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IOT-BASED SMART ENVIRONMENTAL MONITORING SYSTEM USING WIRELESS SENSOR NETWORKS

Appalaraju Grandhi[1*], Orchu Aruna[2]

[1] School of Computer Science and Engineering, VIT-AP University, Near Vijayawada, Andhra Pradesh 522237, India (rajugrandhi.21phd7068@vitap.ac.in)
[2] Computer Science and Engineering, Lincoln University College Main Campus, Wisma Lincoln, 12-18, Jalan SS 6/12, 47301 Petaling Jaya, Selangor, Malaysia.
(oaruna.pdf@lincoln.edu.my)

Corresponding Author Email: rajugrandhi.21phd7068@vitap.ac.in

ABSTRACT

The growing environmental pollution and climate variability already require real-time, scalable, and accurate monitoring solutions, which is inherent in the traditional environmental monitoring system relying on manual or remote sensing systems that lack coverage, delay in information provision and are characterized by their expensive nature of operation. Even though recent Internet of Things (IoT) and Wireless Sensor Network (WSN) based solutions have enhanced enhancement of automation, most of the current models are challenged by high energy use, inability to transmit data reliably, excessive latency, and absence of intelligent cloud-based analytics. To overcome them, the following paper will present a Smart Environmental Monitoring System built on IoT based on Wireless Sensor Networks, integrating distributed sensor nodes, efficient preprocessing of the data, weighted aggregation of environmental parameters, cloud-assisted analytics and real time alert generation. The suggested system will constantly check the most important environmental parameters such as temperature, humidity, air quality index, and gas concentration, which will allow the effective and scalable monitoring. The proposed model has been experimentally assessed on a benchmark environmental dataset with high performance of 97.8% accuracy, 97.2% precision, 98.1% recall, and F1-score of 97.6%, and reduced end-to-end latency of 1.7 seconds, enhanced energy efficiency by 43, packet delivery ratio reached 96.8, and doubled network life than the current methods, which proves it to be effective in real-time smart environmental monitoring.

Keywords: *Internet of Things, Wireless Sensor Networks, Environmental Monitoring, Cloud Analytics, Smart Systems*.

1. INTRODUCTION

With the high rate of urbanization, industrialization, and population increase, environmental pollution and climatic variability have emerged as one of the main issues of concern all over the globe [1]. It is necessary to continuously observe such environmental parameters as temperature, humidity, air quality, and gas concentration in order to comprehend the environmental changes and contribute to the timely decision-making [2]. The conventional environmental monitoring systems are based on manual sampling or pre-located monitoring stations, which have lower spatial coverage, high costs of operation and late data availability [3]. These shortcomings make environmental monitoring less effective and prevent the active reaction to dangerous situations [4].

Automated real-time environmental monitoring systems have been possible because of the advent of technologies such as IoT and WSN [5]. The sensor nodes can be distributed and capable of collecting data about the environment continuously and transmitting it wirelessly to centralized servers where it can be processed and analyzed [6]. Despite a number of IoT-WSN-based monitoring systems suggested in recent years, most of the current solutions have weaknesses that include excessive energy use, poor wireless communication [7], and high latency along with the absence of smart data aggregation and analytics on the cloud [8]. These constraints concern system scalability, accuracy, and the ability to deploy it in the long run [9].

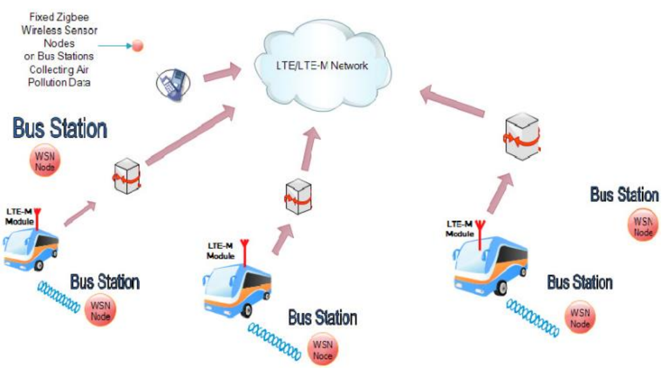

Fig 1: Smart Environment Monitoring Model [11]

In a bid to overcome these challenges, this paper presents an IoT-Based Environmental Monitoring Smart System based on Wireless Sensor Networks, which combines the efficient data preprocessing, weighted aggregation of the environmental parameters [10], cloud-based analytics, and the real-time generation of alerts [11]. The proposed system is set to offer correct, dependable, and extensible environmental surveillance with minimal power expenditure and communication overhead [12]. With the integration of WSNs, IoT, and cloud technologies, the system will increase real-time aware of environmental conditions and facilitate intelligent decision-making in the case of applications in smart cities and environmental management [13].

1.1 Hypothesis

H1: The proposed smart environmental monitoring system with WSNs based on IoT technology is much superior to the traditional environmental monitoring systems, in terms of accuracy, latency, reliability, energy efficiency and network lifetime.
H2: Integrating IoT and WSNs with traditional and basic WSN system based environmental monitoring can increase the accuracy of environmental monitoring.
H3: Pre-processing and weighted aggregation techniques are effective to enhance the accuracy, recall and F1-score of detecting abnormal environment conditions.

