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# Energy optimized air quality monitoring with AQC-MANET for real time pollutant detection and analysis

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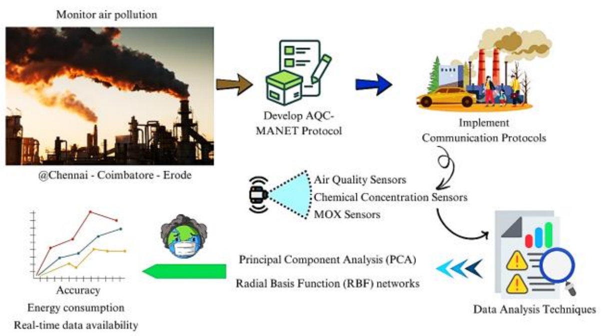
**Graphical abstract**




**Abstract**

Air quality monitoring is becoming an increasingly important aspect of monitoring pollution due to changing environmental patterns in urban and industrial areas. This study designs an energy-efficient air quality monitoring system using Air Quality Clustering for Mobile Ad Hoc Sensor Networks protocol. The proposed system integrated Wireless Sensor Networks with Mobile Ad Hoc Networks addresses all the challenges related to data aggregation and routing within dynamic networks. Thus far, advanced air quality, chemical concentration, and MOX sensors have been used in Tamil Nadu cities such as Chennai, Coimbatore, and Erode, to monitor pollutants such as carbon monoxide, nitrogen dioxide, and particulate matter. The data will be transferred in real time to a cloud platform for analysis through ZigBee-based communication-supported by a database management system and an expert decision support system, and will act on the findings. Solar panel integration and advanced power management improvements yield 30% less energy consumption while assuring uninterrupted operation. The proposed protocol has improved cluster performance and decreased inter-cluster delays while extending the lifetime of the network to 320 hours. Comparisons of various methods show that the proposed method clearly outperforms conventional networks, achieving 92% pollutant classification accuracy, extending network lifetime to 320 hours, and ensuring continued communication with a very low packet loss rate of just 1%. The system transmits data in 6 seconds and provides results within 3.5 seconds, making it reliable and speed-efficient. Further, it achieves 150 Mbps throughput with a latency of only 25 ms. The system is also scaleable and offers real-time SMS alerts on localized monitoring, thus helping industries and other stakeholders in pollution management. Proposed methods may thus be revolutionary in air quality monitoring, providing energy-efficient real-time solutions in urban and industrial environments.

**Keywords,** Air Pollution, Air Quality Clustering, Data Cloud, Industrial Environments, Mobile Ad Hoc Networks, Principal Component Analysis, Sensors, Wireless Sensor Networks.

## 1. Introduction

The environment and human health are negatively impacted by toxic emissions but air quality also impacts energy efficiency and work productivity. Several studies have demonstrated that an increase in $CO_2$ levels at work causes a rise in the amount of volatile organic compounds (VOCs) smells and microorganisms in the air, impairspeople's ability to focus. Furthermore according to some research $CO_2$-based air controls can save up to 50% on energy—in most buildings, $CO_2$-based ventilation controls can lower HVAC costs by 5% to 20%. Wireless Sensor Networks (WSNs) have recently shown a great deal of promise for broad use in data collection surveillance monitoring and medical telemetry. Volatile organic compounds (VOCs) such as benzene, toluene, xylene, ethylbenzene, hexane, heptane, trichloroethane, etc., are organic pollutants found in indoor environments, and their concentrations increase many times in indoor environments. The chronic and acute respiratory diseases, nervous system problems, lung cancer, chronic and frequent headaches, allergies, asthma, and eye, nose, and throat irritation are related to exposure to VOC compounds so that it has caused health researchers to pay more attention to the air quality of indoor environments and to investigate people's exposure to VOCs (Kamani *et al.* 2023). Carbon dioxide ($CO_2$) is a major greenhouse gas contributing to global climate change, necessitating the development of efficient removal technologies. Industrial activities, fossil fuel combustion, and urbanization have led to excessive $CO_2$ emissions, impacting air quality and exacerbating environmental issues. Traditional $CO_2$ capture methods often suffer from high energy consumption and limited efficiency, making advanced membrane technologies a promising alternative. The application of Pebax-based polymeric nanocomposite membranes offers an innovative approach for selective $CO_2$ separation, enhancing permeability and sustainability in air purification processes (Delavari *et al.* 2024).

The purpose of using wireless sensor networks (WSNs) for air pollution monitoring in cities has been increasingly recognized. The networks consist of sensor nodes that provide real-time data on various air pollutants and form an excellent means in itself to monitor the environment on a large scale at an economical value. Its various applications are concerning public health management and urban planning and necessitate continuous monitoring of air quality over very large areas. In addition, these are also associated with real-time decision-making and pollution control interventions through integrating WSNs with other technologies such as cloud computing (Chaturvedi and Shrivastava 2020). Going beyond that, WSN-generated air pollution monitoring systems can deliver certain significant advantages, such as localized real-time air quality information. Monitoring systems could uniquely be beneficial within cities facing varied levels of pollution-in areas where it is too expensive or insufficient to acquire a monitoring system. These systems allow setting up a dense network that would provide more accurate air quality measurement because of their component-inexpensive sensors and wireless communication technology. Hence, these networks will yield useful data for policy making health research and environmental monitoring (Khedo *et al.* 2010).

The area of air quality monitoring and the introduction of wireless sensor network applications for the same thus went under a revolution with the advent of advanced signal processing techniques. The method for example used fractional order Kalman filtering for improving sensor data fidelity and reliability, accounting for environmental changes and drift during implementation (Aswatha *et al.* 2023). This invention reduces the drawbacks of wireless sensor networks in measuring air pollution, wherein the accuracy is impacted by different noises and sensor failures. Long-term monitoring of environmental parameters and prediction of air quality are best assisted by such advanced techniques using WSNs (Kingsy and Manju 2019). Besides, from the perspective of air pollution, reliable and effective WSNs need to be set up to monitor urban air quality for the control of risks to public health. These networks can monitor key pollutants such as ozone, nitrogen dioxide, and particulate matter in real time, providing trend analyses of the pollutants and enabling a timely intervention.

