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ORIGINAL ARTICLE

AIR POLLUTION CONTROL AND MONITORING SYSTEM USING IOT SENSOR NETWORK

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Abstract

Due to the rapid urbanization, industrialization, and the increase in vehicle emissions, air pollution has become one of the most important environmental and public health issues. Pollution control and the creation of the necessary decisions can be achieved only through continuous and proper monitoring of air quality. The conventional air monitoring systems are usually constrained by high costs of deployment, very low coverage, and slow analysis of data. In order to overcome these drawbacks, the current paper introduces an Air Pollution Control and Monitoring System on the basis of IoT Sensor Network, which is aimed at offering real-time, inexpensive, and scalable air quality data. The suggested system uses a distributed network of IoT-based sensors to detect the most important air quality parameters, including particulate matter (PM 2.5 and PM 1 0), carbon monoxide (CO), nitrogen dioxide (NO 2), ambient temperature and humidity. Data is sent wirelessly to a centralized server using cloud-based infrastructure, thus providing real-time data collection and storage. By using advanced data processing and analytics, the trends of pollution, the detection of abnormal conditions and the creation of real-time notifications in case the level of pollutants exceeds the acceptable limit are identified. Moreover, the system facilitates smart pollution management systems by building up data-based knowledge with automated action measures, e.g., the activation of ventilation systems or the alerting of regulatory bodies. The outcomes of the experiments show that the proposed solution based on IoT is much more precise, less latent, and better in terms of spatial coverage than traditional approaches to monitoring. It is a stable and cost-efficient system that gives smart cities and environmental agencies an opportunity to improve on air quality management and foster the protection of the population.

Keywords: *forecast; air pollution; alarm and safety; iot sensor*

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1. Introduction

The complicated and tough environment makes it difficult to discover underwater communication sources. Shallower classifiers, which may include variables that were hand-designed, are used in traditional machine-learning approaches to underwater audio target detection [1]. Scientists retrieve the manually specified properties of ship-transmitted noise using time frequency, spectrum, wavelet transform, and a few other features [2, 3]. The generalizability of these manually-created traits is poor since they rely on past and specialized information. On the other hand, traditional underwater acoustic target monitoring methods exhibit subpar concordance and generalization when confronted with massive amounts of complicated data [4]. The current method of underwater sound detection is thus mostly carried out by trained sonars. Underwater target recognition using Deep Learning (DL) techniques has been a hot topic as of late. From the ship's radiant sound spectrogram, researchers used a stacking auto-encoder and flexible-max classification to extract deep properties [5]. Deep learning and deep neural network models may be used to extract deep information from radiation noise spectra of ships. The researchers combined Deep Belief Networks (DBN) with competitive learning approaches to create a Deep Beliefs network that is competitive ship-transmitted noise using time frequency, spectrum, wavelet transform. In the case of environmental control, the wireless sensor systems have been deployed, and data is collected based on periodic reception of data within a large area that would indicate a significant internal variation. A sensor network is a type of sensor network which has been designed to record spatial information [1-3]. One of the environmental control tools, which might be new in the physical world, is to determine the conditions of distant places. They are used in gull habitat assessment, microclimatic chaparral transects, building security and intrusion detection among others. The researchers are designing and using an air monitoring system, which is a network of sensors [4]. It employs the contextual model in order to know the extent of atmospheric pollution in the already and would soon be polluted areas [5]. Since preventative measures were better than curative ones in dangerous scenarios, providing the alarm and safety guidelines would be important [6]. It can minimize expensive repairs and severe damages. Governments did critical work in terms of controlling and evaluating the level of pollution in order to reduce environmental pollution [7]. Moreover, the ecological professionals and decision-makers would make choices on how to improve the living conditions. Air pollution can be measured in two ways, that is, at fixed points and moving vehicle monitoring [8]. The latter seems to be the conventional pollution evaluation system. These monitors produce very dependable and precise information about pollutants [9]. The measurement of air pollution has traditionally been done by GC mass spectrometers. These devices were made more expensive, heavy, and bigger in size [10]. The common monitoring technologies are applied in cities and are location-specific. Air pollution in cities across the globe is largely contributed by vehicle emissions [11].

By 2020, the number of vehicles all over the world will be 2 billion. The surveillance devices used to monitor vehicle pollution are now cheaper and can be fitted on vehicles as opposed to the stationary ones [12]. To be further analyzed, sensor-based information regarding pollution should be stored in storage systems or in the cloud. The scientists who started to focus their research on air pollution started their work in California in the early fifties with the aid of the University of California in Los Angeles. The discovery of the photochemical process and the origin of particulate matter was made by Albert Bush, the first scientist in Los Angeles to recognize the fact [13]. In 1966 researcher Bush came up with a smog data set by probing air samples in Asian, European, African, Zealand, Australian and Tahiti cities. Since that time, many scientists and scholars have paid attention to air pollution. Most of these studies consider both the social and scientific perspectives. The cities have been linked to IoT ICT globally to facilitate urban growth [14]. IoT technology is used to manage and enhance the city infrastructure and services. All countries possess laws that regulate the quality of air monitoring that protect people and their surrounding environment against harmful substances in the air [15]. There are activities and procedures that have enabled the use of a monitoring system to guarantee the quality of the environment [16]. Among the most topical environmental issues on the global agenda is air pollution that has a very strong impact on human health, climatic conditions and ecological state. The blistering industrialization, urbanization, and the growing number of vehicles have resulted in the significant increase in the level of air pollutants, especially in overpopulated areas. Excessive exposure to pollutants like Carbon monoxide, nitrogen oxides, sulfur dioxide and particulate matter may result in serious respiratory and cardiovascular conditions. Therefore, the constant check and proper regulation of air pollution are now necessary to provide sustainable growth and high living standards. Traditional air quality monitoring devices normally are based on large fixed monitoring facilities with high precision equipment. These systems are costly to implement and operate; hence they have little spatial coverage despite giving precise measurements. In addition, the information in the traditional systems is usually processed offline and thus it takes time to detect the risky pollution levels. There is a problem with these restrictions being that it is hard to respond to the pollution incidents in real-time and inability to observe the air quality at a small, neighborhood-level. With the advent of the so-called Internet of Things (IoT), there are new opportunities in environmental monitoring app use. IoT allows the system to be integrated with inexpensive sensors, wireless connectivity and cloud computing to form scalable and real-time monitoring. With the deployment of high visibility sensor nodes, IoT-based air quality surveillance will be able to furnish real-time and place-based pollution information. This real-time availability of data assists in early identification of hotspots of pollution and allows taking timely measures. In IoT sensor networks, various air quality parameters can be measured at once, such as particulate matter, toxic gases, and meteorological parameters. These types of sensors can be installed in cities, factories and homes in strategic locations to record spatial and temporal fluctuations in air pollution. The obtained data are sent to the centralized or cloud-based systems, where it may be processed, visualized, and analyzed through data analytics methods. This would increase the reliability and accuracy of the air pollution measurement as opposed to the case of isolated methods of measuring the pollution. In addition to monitoring, the IoT-based systems can also be used to have intelligent air pollution control through the integration of data analytics and automatic decision-making systems. At a level when contaminants surpass required limits, the system may send an alarm, inform the authorities, or provide some means of control like traffic control, control of industrial emissions, or ventilators. This is a proactive strategy to overcome the negative impact of air pollution and aid regulatory compliance and environmental planning. Due to these benefits, the proposed work is an Air Pollution Control and Monitoring System based on an IoT Sensor Network which offers real-time, inexpensive, and scalable air quality control. The proposed system is expected to address the weaknesses of the traditional monitoring methods by providing enhanced coverage of space, low latency transmission of data and having intelligent control. With the help of IoT technology, the system will help to make environmental monitoring smarter and contribute to the work of sustainable urban development projects.