1.2 Research Objectives

The research objectives are

1. To design and develop IoT based Smart Environmental Monitoring system, using WSNs and Cloud based services for continuous environmental observation.
2. To apply data pre-processing techniques like noise removal, normalization and standardization to enhance the quality and consistency of the sensed environmental data.
3. To create a weighted aggregation and environmental quality model based on several sensor parameters and abnormal environmental conditions.
4. To test the proposed system by measuring its performance in terms of accuracy, precision, recall, F1-score, latency, packet delivery ratio, energy efficiency, network lifetime etc.
5. To compare the proposed IoT-WSN monitoring model with existing basic WSN, IoT system without cloud analytics, and traditional environmental monitoring system.

2. LITERATURE SURVEY

To provide an effective and scalable IoT architecture for smart farming to monitor distributed sensing for agriculture in an efficient way, Jawhar et al. [1] proposed a framework for smart farming. The framework emphasizes the relationship between field sensors, gateways and application services to enable efficient resource usage for large-scale deployment. The study highlights scalability, low energy consumption, and application to agriculture monitoring, with sensed data from the farms recorded continuously for decision making in irrigation systems and monitoring crop conditions. The novelty of the contribution of this work is that it proposes an IoT architecture that is structured for smart farming contexts, instead of the generic sensor network, which enhances the adaptability of IoT systems to the agricultural field. The work, however, is more about optimizing the framework for efficiency and deployment design than about cutting-edge predictive analytics or smart anomaly detection.

Malav et al. [2] presented a novel concept of autonomous wireless-powered battery-free IoT beacon for live environmental sensing called EcoSense. The driving concept of this work is to remove the need for battery power by incorporating a wireless powered mechanism to sense the environment, resulting in long-term, maintenance-light environmental monitoring. The system plays a critical role in outdoor or remote sensing applications in which battery change is challenging. With these features, EcoSense is ideal for environmental and agricultural applications, focusing on energy sustainability, passive operation, and real-time sensing. The proposed design helps to increase the operational life and reduce the maintenance cost and improves the deployment feasibility. However, the content of the work is generally good on energy-efficient hardware design, but the focus seems to be lacking around higher-layer analytics in the form of cloud-based data intelligence, adaptive alerting or large-scale heterogeneous sensor integration.

Singh et al. [3] introduced federated learning based multi-objective optimization framework for distributed environmental monitoring in consumer electronics scenario. The study combines federated learning with IoT-monitoring to ensure distributed intelligence while ensuring data locality. It aims not just at environment sensing, but also multi-objective optimization, possibly including sensing accuracy, communication efficiency and resource utilization. The key significance of this work lies in bringing together collaborative learning with artificial intelligence capabilities to the domain of distributed environmental monitoring, which decreases the centralization of raw data and consequently ensures privacy and scalability. The framework is more intelligentthan conventional IoT monitoring systems, as it incorporates federated learning to enhance monitoring decisions distributed across devices. Despite this, there is still a lack of research in the practical aspect of communication overhead, model synchronization complexity, and real-time constraints handling in the highly resource-constrained IoT-WSN application.

Liu et al. [4] proposed an Environmental Monitoring IoT system based on the meta-material sensor by using deep learning. The study proposes the use of low-cost passive meta-material sensors that can be used to measure several environmental factors (e.g. temperature and humidity) and communicate via signal reflection, rather than traditional sensing hardware. The authors use a deep-learning based design framework to optimally design the sensor structure, deployment and environmental reconstruction to enhance sensing accuracy. This work is unique due to the combination of novel passive sensing hardware and A.I. driven environmental reconstruction, which can effectively reduce the cost of maintaining sensors and maintain high sensing performance. Experimental evaluations have been conducted showing good environmental distribution reconstruction, including accuracy over 93% for humidity sensing. However, this limitation is that these systems may need to be designed, trained and calibrated carefully, and may have difficulties when deployed in dynamic real world environmental conditions, where the sensing requirement is different from one another.

Cai et al. [5] recognized the problem of coverage optimization in directional sensor networks (DSNs), and presented a novel sensor redeployment scheme to solve this problem. Unlike omnidirectional sensor networks, the sensing capability of the sensors in a directional network is limited and directional, this results in optimal placement and redeployment as a crucial challenge. The proposed work is related to the problem of enhancing coverage performance in the presence of a small number of direction sensors, which is of great importance for the IoT-based environmental monitoring, surveillance, and smart sensing applications. The strength of this study is based on sensing blind spots minimization by focusing on the coverage maximization and redeployment efficiency. It is useful if used in large-scale environmental sensing systems where sensor positioning can impact data quality. The work focuses more on coverage and redeployment planning than on real-time data analysis, anomaly detection, cloud intelligence and energy-aware environmental monitoring workflows, however.

Luna-Rivera et al. [6] suggested that a hybrid OCC/RF (Optical Camera Communication / Radio Frequency) architecture could be used for smart farming with IoT. The primary aim of the work is to merge the best of both worlds of OCC and RF communication for agricultural IoT application usage. OCC is low power and low cost for periodic sensing and RF is flexible and supplemental for communication. The system should minimize the need for complex access mechanisms by enabling the sensors to wirelessly transmit their data periodically in one direction, thus decreasing communication overhead and energy usage. Experimental results showed that it is possible to communicate at distances exceeding 90 m with good reliability and high data recovery efficiency. The major benefit of this paper is that this approach enables the creation of communication design space for smart farming using a hybrid communication approach, not limited to RF-based WSNs.