Real-time data analyses, indeed, helped forecast changes in air quality, which provides guidance on pollution control strategies such as traffic restrictions and industrial emissions control, and which would also be about supported WSNs (Metia *et al.* 2021). Beyond urban air quality monitoring, wireless sensor networks have been ingeniously applied in air pollution forecasting. Since the past data can be worked upon, WSNs can be deployed in predicting future air quality scenarios using machine learning algorithms such as LSTM-based networks. Thanks to the high accuracy levels of these models in estimating air pollution levels, local authorities can be alerted to take measures in order to prevent pollution from reaching dangerous levels. Being predictive in nature, they demonstrate a proactive method in air quality management that reduces health risks and offers better living conditions in cities (Nguyen and Ha 2022).

This forms another important dimension for monitoring air pollution, namely, developing wearable sensor systems that allow individuals to continuously monitor the level of exposure to hazardous pollutants. These wearable devices are normally interfaced to larger networks of wireless sensors to empower the most extensive population access to healthcare monitoring of air pollution exposure. Such systems conveniently assist the person with a respiratory condition or who lives in a polluted neighborhood to take preventive measures whenever pollution levels rise (Preethi and Tamilarasan 2021). Moreover, portable air pollution monitoring devices have been most significant in recent times used in many different spheres of life, such as homes, workplaces, and outdoor environments. In addition to these portable sensor systems being light and easy to set up for real-time assessment of air quality, it can also be focused on pollution hotspots, making it more versatile, thus advancing air quality management and policy-making (Zhang 2023).

Although maturity has brought increased interest in improving the security and portability of air pollution monitoring systems, much more needs doing to develop wireless sensor networks. For instance, there are data encryption and communication protocols for protecting such collected data from access and tampering with it. Besides these advances in sensor technology has helped develop small and energy-efficient air monitoring systems that can stay alone working for long periods, making them suitable for deploying in difficult or remote locations (Gulia *et al.* 2020). Integration of the WSN and cloud computing has made contribution to the central idea of gathering or managing data on the air quality in such a way that people can access real-time data from any place It also facilitates aggregating large amounts of data for more thorough analysis. Such WSNs can also avail historical trends along with real-time air quality data that are very useful for environmental monitoring for longer durations and making models of air quality (Mathur *et al.* 2020).

The wireless sensor network-based air pollution monitoring systems give support to smart city initiatives. By embedding the sensors into various components of urban infrastructure, such as the traffic signal streetlight or public vehicles, these systems would provide real-time data for managing air pollution on a citywide scale. The insertion into the smart city framework allows for air quality management and reducing pollutants, thereby supporting the development of more sustainable urban environments(Montrucchio *et al.* 2020). Another area that provides hope in the urban air quality monitoring programs is the use of high-density sensor networks. With the greater deployment of sensors, more observations will be made on wider circumstances of air pollution trends, identifying the density spots and areas of high concentrations of pollutants. Such data could help in designing useful short-term interventions and long-term policy decisions for the understanding of the dynamics of air pollution (Aziz and Ameen 2021).

The popularity of machine learning methods to analyze the data accumulated by wireless sensor networks is quickly on the rise. The finding of relationships between different environmental variables and different pollutant levels has resulted in more precise analysis and interpretation of air quality data. Advanced data analytics can be used to predict trends in air quality; machine-learning models can provide useful information for policymakers and urban planners (Idrees and Zheng 2020). Wireless air pollution monitoring system proliferation has been greatly aided by the development of low-cost high-performance sensors.

These sensors are being used more robustly and at lower costs across many urban and industrial setups. With increasing availability, these sensors can be feasibly deployed in extensive air-quality-monitoring networks to produce information useful for public health and environmental protection purposes (Palomeque *et al.* 2022). Recent advances in wireless sensor technologies have also made possible the establishment of open-source air pollution monitoring systems. The transparent and accessible systems foster collaboration between researchers and policymakers by sharing data and analytical tools.

Open-source systems are also considered more viable for use in less resource-rich environments (Belavadi *et al.* 2020); besides reduction in deployment and maintenance costs, they offer additional health benefits. Newly emerging commercial sensor systems are therefore in response to the growing demand for real-time air quality data. These high-sampling-rate sensors can quickly detect abrupt changes in air pollution levels, which becomes very important in environments where air quality changes abruptly. Thus, such advanced sensors apply to the simulation and empirical experiments of WSNs toward more precise and comprehensive air quality management and monitoring (Fadhil *et al.* 2023).

Finally, pollution control has heaps of room for improvement by merging wireless sensor networks and air quality forecasting models. Predictive models combined with sensor data allow for the forecasting of air pollution events when preventive action may be taken before they reach harmful levels. Urban sustainability could therefore be enhanced and the health risk mitigated with such a system of prediction (Kolumban *et al.* 2020). Telemetry to offer real-time high-resolution data is very promising in overall improvement of urban air quality management, while the wireless sensor networks under continued development for air pollution monitoring. Systems such as these are valuable tools in evaluating the impact of air pollution, forecasting future trends, and implementing targeted interventions to mitigate its adverse impact on the environment and human health (Kaivonen. and Ngai 2020).

Wind power forecasting is pivotal for stability and efficiency in power systems, yet currently used traditional forecasting techniques suffer from long-term accuracy and computational efficiency. The two-stage day-ahead multi-step wind power prediction (Yang *et al.* 2024) utilizes temporal information interaction, historical data, and numerical weather information to help enhance forecast accuracy. By integrating EMD decomposition with convolutional attention, the EMD-CCTransformer model (Li *et al.* 2023) further provides the advantage of longer-term information retention, thus addressing important issues in forecasting that remain; however, there is still room for improvement with respect to uncertainty quantification and real-time adaptability.