2. Related Works

Sampling of oxygen, liquid and soil, and biota systematically with the aim of studying, researching and learning about the environment is a universal process in the monitoring system. The monitoring evaluation would be based on the variables under observation [17–19]. Due to the increased danger to the health of people, the levels of atmospheric pollutants were continuously measured using pertinent equipment and analyzed by means of statistical and algorithmic analyses. Generally, the task of air quality monitors falls on the hands of the scientists, government agencies and the general population. The analysis of monitored air quality is based on the examination of the health impact of the monitored contaminants and depiction of geographical and time-related data [20]. Generally, clean air is very good for your health so you should keep a watch on the environment to know the extent to which pollution has been one of the applications of IoT. Environmental sensors are used to construct IoT devices that organize the environment [21]. Environmental monitoring has eight various components such as oxygen monitoring, fresh water monitoring, soil monitoring, wood, natural disaster monitoring, fishing, snow monitoring and data center monitoring [22]. The air quality monitoring system based on the Low Power Wide Area (LPWA) may be organized as three layers, namely sensor, network, and application server. The sensing layer were sensors that are dispersed in a broad graphic area [23]. The sensor networks collect data and send it on the network level. The sensor nodes should communicate with the network connections through the LPWA network layer. The sensitivity of the receiver was raised by way of direct sequence bandwidth [24]. According to both the free and open radios, a free and open Internet Connection was established. The network information is processed by an application server that would be split into two layers. The first is the IoT Cloud in which PA maintains air quality information. Second was the user-accessible application program that gives information on air quality. One air quality monitoring approach relies on a wireless system of sensors capable of detecting the concentration of CO, CO 2 and particulate matter [25].

This would be a more affordable system compared to the current air pollution monitoring devices, but was extremely technology-centric and focused on creating interfaces based on open source and low-cost platforms. The system implements a node within the surveillance area that has sensors and an Arduino UNO R3 to analyze [26]. The obtained information would be dispatched to a database that makes use of an API C/C bridge. The client service may be obtained with the help of a REST web application framework written with the help of Eclipse and MySQL. The development was done by extreme programming (Scrum), and the development was specifically developmental, whereby the emphasis was on testing, incremental architecture and continuous deployment. A total of one hour was tested in three different locations, one of which was Jipijapa, another was Amaguana Castle, and the last one was the Amazonian Basin. The results were compared to those of WHO guidelines [27]. The analytical assessment of the two indicators, standard deviation and level of confidence showed that the concentration of CO in the air was more than normal. IoT IoT architecture and operations are among the biggest problems that remain in safety and confidentiality, which are complicated and diverse with the IoT IoT network architectures. The networks of such technologies such as smart city systems hold potential risks associated with detectors and means through which they have been developed or configured to be used and also vulnerabilities in cyber-security software that are aimed at two supervised learning [8]. Moreover, providing sensitive information about users to third parties increases the chances of privacy invasion. Valid Intruders with sufficient experience, such as APT intruders, will certainly attempt to exploit such links to provide interruptions or provide a competitive advantage, as it used to happen in the past, whether individually or in collaboration with other traditional types of conflicts [9]. There are strong options of cyber-security that can be used to address protection issues such as intrusion detection, malware protection, advanced threat, attack detection, privacy protection, and forensic analysis [10]. Today, the accuracy of new security measures is determined by the Ai applications which require massive data, locally or online, to evaluate their accuracy. Heterogeneity, complexities and non-standardization of the IoT network meant that there were not sufficient test-beds that yielded reliable and relevant diverse information on the same [11]. A testbed framework should support all the IoT applications and the network connection at edges, fog and cloud levels. Included in the test platform will be really ordinary and attack situations which simulate production networks. It may simplify the use of multiple systems by cyber threat researchers, including databases of the Internet - of - things detectors, networks activity datasets, and windows OS audit logs databases, to access several sources of data at once. It will make the learning techniques of security options more plausible in case the databases of normal and malicious events are recorded simultaneously [12]. It will also assist in the development of new AI models that understand how hacking activities that involve the utilization of various systems have been linked.