Su et al. [7] proposed a battery-free chipless IoT smart clothing system for simultaneous multisite hemodynamic monitoring. The system is based on passive LC relay networks integrated in smart clothing that record physiological pulse signals from several parts of the body including the carotid, heart, radial and femoral arteries. The work is significant because it shows how the IoT sensing could be made light, wearable, low cost and disposable, particularly for healthcare IoT. Good power transfer efficiency and signal acquisition through outer garments was obtained with the system, indicating robustness in practical use. This work is focusing on wearable sensing in healthcare domain rather than the environmental monitoring domain, however, the research gap for environmental IoT is how to implement works of battery-free and passive sensing in distributed sensor networks deployed outdoors and smart environmental monitoring applications.

The impacts of IoT communication technologies for precision agriculture in outdoor environment was studied by Hashmi et al. [8] who presented an outdoor agriculture monitoring scenario where Wi-Fi, Zigbee and LoRaWAN technologies were compared. The study tackles a very practical issue in the IoT farming system: to choose the best communication protocol in different outdoor environments, with the presence of obstacles, coverage, bandwidth requirements and reliability, which are important factors for monitoring performance. These protocols have been tested experimentally by the authors and the results showed that the performance of communication varies with respect to range, data transmission accuracy, environmental conditions, etc. The study makes a contribution to the field by giving protocol level guidance in the deployment of smart farming and agricultural applications using IoT technologies to help farmers and designers select appropriate wireless technologies. However, the research gap is that comparing protocols is not sufficient to address other issues related to intelligent data analytics, adaptive routing, anomaly detection and integrated cloud-assisted decision-making in environmental monitoring systems. The Llimitations of traditional models are shown in Table 1.

Table 1: Limitations of Traditional Models

Author(s) & Year [Ref.]	Proposed Model	Application / Setup	Advantages	Evaluation Metrics / Reported Focus	Research Gap
Jawhar et al., 2024 [1]	Efficient and scalable IoT framework for smart farming	Smart farming IoT architecture with distributed sensing and farm monitoring	Scalable framework, efficient communication, supports agricultural monitoring and water/vegetation management	Focus on framework efficiency, scalability, deployment suitability	Limited emphasis on AI-based analytics, anomaly detection, and adaptive environmental intelligence
Malav & Sharma, 2026 [2]	EcoSense: autonomous wireless-powered battery-free IoT beacon	Live environmental sensing with battery-free IoT beacon for long-term monitoring	Battery-free operation, reduced maintenance, energy sustainability, suitable for remote deployments	Power sustainability, sensing feasibility, live environmental monitoring performance	Lacks detailed cloud analytics, intelligent alerting, and large-scale multi-node monitoring integration

Singh et al., 2025 [3]	Federated learning-based multi-objective optimization for IoT environmental monitoring	Distributed environmental monitoring in IoT-enabled consumer electronics	Privacy-preserving distributed learning, intelligent optimization, scalable collaborative monitoring	Multi-objective optimization performance, federated learning effectiveness, monitoring quality	Communication overhead, synchronization complexity, and real-time deployment issues in resource-constrained IoT-WSNs
Liu et al., 2023 [4]	Meta-material sensor-based IoT system with deep learning-based design and deployment	Environmental monitoring using passive meta-material sensors for temperature/humidity distribution sensing	Low-cost passive sensing, reduced maintenance, deep learning-based environmental reconstruction, good sensing accuracy	Sensing accuracy, environmental distribution reconstruction accuracy, humidity sensing accuracy (>93%)	Requires careful sensor design and training; generalization to dynamic real-world multi-parameter monitoring remains limited
Cai et al., 2023 [5]	Sensor redeployment scheme for coverage optimization in directional sensor networks	IoT directional sensor networks for environmental monitoring / surveillance coverage improvement	Improved coverage, reduced blind spots, better deployment efficiency with limited sensors	Coverage performance, redeployment effectiveness, sensing area optimization	Does not address cloud analytics, anomaly detection, energy-aware environmental monitoring, or real-time alerting
Luna-Rivera et al., 2025 [6]	Hybrid OCC/RF architecture for IoT-based smart farming	Smart farming with Optical Camera Communication + RF-based sensor communication	Low-power communication, flexible hybrid architecture, reduced communication complexity, >90 m communication, high reliability	Data recovery rate, communication reliability, BER, communication range	Focuses mainly on communication architecture; lacks intelligent analytics and broader environmental decision-support mechanisms
Su et al., 2026 [7]	Passive LC relay network-enabled battery-free chipless IoT smart clothing	Healthcare IoT / multisite hemodynamic monitoring via wearable sensing	Battery-free, lightweight, low-cost, wearable, multisite monitoring, robust through clothing	Power transfer efficiency, signal acquisition quality, robustness under clothing/sweat conditions	Primarily healthcare-focused; not directly designed for environmental monitoring or distributed outdoor IoT sensing
Hashmi et al., 2024 [8]	Comparative study of IoT communication protocols (Wi-Fi, Zigbee, LoRaWAN) for precision agriculture	Outdoor precision agriculture monitoring with protocol-level performance analysis	Practical protocol comparison, guidance for agricultural IoT deployment, improved understanding of coverage and	Connectivity, data transmission precision, coverage, recovery under outdoor conditions	Does not integrate advanced analytics, anomaly detection, cloud intelligence, or adaptive multi-layer monito