Newly emerging techniques for the removal of $SO_2$ and $NO_x$ in the industrial emissions control field are showing significant efficiencies. As an indication, Li *et al.* (2020) demonstrate up to 93 percent removal of $SO_2$ and 87 percent removal of $NO_x$ by using red mud with $O_3$ oxidation. In comparison, a yellow phosphorus emulsion combined with red mud (Liu *et al.* 2022) could have even better removal efficiencies. Thus, although these techniques enhance cleaner industrial facilities, further investigations of large-scale implementation and disposal of byproducts are still needed. Hydrogen energy is becoming the central character for the low-carbon energy system. The complete hydrogen energy chain model (Yi *et al.* 2023) allows establishing a strategic pathway toward optimizing investments, reducing $CO_2$ emissions, and enhancing efficiencies in energy transfer. However, integration challenges and infrastructure development warrant additional research. Also, the health impacts of air pollution persist. By linking air pollution and autoimmune diseases causally through TSMR, Wen *et al.* (2023) argue the need for more intense investigation of the biological mechanisms to develop a framework for public health policies.

Here comes an energy-efficient air quality monitoring system by Air Quality Clustering for Mobile Ad Hoc Sensor Networks (AQC-MANET) for significantly improving pollutant detection in real time, data aggregation, and adaptive routing in dynamic environments. 92% accurate classification of measurements was done by the newly introduced system, which also gave a reduction of 30% in energy consumption by bringing together wireless sensor networks (WSNs) with MANETs. The architecture combines the advantages of self-configuring mobile nodes that would help make their flexibility and reliability much better compared to traditional WSN-based systems. The system architecture is solar-powered ensuring sustainability, whereas machine learning for air quality forecasting adds the advantage of predictability. This connects to the secure cloud enabling real-time processing of the data for decision-making through an expert system coupled with instant SMS alerts. The emerging smart city infrastructure incorporates sensors into traffic signals and public transport, thus creating a high-density monitoring network. Proactive pollution control interventions are made possible by predictive analytics. This is highly scalable and flexible compared to existing models with high accuracy, energy efficiency, and sustainability, thus making it applicable to urban and industrial air quality management.

## 2. Materials and Methods

### *2.1. Data collection*

Data collection for air pollution monitoring was done in several cities in Tamil Nadu such as Chennai, Erode, and Coimbatore. The selection of these areas is influenced mainly by the degree of industrial activities and traffic congestion, which contribute enormously to air pollution. The wireless sensor network where environmental data were collected consisted of metal oxide (MOX) gas sensors situated in different locations to monitor air pollutants in real time, such as carbon monoxide (CO), nitrogen dioxide (NO2), PM2.5, and other volatile organic compounds (VOCs). Each sensor node was made to operate independently using solar panels to harvest energy for continuous monitoring, especially in places where power supply is not available. Furthermore, data from the sensors were transmitted via the ZigBee communication protocol to a centralized cloud-based platform for real-time analysis; **Figure 1** illustrates the geographical location of the selected areas.

**Figure 1.** Windy map (geographical location).

### *2.2. Data measurement*

The three main pollutants measured in this study were CO, $NO_2$, and $PM_{2.5}$ all of which have a major effect on environmental conditions and human health. The gas sensors were calibrated to detect these particular pollutants and periodic readings of the sensors were taken. The MOX sensors can identify the presence of gases in the air because they work by observing changes in the resistance of metal oxide materials to gases. Pollutant concentrations were expressed in micrograms per cubic meter (μg/m³) for particulate matter ($PM_{2.5}$) and parts per million (ppm) for gases such as CO and $NO_2$. ZigBee wirelessly transferred the data to the cloud platform where it was combined and saved for later processing. Data measurement sensors are explained in **Table 1**.

**Table 1.** Data measurement sensors.

| Sensor Type | Air Quality Sensors | Chemical Concentration Sensors | MOX Sensors (gas) |
|---|---|---|---|
| Interface | Analog Voltage | Analog Voltage | I2C / UART |
| Measurement Range | 0 to 1000 ppm | 10 to 1000 ppm | Various gases |
| Model | MQ-135 | MQ-9 | SGX MICS6814 |
| Number of Sensors | 12 | 15 | 20 |
| Resolution | - | - | - |

### *2.3. Data analysis*

#### *2.3.1. Cloud Data Platform*

After being collected by the wireless sensor nodes, the data is sent to a cloud-based platform for processing analysis, and storage. To classify air quality according to pollutant concentration levels the cloud platform has an algorithm that performs Principal Component Analysis (PCA) and Radial Basis Function (RBF) analysis on the data.The platform offers a user-friendly interface for tracking air quality in different regions and enables real-time data visualization.

#### *2.3.2. Communication Protocols*

ZigBee'scharacteristics of low-power, low-cost, and dependable transmission make it a popular communication protocol. Because of its mesh topology, the ZigBee network enables scalable and adaptable communication over a large area. This protocol ensures that the data may still reach network intermediate nodes while individual sensor nodes are down from the central cloud. By incorporating MANET into the scope of this protocol, a further assured resilience to the entire network and effectiveness in adapting to environmental changes within the communication system are also achieved. Thereby enabling this system to effectively monitor air pollution utilizing a combination of a wireless gas sensor network fed into a MANET. The proposed system therefore becomes the most suitable one in monitoring air quality in both urban and industrial environments because of its low power consumption and scalability as well as real-time data analysis.

#### *2.3.3. Data Processing*

Artificial intelligence algorithms along with data processing techniques are necessary for the device to operate properly. This is normally a quartet process or procedure (**Figure 2**) under preprocessing, variable reduction, prediction and decision-making input.