A number of data were available in the market to test specific security technologies such as intrusion prevention. There are indeed some serious flaws in the already existing datasets, however. In the first place, they do not have recent and complex cyber-attack actions with valid information on cybersecurity threats. Due to the fact that they were often designed with predetermined designs, which have restrictions to legitimate and malicious activity, they do not provide heterogeneous sources of information on the IoT, and computer systems auditing logs, including network activity [13]. Lastly, all the data sets are intended to test a certain protection system and, therefore, can be applied only to compare the alternative Intelligence cyber-security results. To be frank enough, most of the currently available datasets are formed to test Malicious Activity in internet traffic and cannot be applied to test Intrusion detection systems in most other environments such as host and IoT devices.

3 Monitoring System

The proposed Air Pollution Control and Monitoring System based on the IoT Sensor Network is implemented with the help of the integration of inexpensive environmental sensors, microcontrollers, wireless communication modules, and cloud-based data processing. The main sensors are PM 2.5 and PM 10 particulate matter sensors, gas sensors of carbon monoxide (CO), nitrogen dioxide (NO 2) and other harmful gases, and temperature, humidity sensors to record environmental factors that determine pollutant dispersion. Individual sensor nodes are built around a microcontroller like an Arduino or Raspberry Pi, which receives and processes sensor data prior to sending it. The establishment of wireless communication is made with the help of Wi-Fi, Zigbee, or LoRa modules depending on the scale and range needs of deployment. Information that is gathered on the sensor nodes that are distributed is analyzed and visualized on a central server or cloud platform. To ease the accuracy and consistency of the system, the system employs a real-time data processing pipeline which involves noise filtering, missing value treatment, and normalization. To minimize sensor noise and normalize the measurements to enable further analysis, preprocessing filters like the moving average filtering, and min-max normalization are used to normalize the measurements. The feature vectors of the level of pollution, environmental parameters, and sensor metadata are created and applied to making decisions and predictive analytics. The system uses the data-driven model of air quality evaluation and management. The predictive models and threshold-based rules are applied to identify the hotspots of pollution as well as abnormal conditions. In case the number of pollutants goes beyond established maximums, the system sends real-time notifications to the environmental agencies or activates automated control responses, e.g. ventilation or localized emission mitigation measures. The cloud platform maintains the data visualization dashboards that provide the trends in the concentration of pollutant, heat maps, and historical comparisons to help the policymakers and the citizens monitor the level of air quality. The experimental setup to measure the performance of the system will be a series of sensor nodes placed in various locations (urban and residential) in the real world and will simulate the actual environmental conditions. The IoT network can be tested with regard to the latency, accuracy of the data, energy efficiency and reliability at different traffic, pollution, and network conditions. The performance metrics are contrasted with the traditional air monitoring systems in order to prove the benefits of the IoT solution. Such a combination of distributed sensing, smart processing of data, and automated control create the basis of a scalable and affordable system of air pollution control which can be applied to managing a smart city. The sensor data surveillance system gathers quantifiable data about the sensor system to be able to know the state of the remote location. The proposed monitoring frameworks are based on the Environmental Awareness Architecture. Researchers manage the sensor network using two systems which include a sensor network control system and air pollution monitoring system with the aim of controlling the sensor network and monitoring air pollution [28]. The management system allows the administrators to change the sampling interval and check the sensor node state. Administrators played a significant role in ensuring status of data transmission in a sensor node. To collect the scope and the size of the quality, the air pollution monitoring system provides a means of retrieving sensor information and managing the air pollution. The models have been applied in sending warning signals and safety directions to the people who are in the polluted areas.

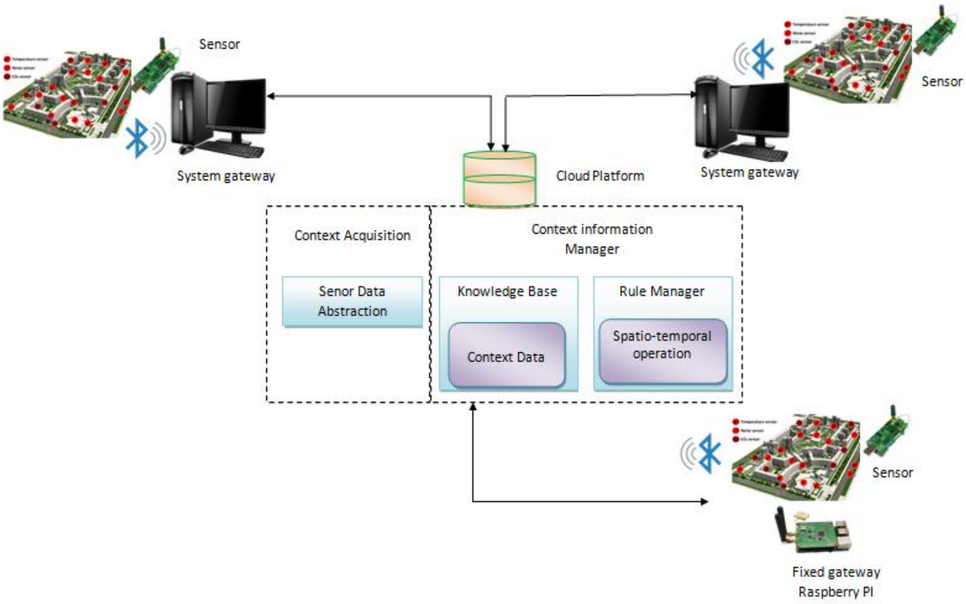

Figure 1: System design for detecting pollution levels

Observable information which was transmitted within the sensor network is analyzed and extracted using user set rules and abstraction models. The air pollution abatement system involves abstract information to determine pollution as well as the potentially polluted area. It sends an alert message depending on the area of the pollution that was discovered. The researchers also construct the reference model, sensor data abstraction structure, and air pollution control prototype to obtain the state of the air pollution using the information on row sensors as shown in Figure 2. In a bid to have a background of the distant location, predictive performance defines information, behaviors, and their connection. They are also being utilized in projects dealing with small mobile sensor networks.