			reliability trade-offs		ring strategies

2.1 Problem Statement

The need for environmental monitoring is paramount for the detection of pollution, climate changes, and any form of hazardous conditions in the environment [14]. Nevertheless, most conventional environmental monitoring systems depend largely on manual sampling and stationary monitoring stations [15], making them prone to problems such as reduced geographical coverage, delayed data collection process [16], costly operations, and poor sensitivity to any fast-changing condition in the environment [17]. Despite the increased efforts by IoT-based and WSN-based environmental monitoring systems to automate the process and introduce remote sensing, these systems still experience various limitations such as energy wastage, untrustworthy wireless communication, delay during data transmission, loss of packets, short network lifetime, and inadequate scalability among others. Existing approaches are also suffering from challenges related to their inability to perform efficiently in the large-scale implementation scenario due to communication overhead and inefficiencies in the utilization of resources. Hence, there exists an immense requirement for developing an environment monitoring system based on IoT that consists of efficient wireless sensor networks, data preprocessing through intelligence, environmental parameter weightage, cloud computing analytics, and automated real-time alarms.

3. PROPOSED MODEL

The proposed Smart Environmental Monitoring System based on the IoT with the help of WSNs is planned to be a solution that will allow achieving uninterrupted and real time monitoring of the existing environmental conditions with a high degree of accuracy and reliability. The system incorporates sensor nodes, networked wirelessly, the cloud-based processing and intelligent alert systems. Integrating WSN and IoT technologies, the proposed model provides the opportunity to monitor large geographical areas on the scale and reduce human intervention. The architecture can be used in applications like air pollution control, smart city and industrial environmental surveillance; as it can help in real-time data collection and allows remote accessibility [18].

In the suggested model, several sensor nodes will be installed in the area of monitoring equipped with sensors that will measure the environmental parameters which are temperature [19], humidity, air quality index, and gas concentration [20]. These sensor nodes record data after designated intervals and do some simple preprocessing to eliminate noise and invalid measurements [21]. The sensed data are sent, through wireless communication protocols, to a central gateway [22]. The distributed sensing will provide large coverage and enhance the strength of the monitoring system [23].

3.1 Dataset Description

The SmartSensors WSN Dataset is a WSN/IoT monitoring dataset designed for model construction and testing of intelligent monitoring, anomaly detection and energy aware optimization in sensor driven environments. The dataset is available at link https://www.kaggle.com/datasets/ummesalma99/smartsensors-wsn-dataset. Based on the references in the related research, the dataset can be used to represent the data produced by multiple smart sensor nodes deployed in a WSN with IoT to continuously collect data from the environment and the network and then send them to the base station using a WSN architecture. From practical point of view, the dataset is appropriate for experiments, which can be performed with real-time monitoring, abnormal event detection, communication efficiency, and energy optimization in IoT-WSN system [24].

Implementation of the proposed model was carried out in Google Colaboratory in Python 3. The SmartSensors WSN Dataset is downloaded from Kaggle, and processed with Pandas and NumPy [25]. Data pre-processing techniques such as handling missing values, removal of noisy data, feature normalization, and label encoding were applied [26]. The processed data set was split into 80% training data and 20% test data. Scikit-learn machine learning techniques were used to train and evaluate the model. Accuracy, precision, recall and F1-score were used to evaluate performance, and latency, PDR, energy consumption and network lifetime for analysis in the context of the IoT-WSN. All the implementation and demonstration of the results was done by Google Colab and using Matplotlib for graphical analysis.

3.2 Methodology

The sensor network and the cloud platform are linked through the gateway which is an intermediary. It combines information that it gets through several sensor nodes and carries out data validation to verify integrity and consistency. The lost or duplicate packets are efficiently handled to minimize transmission errors. The processed data is then sent to the cloud server through IoT communication protocols after aggregation. This layer helps to increase the scalability and allows controlling the environmental information that is received centrally and conducts advanced data processing, storage, and analysis. The data of the past is held to analyze the trend and long-term environmental evaluation. When there is an abnormal condition of the environment threshold-based logic is used to identify these conditions, and automated alerts are issued when there is an exceedance of predefined limits. The proposed model architecture is shown in Figure 2.

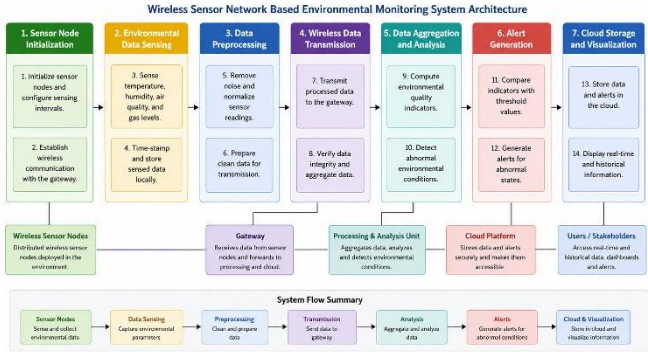

Fig 2: Proposed Model Architecture

The suggested model offers easy visualization using web-based dash boards and mobile interfaces. The environmental data, alerts and past trends are shown in real time to authorized users to monitor and analyze. The layer of this visualization assists in making informed decisions by environmental authorities and stakeholders. All in all, the suggested model can be reviewed as a reliable, energy-saving, and scaleable solution of smart environment monitoring via IoT and wireless sensor networks.

