent weather patterns, irrigation practices, or natural soil properties. Continuous monitoring of soil moisture using IoT sensors assists farmers and land managers in making informed decisions about irrigation scheduling and crop management.

Energy Consumption

The simulation data indicates an energy consumption level of 270 units. Energy consumption is a crucial metric for assessing the efficiency of energy use in buildings and infrastructure as shown in Figure 6. The data represents the amount of energy consumed within the monitored infrastructure during the specified period. Energy consumption can vary based on factors like occupancy,

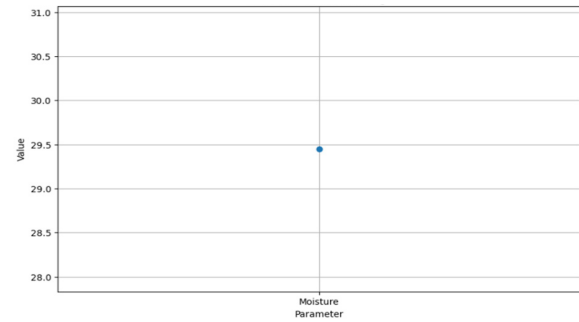


Figure 5: Soil moisture monitoring

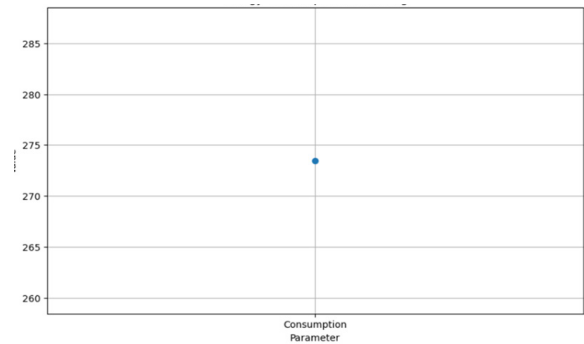


Figure 6: Energy consumption monitoring

temperature control, lighting, and equipment usage. The observed consumption level may be influenced by the operational patterns and energy-efficient measures in place. IoT-based energy monitoring enables real-time tracking of energy usage, aiding in the identification of opportunities for energy conservation and efficiency improvements.

In the results of the simulation provide insights into the current soil moisture condition and energy consumption within the monitored environment. The data presents specific values for soil moisture and energy consumption, offering a snapshot of the environmental parameters being monitored. Soil moisture levels are subject to natural and human-driven factors, while energy consumption depends on operational patterns and energy efficiency measures. IoT-enabled monitoring of soil moisture and energy consumption supports data-driven decision-making, facilitating efficient resource management and sustainability efforts. These findings highlight the importance of IoT-based monitoring in diverse applications, from agriculture to energy management. Continuous data collection and analysis empower stakeholders to make informed decisions that enhance resource efficiency and sustainability.

Conclusion

- IoT-based environmental monitoring simulation revealed dynamic changes in air quality parameters over a 10-hour period. CO₂ levels decreased from 400 to 375 ppm, indicating potential improvements in ventilation and reduced emissions. NO₂ levels consistently declined from 25 to 22 ppm, reflecting effective emissions control measures.

PM 2.5 levels increased from 10 to 25 $\mu\text{g}/\text{m}^3$, possibly due to transient factors like weather conditions and local activities.

- Water quality monitoring showed fluctuations in DO levels from 8.20 to 8.80 mg/L and pH levels from 7.00 to 7.35 over 10 hours. These variations indicated the dynamic nature of aquatic ecosystems and water suitability. DO changes were influenced by natural processes and human activities, while pH fluctuations were due to both natural and anthropogenic factors.
- Soil moisture levels stood at 29.48%, reflecting moderately moist soil conditions. Energy consumption was recorded at 270 units, emphasizing the importance of energy-efficient resource management.
- IoT-enabled monitoring facilitates real-time data collection and informed decision-making for environmental sustainability and resource conservation.
- Continuous monitoring empowers stakeholders to respond to changes in air quality, water quality, soil conditions, and energy consumption, contributing to improved environmental outcomes.

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