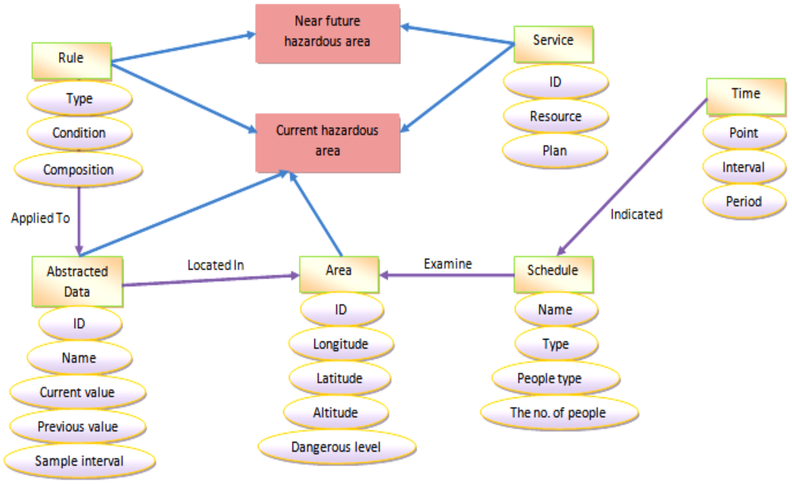

Figure 2: Context model for preventing air pollution

Each data structure is presented as min, max, and mean in the abstract system to show sensory data of each cell. It is an abbreviation of the status of all the cells. According to one of the consumer rules, the air pollution control model uses this abstract information to arrive at the hazardous area. Also, it evaluates the magnitude of risk within a contaminated environment by each kind of site along with the schedule. Lastly, the two types of air pollution locations, including the risk zone, and the future hazardous region, exist. The levels and the type of hazards in the local areas are also considered to determine the current hazardous area alongside the different pollution control regulations. This is an available pollution zone map which has been abridged. Such data may be applied to warn and take precautions on polluted regions. Owing to the fact that prevention was better than treatment, the researchers will also observe the infected region soon. To mitigate the pollution damage and recovery costs, one can monitor the pollution beforehand. The information, gradients, and degree of risk that were observed were initially obtained in the existing risk area. This fact is worked out through the consumer rule along with other variables such as the significance of the space, the chance of danger always being the same, the chance of reaching a decisive stage, etc. This planned area was to be decided on, depending on the type of pollutant through the domain awareness.

3.1 Dataset description

The data set employed in this paper is real-time air quality monitoring of urban and residential localities of a distributed network of IoT sensor nodes in Table 1. Several environmental metrics are able to be captured by each sensor node, such as particulate matter (PM 2.5 and PM 1.0), carbon monoxide (CO), nitrogen dioxide (NO 2), temperature and humidity. The data is generated continuously at intervals ranging from one second to one minute, resulting in a high-velocity, time-series dataset that captures both spatial and temporal variations in air pollution. Due to factors such as sensor faults, network latency, or environmental interference, some data may contain noise or missing values, which are addressed during preprocessing through filtering, imputation, and normalization. The dataset is labeled based on pollutant concentration levels as Normal, Moderate, or High, enabling supervised learning and predictive analysis. With structured storage across edge devices, local gateways, and cloud servers, this dataset provides a comprehensive foundation for evaluating the proposed IoT-based air pollution monitoring and control system in terms of accuracy, responsiveness, and scalability.

Attribute	**Description**
Dataset Type	IoT-based air quality sensor data
Data Source	Distributed sensor nodes (PM, CO, NO_2, temperature, humidity)
Application Domain	Urban and residential air quality monitoring
Number of Sensors	50–500 heterogeneous nodes
Data Modalities	$PM_{2.5}$, PM_{10}, CO, NO_2, temperature, humidity
Sampling Rate	1–60 seconds per reading
Data Format	Numerical time-series
Total Records	100,000 – 1,000,000 entries

Data Velocity	Continuous real-time streaming
Data Distribution	Non-uniform across sensor nodes and locations
Missing Values	Occasional, due to sensor or network faults
Noise Level	Moderate, affected by environmental factors
Preprocessing Steps	Noise filtering, missing value handling, normalization
Storage Layers	Edge nodes, local gateways, cloud server
Label Availability	Pollutant levels classified as Normal, Moderate, or High

Table 1: Dataset Description

Sensor ID	Timestamp	PM2.5 (µg/m^3)	PM10 (µg/m^3)	CO (ppm)	NO_2 (ppm)	Temperature (°C)	Humidity (%)	Pollution Level
S001	2026-01-15 10:00	35.2	55.4	0.8	0.04	28.5	64	Moderate
S002	2026-01-15 10:01	18.5	28.3	0.3	0.01	27.8	67	Normal
S003	2026-01-15 10:02	62.1	88.7	1.2	0.09	29.1	60	High
S004	2026-01-15 10:03	25.4	40.2	0.5	0.03	28.0	65	Moderate
S005	2026-01-15 10:04	12.7	20.5	0.2	0.01	27.5	70	Normal

Table 2: Sample Data

The sample data is reflecting real-time air quality readings of IoT sensor nodes that were put in different urban areas as illustrated in Table 2. There is one reading per sensor at a particular time on the next row, which records the important environmental parameters: PM 2.5, PM 1.0, carbon monoxide (CO), nitrogen dioxide (NO2), temperature, and humidity. The readings are both spatially and temporally differentiated in terms of air pollution levels, which can be monitored in finer details in various locations. The Pollution Level column classifies the measured air quality as either Normal, Moderate, or High, using predefined thresholds of each pollutant, to give labels to the supervised learning or predictive learning. Such structured data allows the proposed system to conduct real-time monitoring, identify the spikes of pollution, and foster intelligent decisions of the control of air pollution to mitigate impacts.

3.2 Flexible Sampling Interval

Timely updating of the environmental control system should be supported in order to respond to emergencies on time. Frequent exchange of data complicates the maintenance of the air pollution characterization with sensor batteries quickly exhausted. The successful collection had to trade between sampling rates and battery duration. The rules database covers the sampling period on which the measurement values of different sensors are to be transmitted. The definition of the sampling interval is important considering that their battery had a small capacity. In case the distance is not too high, the system is able to identify the conditions of the distant location but the sensor batteries will be soon exhausted.