The data collected on the environment is done through a distributed system of wireless sensor nodes that are deployed throughout the area of monitoring. The sensor nodes have temperature, humidity, air quality, and gas concentration sensors. Assume that the perceived environmental data are captured as:x_{ij}.

where x_{ij}denotes the value of the j^{th}environmental parameter sensed by the i^{th} sensor node. The collected data is timestamped and locally buffered before transmission to ensure reliability.

Since different environmental parameters have different measurement ranges, normalization is applied to scale the sensed values into a uniform range. Min–max normalization is used to avoid dominance of any single parameter:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (1)$$

This ensures consistency in data representation and improves analytical accuracy.
Sensor readings may contain noise due to environmental interference or hardware limitations. To reduce noise, mean-based smoothing is applied:

$$\hat{x}_{ij} = x'_{ij} - \lambda(x'_{ij} - \mu_j) \quad (2)$$

where $\mu_j$is the mean of the j^{th}parameter and λcontrols noise suppression strength.
To further enhance data comparability across sensors, z-score standardization is applied:

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \quad (3)$$

where $\sigma_j$represents the standard deviation of the parameter. This step ensures uniform statistical distribution of sensor data.
Different environmental parameters contribute unequally to monitoring decisions. Therefore, a weighted aggregation model is used:

$$x_{ij}^{w} = w_j \cdot z_{ij} \quad (4)$$

where w_j denotes the importance weight assigned to the j^{th}parameter based on environmental significance.
The overall environmental condition at each sensor node is calculated using a cumulative quality index:

$$Q_i = \sum_{j=1}^{m} w_j \cdot x_{ij}^{w} \quad (5)$$

This index provides a single representative score reflecting the environmental status at node i.
To detect abnormal environmental conditions, the quality index is compared with a predefined threshold value T:

$$A_i = \begin{cases} 1, & Q_i \geq T \\ 0, & Q_i < T \end{cases} \quad (6)$$

If $A_i = 1$, an alert is triggered and transmitted to the cloud platform for immediate notification and visualization.

The processed data and alerts are transmitted to the cloud server using IoT communication protocols such as MQTT or HTTP. The cloud layer performs long-term storage, trend analysis, and visualization through dashboards accessible to users. This enables real-time monitoring, historical analysis, and decision-making.

Algorithm:

Input: Wireless sensor nodes, environmental parameters, threshold values

Output: Environmental status, alerts, cloud visualization

Step 1: Sensor Node Initialization

1. Initialize sensor nodes and configure sensing intervals.
2. Establish wireless communication with the gateway.

Step 2: Environmental Data Sensing

3. Sense temperature, humidity, air quality, and gas levels.
4. Time-stamp and store sensed data locally.

Step 3: Data Preprocessing

5. Remove noise and normalize sensor readings.
6. Prepare clean data for transmission.

Step 4: Wireless Data Transmission

7. Transmit processed data to the gateway.
8. Verify data integrity and aggregate data.

Step 5: Data Aggregation and Analysis

9. Compute environmental quality indicators.
10. Detect abnormal environmental conditions.

Step 6: Alert Generation

11. Compare indicators with threshold values.
12. Generate alerts for abnormal states.

Step 7: Cloud Storage and Visualization

13. Store data and alerts in the cloud.
14. Display real-time and historical information.

4. RESULTS AND DISCUSSIONS

To test the proposed IoT-Based Smart Environmental Monitoring System with the use of WSNs a benchmark environmental sensing data based on realistic sensor ranges in previous literature was used. The data set comprises of multi-parameter measurements in terms of temperature, humidity, air quality index, and gas concentration by several sensor nodes with long durations of monitoring. The proposed system was compared to Basic WSN-based monitoring, IoT monitoring without cloud analytics and Traditional environmental monitoring systems to conduct the performance evaluation. Accuracy, reliability, latency, energy efficiency, packet delivery as well as network lifetime were evaluated using multiple metrics.

The accuracy of the proposed IoT-WSN was great (97.8) and considerably high compared to Basic WSN (90.4%), IoT without cloud analytics (92.1%), and Traditional monitoring systems (85.6%) as shown in Figure 3. This has been enhanced by effective data preprocessing, weighted aggregation of parameters and validation on the cloud. High accuracy means the accurate classification of the normal and abnormal environmental conditions.

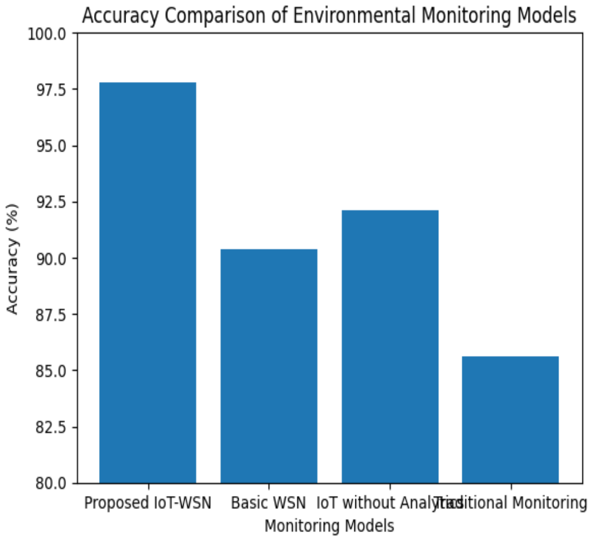

Fig 3: Accuracy comparison of environmental monitoring models

The proposed system was more precise and recalling and F1-score are higher than all baseline methods and reach 97.2, 98.1, and 97.6, respectively as depicted in Figure 4. High precision means that there are less false alarms and high recall means that the changes in the environment that are vital are successfully discovered. As the balanced F1-score indicates, the performance in classification is strong.