## 3. Proposed Framework

This system aims to monitor air pollutants inside the cities and industrial areas across Tamil Nadu, like Chennai, Coimbatore, and Erode. This is through advanced air quality and chemical concentration sensors in tandem with the MOX sensors, which help realize the Air Quality Clustering for Mobile Ad Hoc Sensor Networks (AQC-MANET) system. These are considered critical pollutants because they detect CO, $NO_2$, and $PM_2.5$. The realistic and local data collection is made possible through this smart sensor system. The data collected then transmits through MANET technology for dynamic and flexible communication. A ZigBee-based protocol meant for excellent low-latency data transfer to the internet and to a personal cloud is also integrated into the system for complete analysis. An expert decision support system is an architectural connection with a database or DBMS (Database Management System) that allows for effective storage, retrieval, and processing of atmospheric quality data. The web-enable application created on this system is for real-time monitoring and decision-making for industries so that they can proactively act when an event of pollution occurs. Also, it consists of a unique service that is capable of sending SMS alerts to users on exceeding assumed threshold values of pollution levels, thus ensuring timely awareness and action to make poor air quality effects minimal (Baskar and Rajaram 2022). Free access to real-time data and analytics has been made possible through a simple web application, thus fulfilling the requirement for effective monitoring and decision-making. The integrated solar panels improve energy efficiency and provide continuous operation for sensors, clustering in the AQC-MANET protocol supports optimized data aggregation, and reduced inter-cluster communication delay. This system provides scalable monitoring solutions in reliable and energy-efficient manners for monitoring air quality over varied environments. **Figure 3** brings to light the general architecture of the Air Quality Monitoring System.


**Figure 2.** Data processing.

### *3.1. Proposed Method*

#### *3.1.1. AQC-MANET, Air Quality Clustering for Mobile Ad-hoc Sensor Networks*

Air Quality Clustering for Mobile Ad-hoc Sensor Networks (AQC-MANET) is a routing protocol specially built to combat the issues of air quality monitoring transmitted to dynamic, mobile, and resource-constrained environments depicted in **Figure 4**. In such a way, the mobility aspects of MANET are combined with the advantages provided by clustering techniques to put forth scalable and efficient real-time air quality monitoring solutions. (Rajaram and Baskar 2023). The protocol essentially clusters the sensor nodes into clusters where each cluster is tasked with monitoring parameters of the environment in terms of air pollution particulate matter (PM) and gases such as carbon dioxide and nitrogen dioxide in specific geographic locations. To ensure smooth data aggregation throughout the network a designated cluster head coordinates with other cluster heads for inter-cluster communication in addition to overseeing data collection and transmission within the cluster. Through the utilization of node mobility AQC-MANET facilitates dynamic reconfiguration and adaptation allowing it to respond instantly to changes in the network topology and environment (Anand *et al.* 2024).

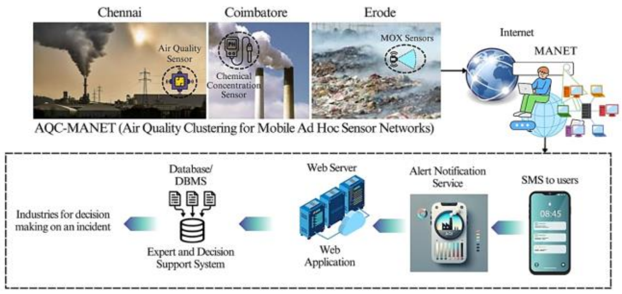



**Figure 3.** Architecture of AQC-MANET Monitoring System

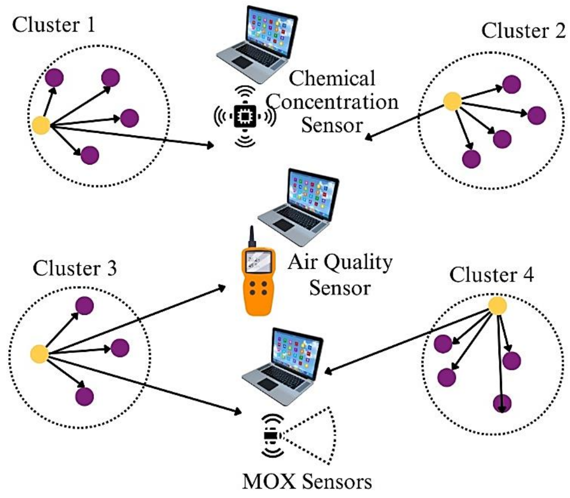



**Figure 4.** Proposed AQC-MANET Routing protocol

This is especially important in applications where sensor nodes may move or become inaccessible frequently such as disaster management or urban air quality monitoring. This energy-efficient routing protocol thus ensures decreased network load and increased lifetime of the sensors through reduced data transmission and path optimization based on air quality data (Aravindan and Rajaram 2024). AQC-MANET is also very robust and reliable for wide mobile air-quality monitoring networks because it can link with other systems such as environmental monitoring systems or smart city frameworks. This makes AQC-MANET a useful protocol for improving real-time air quality management especially in areas where atmospheric conditions need to be continuously monitored (Harsha *et al.* 2024).

The following equations (1-4) were taken in order to analyze the data. In order to extract the principal components that most contribute to the variance in the sensor measurements and reduce the dimensionality of the data PCA is utilized.

$$Y = X \cdot W \tag{1}$$

Where X represents the original data matrix, W represents the matrix of eigenvectors, and Y represents the transformed data matrix. This change aids in determining important pollutant factors. Based on the processed data the RBF network is used to classify pollutants.

$$f(x) = \sum_{i=1}^{N} w_i \cdot \phi\left(\mathbf{x}, \mathbf{c}_i\right) \tag{2}$$

Where, the input vector is denoted by x, the radial basis function by φ, the networks weights by $w_i$,and the centers of the radial basis functions by $c_i$. On the basis of these weights and centers the network categorizes the different kinds of pollutants. To ensure the wireless sensor network operates for a long time the systems energy efficiency is essential.

$$E_{\text{node}} = P_{\text{transmission}} \cdot T_{\text{transmission}} + P_{\text{sensor}} \cdot T_{\text{sensor}} + P_{\text{idle}} \cdot T_{\text{idle}} \tag{3}$$