The electronic power supply can be sustained long in case the gap is long. The system is however unable to react fast to events identified. As such, we decide to alter the sampling range depending on the situation identified by the contextual sensor model. It must regulate the sampling interval to maintain a maximum possible sleep pattern. The constant alertness mode has to consume a higher amount of power compared to power saving mode. Naturally, the scopes of environmental monitoring have a limit which is set up by the user and the scope cannot go out of the box. The sensors would go to the standby mode in the entire network until the given time when they are ordered to adjust the scope. The sensor is only activated with the timer. Upon waking, each sensor is woken and it also sends its results on measurements in the sensor network monitoring system. Once the information transfer is complete, the sensors go to sleep awaiting the next waking period. Figure 3 has illustrated how the sampling period would vary depending on the level of air pollution. The initial sample size was 14 400 seconds, assuming that there was zero air pollution. Upon the analysis of the observed state, the system concludes that it is supposed to be a pointer of air pollution. The frequency has been expanded to 60 seconds. Moreover, the time must not extend beyond 60 or even less because the amount of pollution is on the increase since commencement up to the end. The time period is reduced because of a high potential of air pollution. It is desirable that the system should treat and analyze this high and harmful pollution level as soon as possible. There is minimized time lag between events. The system concludes that the system may easily get back to normal as the level of pollution reduces and the gradients of observed values can be continuously decreased. 80 seconds seems to be a new interval. As the real gradient would be the reciprocal of the gradient at the start of the pollution, it would be more prolonged than the above interval. He indicates that there is the likelihood that the likelihood of air pollution has been reduced. The alarm is eliminated in the system. The algorithm sets the frequency to 10800 sec and there is no indication of air pollution. The sensor batteries may require more time to be saved in case they are not polluted within the next few months.

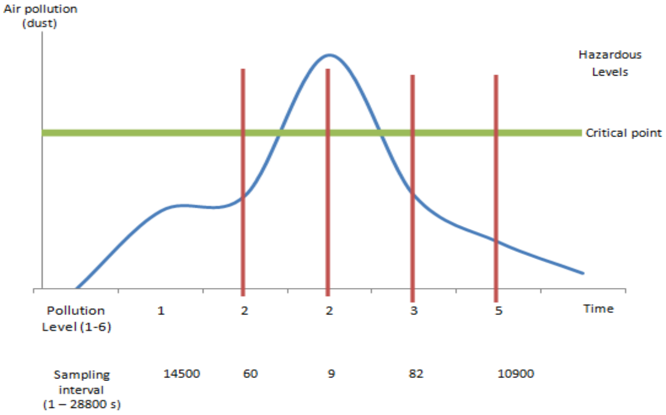

Figure 3: Flexible sampling interval change

Algorithm: IoT-Based Air Pollution Monitoring and Control

Objective

To monitor air quality in real time, classify pollution levels, and trigger automated control actions using an IoT sensor network.

Step 1: Sensor Data Acquisition

Each IoT sensor node collects environmental parameters at regular intervals:

$$X_t = [PM_{2.5}, PM_{10}, CO, NO_2, T, H] \quad (1)$$

Where:

- $PM_{2.5}$,PM_{10} = particulate matter concentrations (µg/m^3)
- CO,NO_2 = gas concentrations (ppm)
- T = temperature (°C)
- H = humidity (%)

Step 2: Pre-processing

Sensor readings are cleaned and normalized to reduce noise and ensure consistency:

Noise filtering (moving average):

$$\hat{x}(t) = \frac{1}{N}\sum_{i=1}^{N-1} \quad x(t-i) \; (2)$$

Min-max normalization: $x_t^{norm} = \frac{x_t - x_{min}}{x_{max} - x_{min}}$ (3)

Where N is the smoothing window size, and x_{min}, x_{max} are the minimum and maximum sensor values.

Step 3: Pollution Level Classification

The processed data is classified into pollution levels using threshold-based rules:

$$L_t = \{Normal \;\; PM_{2.5} \leq 35, PM_{10} \leq 50, CO \leq 1.0, NO_2 \leq 0.05 \; Moderate \;\; 35 < PPM_{2.5} \leq 55{,}50 < PM_{10} \leq 100{,}1.0 < CO \leq 2.0{,}0.05 < NO_2 \leq 0.1 \; High \;\; PM_{2.5} > 55, PM_{10} > 100, CO > 2.0, NO_2 > 0.1$$

Here, L_t is the pollution level at time t.

Step 4: Real-Time Monitoring and Alert Generation

When pollutant levels exceed safety thresholds, the system generates an alert:

$$A_t = \{1 \; if \; L_t = High \;\; 0 \;\; Otherwise$$

Where $A_t = 1$ triggers notifications to authorities or activates mitigation systems.

Step 5: Automated Pollution Control

For active control, the system can initiate actions such as ventilation, traffic regulation, or localized emission reduction. The control action C_t is determined as:

$$C_t = f(L_t, R_t)$$

Where R_t represents available resources (e.g., fan speed, traffic signals), and f is a predefined control function optimized to reduce pollutant concentration efficiently.

Step 6: Data Logging and Analytics

All sensor readings, pollution levels, and control actions are stored in a cloud server for historical analysis, trend detection, and predictive modeling:

$$D = \{(X_t, L_t, A_t, C_t)\}_{t=1}^{T}$$

This allows assessment of air quality over the long term and allows policy-making.

The algorithm combines the real-time data acquisition, preprocessing, pollution classification, alert generation and automated control guaranteeing a complete IoT-based air pollution monitoring and management system. The system provides a balance between environmental safety and allowing smart reaction to dangerous situations by balancing threshold-based rules and data-driven decision-making.