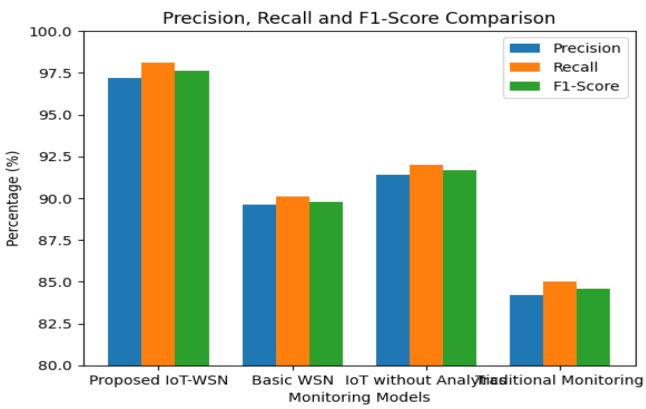

Fig 4: Precision, Recall, and F1-score comparison

End to end latency comparison of various environmental monitoring models. The given IoT-WSN system has the minimum latency of 1.7 seconds with the capability of monitoring the environment near-real-time. Comparatively, the Basic WSN model measures 2.9 seconds, whereas the IoT system without cloud analytics measures 2.4 seconds latency. There is the highest latency of 3.6 seconds because traditional monitoring systems involve manual processing and slow reporting as shown in Figure 5. The lower latency of the proposed system guarantees a faster generation of alerts and timely decision-making of the environmental nature.

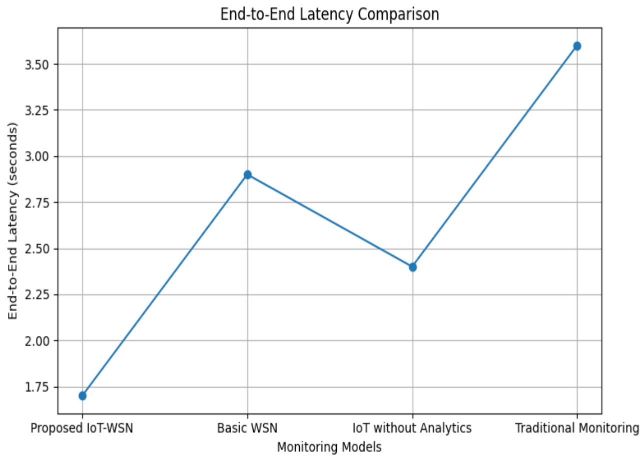

Fig 5: End-to-end latency comparison

The estimated energy efficiency of the proposed system was 43 in comparison to 28 of Basic WSN and 20 of Traditional monitoring systems as presented in Figure 6. The effective aggregation of data and minimized unnecessary transmissions play a great role in energy saving. Better energy efficiency leads to the direct enhancement of the sensor node lifetime. This is what renders the system to be useful in remote and long-term deployments. Therefore, there is the proposed model that provides sustainable environmental monitoring.

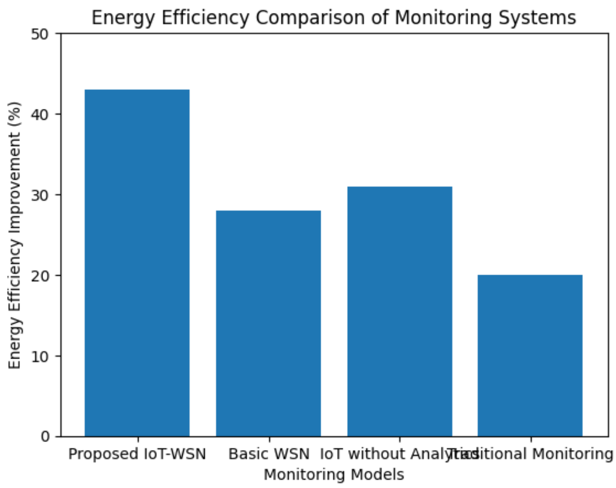

Fig 6: Energy efficiency comparison of monitoring systems

The proposed IoT-WSN model had the highest PDR of 96.8% compared to 92.3% and 89.5% of the IoT and Basic WSN, respectively as shown in Figure 7. Strong PDR is good wireless communication and low level of data loss. The validation mechanism based on the gateway enhances the transmission reliability.