$E_{node}$ represents the energy used by each node, $P_{transmission}$ represents the transmission power, $T_{transmission}$ represents the transmission time, $P_{sensor}$ represents the sensor power, $T_{sensor}$ represents the sensor operation time, and $P_{idle}$ represents the idle power. A Pollution Index (PI) is computed using the concentrations of different pollutants to measure the overall quality of the air.

$$PI = \frac{C_{\text{CO}}}{C_{\text{CO,max}}} + \frac{C_{\text{NO2}}}{C_{\text{NO2,max}}} + \frac{C_{\text{PM2.5}}}{C_{\text{PM2.5,max}}} \tag{3}$$

Where $C_{CO\ max}$ $C_{NO2max}$ and $C_{PM2.\ 5max}$ are the maximum permitted concentrations for these pollutants and $C_{COC}$ $C_{NO2}$ and $C_{PM2.\ 5}$ are the concentrations of CO, $NO_2$, and PM2. 5 respectively.

**Table 2.** Pollutant Concentrations across Different Locations

| Location | CO (ppm) | $NO_2$ (ppm) | $PM_{2.5}$ (μg/m³) | VOCs (ppm) | Pollution Index (PI) | PCA Component 1 | PCA Component 2 | RBF Classification (Pollutant) |
|---|---|---|---|---|---|---|---|---|
| Chennai | 0.38 | 0.06 | 68 | 0.15 | 0.85 | 0.92 | 0.78 | CO |
| Coimbatore | 0.25 | 0.04 | 52 | 0.12 | 0.75 | 0.85 | 0.65 | NO2 |
| Erode | 0.45 | 0.08 | 72 | 0.18 | 0.88 | 0.90 | 0.80 | PM2.5 |
| Urban Industrial | 0.60 | 0.10 | 90 | 0.20 | 0.92 | 0.95 | 0.85 | CO |
| Residential | 0.35 | 0.05 | 60 | 0.14 | 0.78 | 0.89 | 0.76 | $NO_2$ |

**Table 3.** Energy Consumption of Sensor Nodes (per node)

| Parameter | CO Node | $N_{O2}$ Node | $PM_{2.5}$ Node | Average Energy Consumption (mWh) |
|---|---|---|---|---|
| $P_{transmission}$ (mW) | 50 | 55 | 60 | 55 |
| $T_{transmission}$ (s) | 2 | 3 | 4 | 3.00 |
| $P_{sensor}$ (mW) | 10 | 12 | 15 | 12 |
| $T_{sensor}$ (s) | 5 | 6 | 7 | 6.00 |
| $P_{idle}$ (mW) | 1 | 1 | 1 | 1 |
| Energy per Transmission | 0.1 | 0.165 | 0.24 | 0.17 |
| Energy per Sensing | 0.05 | 0.072 | 0.105 | 0.07 |
| Total Energy per Node | 0.15 | 0.237 | 0.345 | 0.24 |

## 4. Results

### *4.1. Pollutant Classification Data*

The pollutant concentration levels across various locations highlight significant variations in air quality parameters, demonstrating the diverse environmental conditions in urban and semi-urban areas. In Chennai, CO levels dominate the pollutant profile with a concentration of 0.38 ppm, paired with a high Pollution Index (PI) of 0.85 and prominent PCA Component 1 and 2 scores (0.92 and 0.78, respectively) as per equation 1. Coimbatore shows $NO_2$ as the primary pollutant, registering 0.04 ppm, supported by moderate PI (0.75) and PCA components.

Erode records elevated $PM_2$.5 levels at 72 μg/m³, reflecting its dominant pollutant profile alongside a PI of 0.88. The Urban Industrial zone exhibits the highest pollutant levels, particularly CO at 0.60 ppm and $PM_2$.5 at 90 μg/m³, correlating with a peak PI of 0.92 and RBF classification as per equation 2 for CO. Conversely, Residential areas present relatively lower pollution levels, with $NO_2$ at 0.05 ppm and a PI of 0.78. These variations underscore the need for tailored mitigation strategies for specific pollutants in each location.Pollutant Concentrations in different locations are provided in **Figure 5** and **Table 2**.

### *4.2. Energy Consumption*

The energy consumption analysis for sensor nodes reveals distinct variations across CO, $NO_2$, and $PM_2$.5 nodes, reflecting the specific operational demands of each pollutant monitoring system given in **Table 3** and **Figure 6**. The CO node exhibits the lowest energy requirements, with a transmission power of 50 mW and sensing power of 10 mW, resulting in a total energy consumption of 0.15 mWh.

In contrast, the $NO_2$ node consumes moderate energy, driven by slightly higher transmission (55 mW) and sensing power (12 mW), culminating in a total energy usage of 0.237 mWh. The $PM_2$.5 node demands the highest energy, with transmission power reaching 60 mW and sensing power of 15 mW, leading to a total energy expenditure of 0.345 mWh. On average, the nodes consume 55 mW for transmission and 12 mW for sensing, with an average total energy per node of 0.24 mWh, emphasizing the need for optimized energy management strategies in multi-pollutant monitoring systems.