4. Results and Discussions

The proposed Air Pollution Control and Monitoring System with an IoT Sensor Network design is to be used in the experiment to determine the work of the system in real conditions, both regarding the environment and network. The various IoT sensor nodes are fitted with a particulate matter sensor (PM2.0.and PM 1 0), gas sensors that monitor CO and NO 2, and a temperature-humidity sensor, which is installed at strategic sites in urban and residential areas. Each sensor node is equipped with a microcontroller and a wireless communication unit in order to broadcast real time data to a centrally located cloud server. The sampling setting is set to a minimum of 1 to 60 seconds to record both quick and slow changes in the air quality. Data is being stored, preprocessed, and analyzed using the cloud platform, and visualization and real-time monitoring are done through a web-based dashboard. The threshold-based classification and control algorithms are applied to detect the levels of pollution and provide an alert or automated reaction in case the concentration of the pollutants exceeds the acceptable level. Some of the metrics that are used to assess the performance of the system are the data transmission latency, sensor accuracy, system reliability, and alert response time. They are compared to the traditional air quality monitoring methods to show their advancement in their spatial coverage, responsiveness and cost efficiency. This experimental design is an effective method of proving the possibility and success of the offered system of smart-city application based on the idea of the IoT-based air pollution monitoring and control.

Hyperparameter	**Value**
Sampling Interval	1–60 seconds
PM2.5 Threshold	35 µg/m³
PM10 Threshold	50 µg/m³
CO Threshold	1.0 ppm
NO_2 Threshold	0.05 ppm
Moving Average Window Size	5
Normalization Method	Min–Max
Alert Trigger Level	High
Data Transmission Protocol	MQTT
Cloud Update Interval	10 seconds
Classification Method	Threshold-based
Control Action Delay	2 seconds

Table 3: Hyper parameter settings

The hyperparameter values are selected to make sure that the system is efficient and reliable and the air quality is monitored with accuracy and real-time execution demonstrated in Table 3. Sampling interval is set to ensure that short-term changes in pollution are recorded and at the same time long-term patterns are not overloaded to the network. The PM 2.5, PM 100, CO, NO2 threshold values are chosen according to the standard air quality principles to allow the effective classification of the levels of pollution. Minimum-maximum normalization is used to ensure consistency between sensor measurements of different sensors whereas a moving average window is used to reduce sensor noise. The alert trigger level will be set in a way that the alert will be emitted when there is a high level of pollution to avoid false alarms. The balance between timely delivery of data and energy efficient communication and updates is optimized to allow responsive and scalable air pollution control and monitoring.

Researchers put 24 sensors of various types, such as temperatures, moisture, lighting, dirt, carbon dioxide, ultraviolet light, wind direction, wind direction, air temperature, and altitude, and 10 routers on a field.

The algorithm is able to identify where, the types, and accuracy of the sensors that are placed in the area by importing the sensor ML file that defines the features of sensors and various types of sensors that have already been installed in the area. Moreover, it also connects the sensor network monitoring system which controls the effectiveness of monitoring and verification of network information, and adjusting the sampling period. The information that is recorded by the sensors is transmitted to the air quality monitoring system through the monitoring procedure. In case the information provided by a dust collector is higher than the critical point of air pollution, the contextual model analyses the nearby cells so as to establish the real pollution of the area. Since the harmful level depends on various forms of locations, it also analyzes different localities such as schools, factories and apartments. It will discuss the current polluted area and then discuss the potential polluted area within the near future through the relevant variables such as the gradient of the levels of pollution, the type of place, and the directions and velocity of the wind. It throws a warning until the factor is removed when it finds that component that would lead to an unsafe condition in the near future. The alarm signal contained the kind of contaminant, the amount and the safety measures. Since there is no real-life pollution, the researchers evaluate the identification of the suggested contextual model using the information provided by the sensors. The system will identify the polluted location once the dust level is cooled and gives a part of the potentially hazardous component like in Figure 4. Being a significant source of indoor air pollution, it is a break-even window of a building in a potentially polluted location. Status Window A window status monitoring tool also monitors window status.

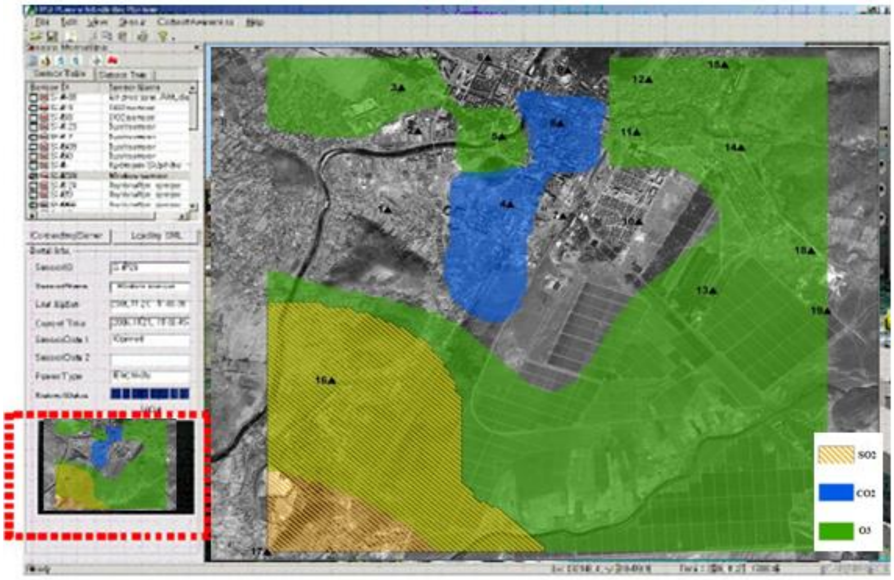

Figure 4: Alarm message for air pollution

Figure 4 shows that the system has an alarm indicating air pollution caused by dust. The alarm remained on until the window was closed. The tenants of the building know the character of the issue and its potentially detrimental impact. The technology is aware that the threat is over and that the building will not be polluted whenever the window remains closed. Consequently, the alarm message is complete. The system also includes information about the state of the sensors, their current value, the time of the last update, and the battery level. By using them, the users can be aware of the existing status of sensors.