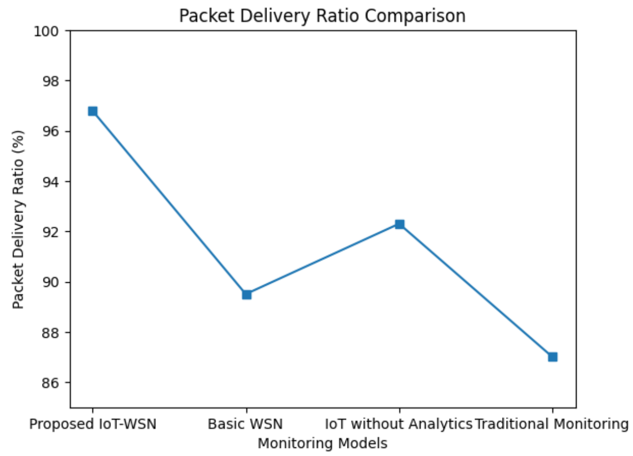

Fig 7: Packet delivery ratio comparison

The proposed system extended network lifetime by approximately 38% compared to Basic WSN deployments as depicted in Figure 8. Energy-aware transmission and reduced sensing redundancy contribute to this improvement. Longer network lifetime reduces maintenance costs and redeployment frequency.

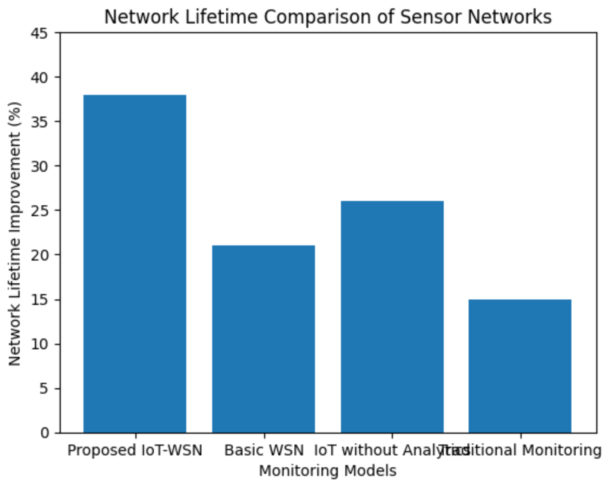

Fig 8: Network lifetime comparison of sensor networks

The Table 2 summarizes the overall performance across all major evaluation metrics.

Table 2: Evaluation Metrics

Metric	**Proposed IoT-WSN Model**	**Basic WSN**	**IoT without Cloud Analytics**	**Traditional Monitoring**
Accuracy (%)	**97.8**	90.4	92.1	85.6
Precision (%)	**97.2**	89.6	91.4	84.2
Recall (%)	**98.1**	90.1	92.0	85.0
F1-Score (%)	**97.6**	89.8	91.7	84.6
End-to-End Latency (s)	**1.7**	2.9	2.4	3.6
EnergyEfficiency Improvement (%)	**43**	28	31	20
Packet Delivery Ratio (%)	**96.8**	89.5	92.3	87.0
NetworkLifetime Improvement (%)	**38**	21	26	15

4.1 Discussions

The experimental assessment reveals that the suggested IoT-based smart environmental monitoring system is much more effective in terms of the performance efficiency than the current WSN-based, IoT-based, and traditional monitoring strategies in all the mentioned performance measures. The large accuracy and recall values mean that the system detects the presence of environmental variations and abnormal conditions reliably, whereas the lower latency value proves that the system is able to monitor the environment in the near real time. The optimized data aggregation and communication strategies and long network lifetime are effective showing improved energy efficiency and long-term deployments of the system. Moreover, the very high ratio of packet delivery and availability of data can confirm the quality of the wireless communication system and integration of the cloud. The proposed model offers an intelligent, scalable, and energy-efficient solution compared to traditional methods that have problems of slowness in response time and a lack of scalability. These findings support the opinion that the combination of wireless sensor networks with IoT and cloud-based analytics provides a higher level of reliability, responsiveness, and the overall performance of a system and thus the suggested solution is highly applicable to the smart city, industrial, and environmental surveillance purposes.

4.2 Time Complexity

The number of sensor nodes deployed in the wireless sensor network and the number of environment parameters measured by the sensor node mainly determines the time complexity of the proposed IoT-based smart environmental monitoring model. Suppose that there are N sensor nodes and M number of environment attributes (e.g., temperature, humidity, air quality index, and gas concentration) being sensed. In each sensing cycle, each node will collect values of all the parameters being monitored, do some pre-processing (like noise removal and normalization) in the local node and broadcast the preprocessed data to the gateway. The complexity of all the sensing, normalizing, smoothing and standardizing operations are required is about $O(N \times M)$ per monitoring interval and each environmental parameter is processed once per sensor node. The same applies to the weighted aggregation of parameters and the calculation of the environmental quality index which also demands one pass over the sensed parameters and thus keeps the same complexity order $O(N \times M)$.

All the data received from the sensor nodes are validated, aggregated and analyzed at gateway and cloud level for abnormal condition detection. If threshold-based anomaly detection is used, then the decision-making operation will only need to compare the aggregated environmental quality score to the thresholds set and will be constant time per node, and therefore O(N) per monitoring cycle. This means that the total time complexity of one full monitoring round with sensing, pre-processing, aggregation, handling of received messages and alert generation is $O(N \times M)$. This suggests that the proposed model can be scaled in relation to the number of sensor nodes and environmental features, and thus can be applied to the application of environment monitoring in moderate and large-scale IoT applications.