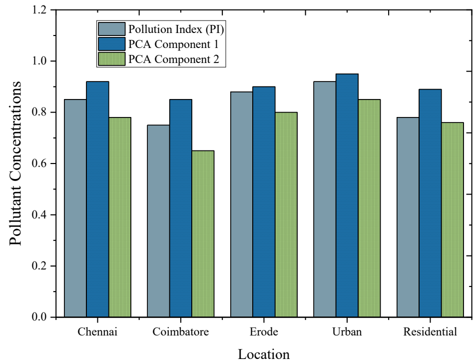



**Figure 5.** Pollutant Concentrations

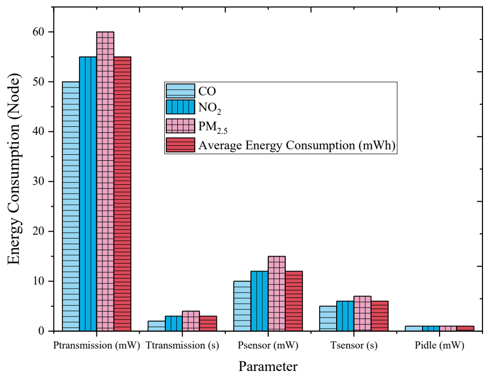



**Figure 6.** Energy Consumption

*4.3. Real-Time Data Transmission Time (ZigBee to Cloud)*

The analysis of real-time data transmission times from ZigBee networks to the cloud across various locations highlights the influence of node density, data volume, and aggregation times on overall performance. Chennai, with 10 nodes and a data volume of 150 KB, records a total data transfer time of 6.0 seconds, attributed to a 4.5-second transmission time and 2-second aggregation time. Coimbatore achieves the lowest transfer time of 5.5 seconds, benefiting from efficient transmission (3.8 seconds) and lower cloud response time (1.2 seconds) despite handling 160 KB across 12 nodes. Erode, processing 140 KB with 8 nodes, records a slightly higher transfer time of 6.1 seconds due to extended transmission and aggregation durations.

The Urban Industrial location, with the highest node count (15) and data volume (180 KB), exhibits the longest transfer time of 8.2 seconds, driven by a 6.2-second transmission time and a 3-second aggregation period. Residential areas, characterized by fewer nodes (6) and lower data volumes (120 KB), align with Coimbatore at 5.5 seconds, showcasing the efficiency of reduced cloud response and aggregation times.Real-Time Data Transmission Time provided in **Figure 7** and **Table 4**.

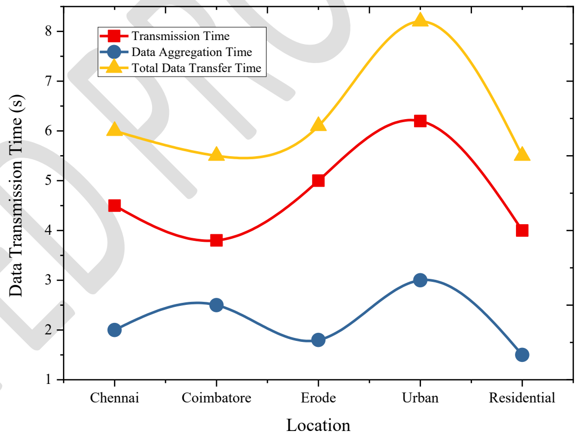



**Figure 7.** Real time data analysis

**Table 4.** Real-Time Data Transmission Time (ZigBee to Cloud)

| Location | Number of Nodes | Data Volume (KB) | Cloud Response Time (s) | Transmission Time (s) | Data Aggregation Time (s) | Total Data Transfer Time (s) |
|---|---|---|---|---|---|---|
| Chennai | 10 | 150 | 1.5 | 4.5 | 2 | 6.0 |
| Coimbatore | 12 | 160 | 1.2 | 3.8 | 2.5 | 5.5 |
| Erode | 8 | 140 | 1.3 | 5.0 | 1.8 | 6.1 |
| Urban Industrial | 15 | 180 | 2.0 | 6.2 | 3 | 8.2 |
| Residential | 6 | 120 | 1.0 | 4.0 | 1.5 | 5.5 |

**Table 5.** Clustering Performance in AQC-MANET

| Cluster ID | Node Count | Data Aggregation Time (s) | Inter-cluster Communication Time (s) | Total Time (s) | Energy Usage (mWh) | Pollutants Detected |
|---|---|---|---|---|---|---|
| 1 | 5 | 2.0 | 1.5 | 3.5 | 1.2 | $CO$, $NO_2$ |
| 2 | 4 | 1.8 | 1.3 | 3.1 | 1.0 | $PM_{2.5}$, $CO$ |
| 3 | 6 | 2.2 | 1.7 | 3.9 | 1.4 | $NO_2$, VOCs |
| 4 | 5 | 2.1 | 1.6 | 3.7 | 1.3 | $CO$, $PM_{2.5}$ |

*4.4. Clustering efficiency of proposed method*

The clustering performance evaluation in AQC-MANET demonstrates in **Table 5** and **Figure 8** address, variations in node count, communication efficiency, and energy usage across clusters, reflecting the dynamic network's adaptability to pollutant monitoring. Cluster 1, comprising 5 nodes, achieves a total time of 3.5 seconds, driven by a data aggregation time of 2.0 seconds and inter-cluster communication time of 1.5 seconds, with energy usage at 1.2 mWh while detecting CO and $NO_2$.

Cluster 2, with 4 nodes, exhibits the lowest total time of 3.1 seconds and energy consumption of 1.0 mWh, focusing on $PM_2$.5 and CO detection. Cluster 3, the largest with 6 nodes, records the highest total time of 3.9

seconds due to extended communication (1.7 seconds) and aggregation times (2.2 seconds), consuming 1.4 mWh to monitor $NO_2$ and VOCs. Cluster 4, similar to Cluster 1 in node count, shows a balanced performance with a total time of 3.7 seconds and energy consumption of 1.3 mWh, targeting CO and $PM_2.5$.