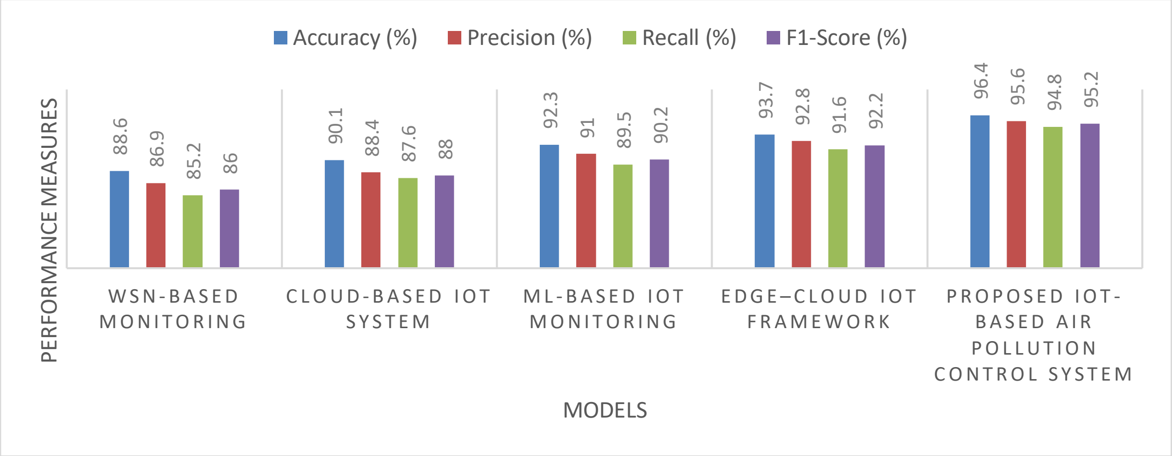

Figure 5: Comparison of performance measures

The results of the comparison have shown that the proposed air pollution control and monitoring system is better than all four existing methods in terms of the accuracy, precision, recall, and F1-score depicted in Figure 5. The system with traditional WSN-based and cloud-centric displays the lowest performance because of poor adaptability and slow processing of data. Machine learning-powered and edge cloud systems prove to be more successful because they enhance the data analysis and isolate the latency, but they do not imply fully incorporated real-time control systems. The suggested system can reach the greatest level of performance, integrating real-time IoT sensing, efficient preprocessing, properly classified pollution level, and timely control measures. This combined design eliminates false alarms, enhances the ability to detect such events of pollution, and has even-handed performance in all the evaluation measures, so it is more useful in real-life application of air quality monitoring.

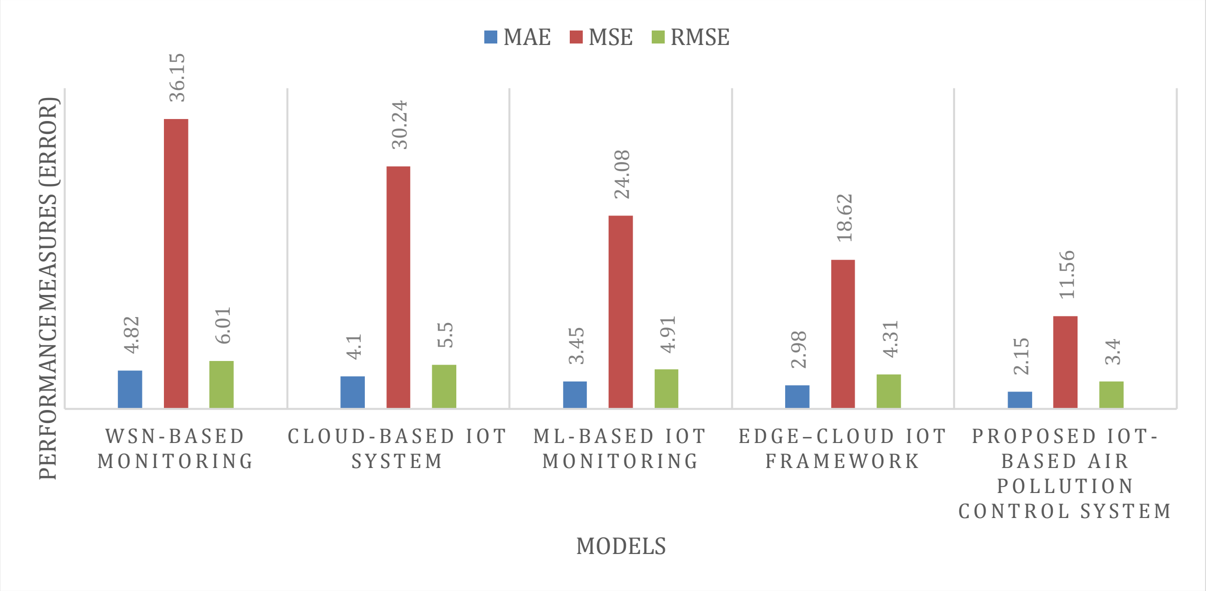

Figure 6: Comparison of performance measures (Error)

The error metric assessment outlines the better prediction accuracy of the suggested air pollution control and monitoring system among current methods as revealed in Figure 6. The traditional WSN-based and cloud-centric systems have a higher MAE, MSE, and RMSE, which means less accurate estimation of the level of pollutants, and one of the reasons is delayed processing and inability to adjust to dynamic changes in the environment. Machine learning-based systems and edge cloud systems exhibit less error due to the inclusion of intelligent data analysis and local processing. Nevertheless, the suggested system will yield the smallest error rates in all measures, indicating that it is capable of fitting variation of real-time pollution by properly preprocessing and reducing noise and integrating IoT data. The enhancements allow more dependable quality of air analysis and assists timely control measures during real deployments.