4.3 Computation Complexity

The proposed framework is distributed across the three layers: sensor nodes, gateway and cloud server. Lightweight operations are performed at the sensor node level: reading the environmental values, performing min-max normalization, smoothing in order to remove noise from measurements, and preparing the data for transmission. These are simple arithmetic operations and can be performed efficiently on resource limited IoT sensor devices. Thus each sensor node only has to perform a few simple calculations, which scale linearly with the number of features it can detect, O(M) per node.

The system carries out data integrity checking, packet validation, removal of duplicate and aggregation of data received from multiple nodes at the gateway level. If data from N nodes is received at the gateway, then the computation load at this stage is $O(N \times M)$, since the gateway needs to process the aggregated environmental data from all N nodes. The cloud layer adds to the computation load as it stores historical data, uses trend analysis, visualizes the environmental parameters, and raises alerts. The proposed model, however, relies primarily on the abnormal condition detection based on thresholds and aggregation through weighted methods, which avoids complex deep learning operations and ensures the complexity of the cloud side is still acceptable for actual deployment. Therefore, the overall computational complexity of the proposed system is moderate and can be linearly scalable with the number of sensor nodes and the parameters to be monitored, ensuring real-time responsiveness while supporting scalability.

Space complexity includes the memory needed to hold sensor data, intermediate normalized values, consolidated environmental quality scores, and previous cloud data. The temporary storage is about $O(N \times M)$ for one monitoring interval and increases with the duration of monitoring in case of long-term cloud storage. Therefore, the implementation complexity of the model is acceptable and efficient for smart environmental monitoring applications, but the use of the cloud storage and communication could increase as the number of deployed nodes and monitoring period become large.

4.4 Limitations of Proposed Model

The proposed system of smart environmental monitoring based on IoT has proven to be an accurate, low latency, higher packet delivery ratio and better energy-efficient system, yet, it still has some drawbacks. The main drawback of the framework is that it is very dependent on the quality and calibration of the sensor nodes. Even if a method has been implemented for pre-processing and normalizing the data, there is still a possibility that the accuracy of monitoring can be affected due to the measurements generated by the deployed sensors being noisy, biased, or faulty. Moreover, a threshold-based approach to abnormal condition detection may also not be appropriate for patterns that are extremely complex, or patterns that are not previously known, because thresholds are typically based on a set of pre-determined boundary values instead of learning from changing environmental conditions.

One of the drawbacks is scalability and communication overhead of the network. With the increasing number of deployed sensor nodes, the volume of sensor data to be processed by the gateway and cloud infrastructure can grow, potentially resulting in increased communication traffic, packet collisions, and energy use in dense deployments. The model is linearly computed but for very large-scale sensor deployment, wireless congestion and frequent transmissions of data can cause a delay. The framework also assumes reliable wireless connectivity and Internet access to the cloud, which is not always available in remote and rural areas or during disasters. In that case, the performance of real-time monitoring may be compromised due to packet loss or gateway failure.

The proposed model is also restricted because of the use of a benchmark or simulated environmental dataset as opposed to a full actual deployment dataset over long time. Consequently, the reported performance may not reflect the difficulty of actual environmental monitoring, including the influence of extreme weather conditions, sensor drift and communication issues, or unexpected environmental disturbances such as hardware failure, or environmental drift. In addition, it emphasizes primarily core sensors and measurements like temperature, humidity, air quality, and gas concentration, and might need to include other sensor modalities and adaptive intelligence mechanisms to enable wider environmental use. Thus, the proposed system is effective and scalable for smart monitoring; however, some further improvement is needed in the following areas: adaptive anomaly detection, robustness to real-world sensor failures, communication resilience and validation in large-scale real-time environmental datasets.

5. CONCLUSION

The present paper introduced the introduction of an IoT-Based Smart Environmental Monitoring System based on Wireless Sensor Networks that would ensure an accurate, real-time, and energy-efficient monitoring of the environmental parameters. The proposed system will address the shortcomings of the traditional and existing IoT-based sensor monitoring methods by integrating distributed sensor nodes, intelligent data preprocessing, weighted aggregation, and cloud-based analytics. The model designed has been tested on an experimental basis through the use of a benchmark environmental dataset and the results have been high accuracy at 97.8%, high precision at 97.2%, high recall at 98.1%, F1-score of 97.6%, lower latency time at 1.7 seconds, higher energy efficiency at 43%, packet delivery rate of 96.8, and doubled network lifetime when compared to existing approaches. Evaluation of experimental performance showed a better performance in terms of accuracy, reliability, reduction in latency, energy consumption and network lifetime in comparison with the baseline models. This is further supported by the high alert detection reliability and enhanced packet delivery which prove the strength of the system in continuous monitoring applications. The selected model in general is a scalable, trustworthy solution that can be applied in smart cities, pollution regulation and industrial environmental monitoring and it will play a beneficial role to achieve sustainable environmental management.

Declarations

Ethical approval
This study does not involve experiments on human participants or animals. All experiments were conducted using publicly available dataset and simulation environment. Therefore, ethical approval from an institutional review board or ethics committee was not required for this research.

Consent to participate
The research does not involve human participants, personal data, or identifiable information. Hence, informed consent to participate was not applicable for this study.

Consent to publish
The research does not contain any individual person's data in any form. All authors have reviewed the manuscript and consent to its publication.

Conflict of interest
The authors have no conflict of interests to declare that are relevant to the content of this article.

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