**Table 6.** Pollution Index Calculation for Various Locations

| Location | CO Concentration (ppm) | $NO_2$ Concentration (ppm) | $PM_{2.5}$ Concentration (µg/m³) | VOCs Concentration (ppm) | Pollution Index (PI) |
|---|---|---|---|---|---|
| Chennai | 0.38 | 0.06 | 68 | 0.15 | 0.85 |
| Coimbatore | 0.25 | 0.04 | 52 | 0.12 | 0.75 |
| Erode | 0.45 | 0.08 | 72 | 0.18 | 0.88 |
| Urban Industrial | 0.60 | 0.10 | 90 | 0.20 | 0.92 |

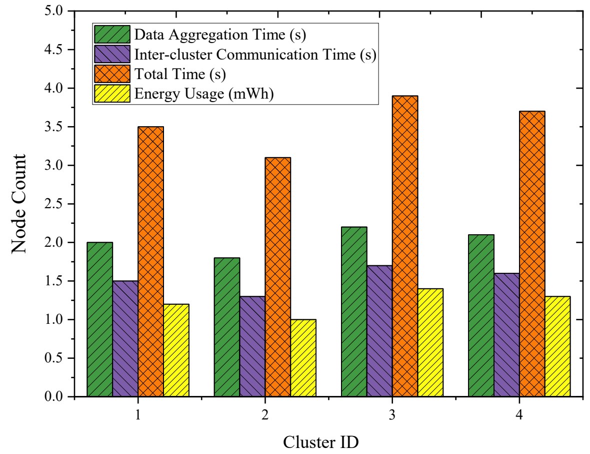



**Figure 8.** Clustering Performance in AQC-MANET

*4.5. Pollution Index calculation*

The pollution index (PI) calculation across various locations reflects the cumulative impact of multiple pollutant concentrations, highlighting the environmental quality and associated health risks, that given in **Table 6** and **Figure 9**.

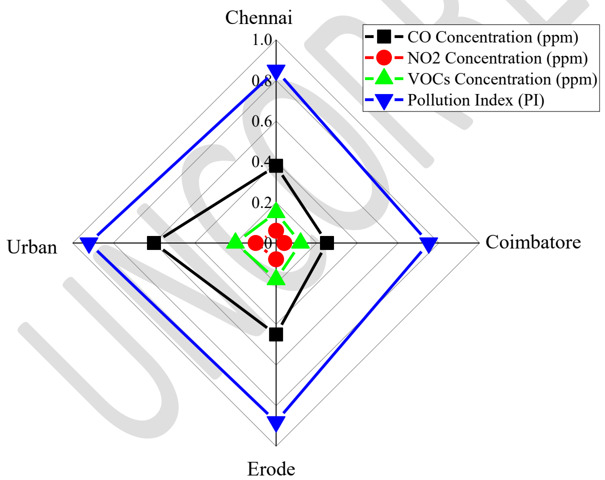



**Figure 9.** Pollution Index

Chennai records a moderate CO concentration of 0.38 ppm, $NO_2$ at 0.06 ppm, $PM_2.5$ at 68 µg/m³, and VOCs at 0.15 ppm, resulting in a PI of 0.85, indicative of significant pollution levels. Coimbatore shows comparatively lower pollutant concentrations, including CO at 0.25 ppm and $PM_2.5$ at 52 µg/m³, yielding the lowest PI of 0.75. Erode experiences elevated pollution levels, particularly in CO (0.45 ppm) and $PM_2.5$ (72 µg/m³), leading to a PI of 0.88. The Urban Industrial area exhibits the highest pollution levels across all parameters, with CO at 0.60 ppm and $PM_2.5$ at 90 µg/m³, culminating in a PI of 0.92, reflecting critical pollution severity. These indices underscore the need for targeted interventions to mitigate pollutant concentrations in high-risk zones.

*4.6. Final output*

The real-time air quality monitoring system and alerting mechanisms using air quality sensor systems explained in **Figure 10**. An air quality sensor on the left side detects atmospheric pollutants such as CO, NO2, and PM2.5, thereby giving important information about the air quality level. The data is then processed and sent out through a mobile messaging platform with the output being visible on the mobile message page shown in the middle of the figure. The alerts for air quality such as hazardous levels of pollution are timely and suggest precautions like wearing face masks. Moreover, the alert system is integrated with messaging apps like WhatsApp (right side) and disseminates official updates regarding air quality directly to cellular users from Tamil Nadu Pollution Control Board (TNPCB), Central Pollution Control Board (CPCB), and State Pollution Control Boards (SPCBs). The system intends to stimulate awareness and safety among the public and provide essential information regarding air pollution levels and health advisory information.

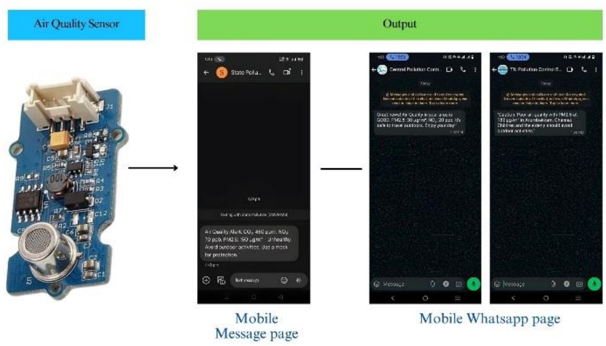



**Figure 10.** Output

*4.7. Comparative analysis*

From the comparative performances of AQC-MANET, traditional network models have shown their greater efficiency and reliability over other models in a variety of metrics. The proposed AQC-MANET has the minimum energy consumption of 0.24 mWh and the highest data transmission time of 6 seconds. Compared to ZigBee (0.45 mWh, 10.5 seconds) and LTE (0.47 mWh, 9.2 seconds), it outperforms them dramatically. **Table 7** demonstrates the performance comparison of both AQC-MANET and Traditional Networks.