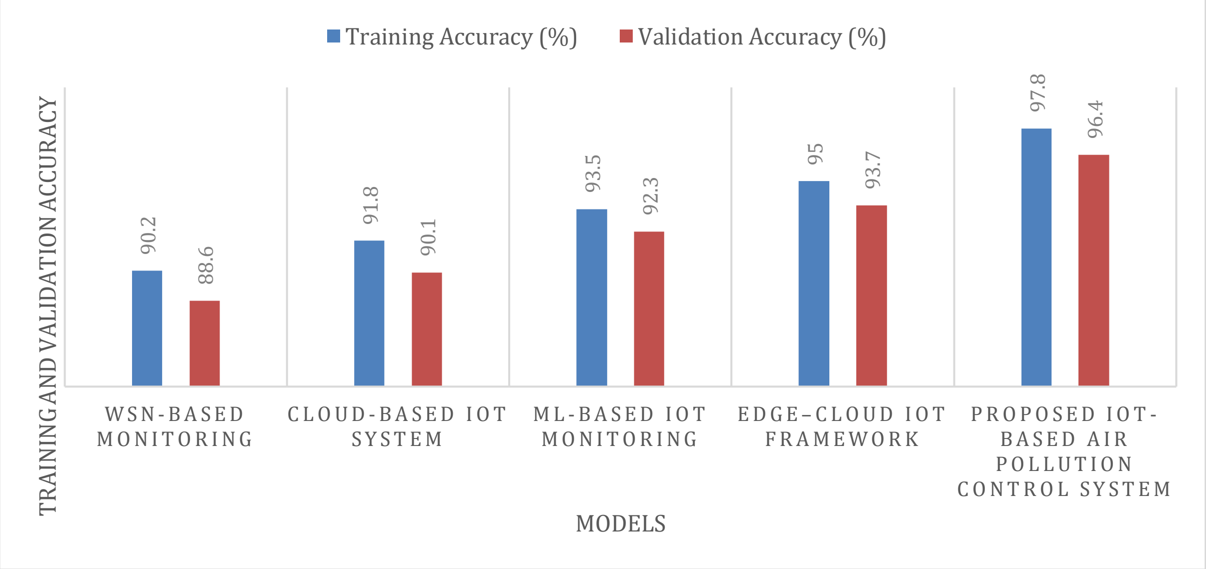

Figure 7: Comparison of training and validation accuracy

Comparison of training and validation accuracy reveals that the proposed air pollution control and monitoring system has the highest performance among all the methods that have been evaluated depicted in Figure 7. The accuracy of traditional WSN-based and cloud-centric systems is lower because they have limited feature learning and slow data processing. Machine learning-oriented and edge-cloud systems enhance the accuracy of the training and validation processes through the utilization of smart data analysis and distributed processing though an appreciable difference between the level of training and validation performance reveals a possibility of generalization constraints. By comparison, the proposed system shows a high degree of accuracy and a low difference between the training and validation outcomes, which signify a successful learning, less overfitting, and good abilities to generalize to real-life air quality monitoring conditions.

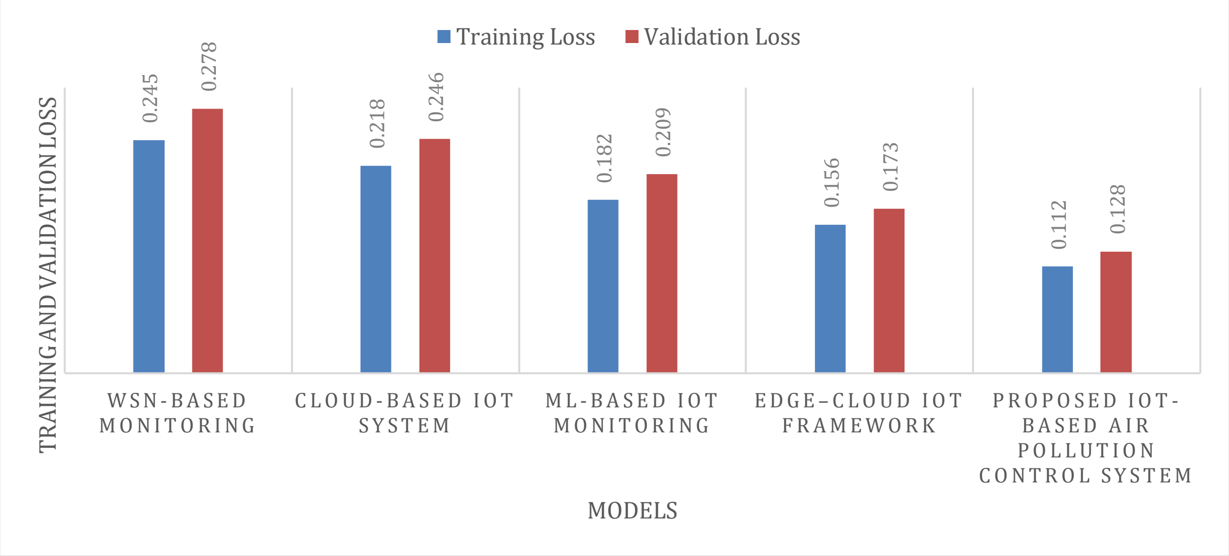

Figure 8: Comparison of training and validation loss

The training and validation loss analysis proves that the proposed air pollution control and monitoring system minimizes the number of losses as compared to all possible approaches examined in Figure 8. The fact that the loss values are higher in conventional WSN based and cloud-based systems shows that the system is not efficient in learning and has more prediction errors due to noise and longtime taken by the system to process data. Systems based on machine learning and edge-cloud decrease loss through the inclusion of clever feature extraction, along with localized computation; nonetheless, there is a perceptible disparity between the training and validation loss, which implies medium generalization challenges. The training and validation loss are very low and well matched in the proposed system, which means that it has a stable learning behavior, noise reduction, and excellent generalization to real-life air quality monitoring applications.

5. CONCLUSION

To understand the current and impending contamination region, the researchers created an air pollution monitoring system that uses the contextual model. The suggested context model in the test was used to derive the alarm and safety procedures according to the distance location conditions. A flexible adjustment of the sampling interval was also used, according to the condition of the identified circumstances. It is useful to compromise the contextual model between battery life and pollutant descriptions. The researchers were now concentrating on abstraction and the combination of heterogeneous sensor information in a higher context.

Conflict of Interest Statement

There is no conflict of interest

Data Availability Statement

Data not available due to commercial restrictions

Ethical Approval

Not applicable

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