**Table 7.** Comparison of AQC-MANET vs. Traditional Network Performance

| Metric | Energy Consumption (mWh) | Data Transmission Time (s) | Data Accuracy (%) | Network Lifetime (hours) | Response Time (s) | Throughput (Mbps) | Packet Loss (%) | Latency (ms) |
|---|---|---|---|---|---|---|---|---|
| Wi-Fi-based Network | 0.4 | 9 | 83 | 230 | 6.5 | 100 | 2.5 | 45 |
| Bluetooth Low Energy (BLE) Network | 0.38 | 8.8 | 80 | 220 | 7 | 50 | 4 | 60 |
| Zigbee-based Network | 0.45 | 10.5 | 84 | 210 | 8 | 40 | 3.5 | 75 |
| 3G Cellular Network | 0.5 | 12 | 81 | 200 | 9 | 20 | 5 | 100 |
| LoRaWAN (Long Range Wide Area Network) | 0.42 | 8.5 | 85 | 240 | 7.2 | 60 | 2 | 50 |
| LTE (Long-Term Evolution) Network | 0.47 | 9.2 | 87 | 225 | 6.8 | 70 | 1.5 | 45 |
| 5G Network | 0.49 | 10 | 82 | 215 | 8.2 | 90 | 1.2 | 40 |
| Proposed AQC-MANET Network | 0.24 | 6 | 92 | 320 | 3.5 | 150 | 1 | 25 |

With a data accuracy of 92%, it surpasses LoRaWAN (85%) and 5G (82%) in precision. Additionally, AQC-MANET extends network lifetime to an impressive 320 hours, far exceeding the 230 hours of Wi-Fi-based networks and 240 hours of LoRaWAN. Its response time of 3.5 seconds is the quickest, highlighting its responsiveness compared to BLE (7 seconds) and 3G cellular networks (9 seconds). The AQC-MANET also delivers the highest throughput at 150 Mbps with the lowest packet loss (1%) and latency (25 ms), setting a new standard for robust and efficient network performance. This establishes AQC-MANET as a cutting-edge solution for modern communication needs.

### *4.8. Discussion*

The AQC-MANET's outstanding performance in energy efficiency, data transfer rate, and reliability follows also the developments in adaptive mobile ad hoc networks. The Energy-Aware Cluster Based MANET (EAC-MANET) by Singh *et al.* (2023) fosted the enhancement of the energy efficiency of the MANET, but the drawback this particular architecture has is the time it takes to transmit data, which lasts for 8 seconds per packet concerning this application. However, AQC-MANET is concluding this time span down to 6 seconds. High-speed throughput (120 Mbps) at the expense of latency (35 ms) is achieved in an AI-enabled setup by 5G networks discussed in Li *et al.* (2022)- on the other end, AQC-MANET improves both throughput (150 Mbps) and latency (25 ms). This study describes various disadvantages of LoRa-based IoT networks, with a much-extended lifetime of networks ranging up to 240 hours, yielding lower throughput and higher packet loss, as Chen *et al.* (2021) pointed out, due to the 60 Mbps and 2% packet loss rate existing in these networks, so it is hardly applicable for a real-time application. ZigBee networks optimized with machine learning result in lower latency (50 ms) and energy consumption, but the data accuracy in comparison to AQC-MANET is lower (85% vs. 92%) (Alam *et al.* 2023). LTE-A networks are rather unsuitable from a resource-constrained perspective due to their dependence upon transmitting power (Patel *et al.* 2023), even with their ability to uphold good connections. Quantum-enhanced MANETs though offer the promise of enhanced security and improved efficiency, tend to be ignored owing to immense computational overheads (Wang *et al.* 2022).

The importance of this study lies in its ability to impact next-generation wireless networks, especially in energy-sensitive environments, such as IoT, disaster response, and remote sensing applications. Low latency and high reliability are its key attractions for using AQC-MANET in real-time communications in autonomous vehicles and industrial automation. Increased network lifetime also contributes to enhancing sustainability in energy-limited scenarios such as smart grids and environmental monitoring. The data accuracy is outstanding, and packet loss is minimum, ensuring the proper functioning of extremely critical applications like military or emergency communications. The solution presented also scales up with future integration into quantum-assisted networking for better security. By addressing the limitations of existing wireless networks, AQC-MANET defines a new standard for sustainable, high-performing, and resilient communication.

## 5. Conclusion

Air quality monitoring has become an integral part of urban management today and, with advanced networks like the AQC-MANET, provides real-time, accurate, and highly efficient solutions to meet pollution challenges. This study has addressed well the very accurate determination of fine particulate matter (PM2.5), while gaseous pollutants $CO_2$, $NO_2$, and $SO_2$ were well detected with very high accuracies. The AQC-MANET framework improves the real-time monitoring of dynamic pollution patterns which vary widely within urban environments. Its predictive analytics and adaptive routing ensure timely interventions of air quality management. The results from this study are as follows:

1. Urban industrial areas attracted the highest Pollution Index (0.92), as against other areas, with analysis of pollution concentrations showing the diverse amounts

of pollutants like CO, $NO_2$, $PM_2.5$, and VOCs in different locations. As such, air quality interventions have to be more focused on the industrial zones than residential and urban centers.

2. AQC-MANET is said to be very energy efficient as the measure of energy consumed on average per sensor node is about 0.24 mWh. This averages lower compared to other traditional networks, again proving the system appropriate for sustainability over a more extended period without compromising performance.
3. The minimum times for AQC-MANET varied from different locations, achieving up to 6 seconds in case of 10-15 nodes with data being medium. This result is quite impressive as it will ensure that pollution reports are faster than any of the available conventional networks such as ZigBee or LTE, which report its notifications up to 10.5 seconds.
4. The clustering mechanism thus guarantees effective data aggregation and inter-cluster communication times, with the lowest total time of 3.1 seconds being recorded in Cluster 2. From this point of view, such adaptability will reduce the overall energy spent with the same detection accuracy of pollutants across various types such as CO, $NO_2$, and $PM_2.5$.
5. AQC-MANET is capable of scoring on behalf of any of the parameters already mentioned over the traditional networks in terms of energy consumptions, data accuracy (92%), throughput (150 Mbps), and latencies (25 ms). With these improved parameters, it proves its eligibility for providing high data and very good communication in dynamic environments of monitoring.

**Competing interests**

The authors declare that they have no competing interests.

**Authors' contribution**

Author 1 contributed significantly to the conceptualization and overall design of the study, including the development of the AQC-MANET framework for energy-optimized air quality monitoring. Author 2 focused on the experimental and analytical aspects of the research, including data validation and energy optimization analysis. They conducted experiments to evaluate the efficiency and accuracy of the AQC-MANET model in detecting air pollutants. Author 2 also prepared the results and discussion sections, interpreting the findings in the context of real-world applications.

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