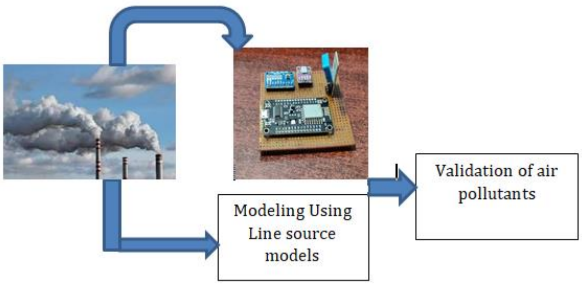
Global NEST Journal, Vol 27, No 5, 06372

Air quality assessment and validation – integrating sensor network with line source modeling

M. Selvakumar[1]* and S. Geetha[1]
[1]Professor, Department of Civil Engineering, Rajalakshmi Engineering College, India.
Received: 04/07/2024, Accepted: 27/02/2025, Available online: 04/04/2025
*to whom all correspondence should be addressed: e-mail: selvakumar.m@rajalakshmi.edu.in
https://doi.org/10.30955/gnj.06372

Graphical abstract



Abstract

This study presents an innovative approach to air quality assessment by integrating low-cost sensor networks with line source modeling. The research focuses on monitoring air pollutants in urban environments, particularly along a busy highway corridor in Chennai, India. A portable sensor kit was fabricated using metal oxide semiconductor sensors (MICS) to measure NO_2 and CO concentrations, along with temperature, humidity and wind speed. Ten monitoring stations were strategically selected based on traffic congestion levels. A portable sensor kit with MICS sensor to measure CO and NO_2, a Wi-Fi module (NODEMCU), an analog to digital converter (ADC16 BIT) and DHT-11 sensor to measure temperature (℃) and humidity(%). Also meterological parameters like wind speed and wind direction was also recorded. To validate the sensor data, the Delhi Finite Line Source Model (DFLSM) was employed. The study revealed maximum CO concentration ranging from 1.8 to 5 mg/m^3 and NO was from 8 to 32 µg/m^3. There has been occasional spike in CO concentration in monitoring stations 5, 6 and 10 beyond the threshold limit of 4 mg/m^3. The correlation between observed and modelled data showed R^2 values from 0.82 for CO and 0.95 for NO_2 indicating good agreement. This integrated approach offers several advantages over traditional monitoring methods, including cost-effectiveness, real-time data collection, and the ability to cover larger areas. This study demonstrates the potential of this method for comprehensive air quality monitoring in urban settings, which can aid in identifying pollution hotspots and informing urban planning and policy decisions.

Key words: Air Quality Assessment, Sensor Network, Line Source Modeling, Emission Sources, Data Validation, Atmospheric Dispersion

1. Introduction

The expansion of urban areas and industrial growth has led to increased traffic and industrial activity, resulting in environmental issues such as water, air, and soil contamination. As essential components for human survival, any alteration in the composition of air and water can have detrimental health effects. (Pandey A. *et al.* 2021, Li Lin. *et al.* 2022). Consequently, environmental protection agencies prioritize the preservation of these elements and have established standards for quality monitoring. While water pollution is often easily detectable through visual and olfactory cues, air pollution is less visible and more challenging to measure. The primary air pollutants include particulate matter, SO_2, NOx, O_3, CO, and CO_2. A research study found that air pollutants were related in causing various symptoms in humans that ultimately lead to causing autoimmune disease. (Wen J. *et al.* 2024). Certain components of PM2.5 especially polycyclic aromatic hydrocarbons (PAH) are found to cause systemic lupus erythematosus after long term exposure in humans especially children, pregnant women and patients (Alves AGF *et al.* 2018, Conde PG *et al.* 2018). Due to the high costs associated with establishing monitoring stations, only a limited number are set up in select metropolitan areas, making it difficult to measure pollutant concentrations according to National Ambient Air Quality Standards (NAAQS) guidelines. Although portable monitoring devices exist, comprehensive tools for measuring multiple pollutants simultaneously are scarce. It has also been proved that gases like CO, NO_2, SO_2, and CO_2 in the atmosphere can be detected using multi-pass cavity-enhanced Raman spectroscopy technique in lower concentrations. (Wang M *et al.* 2025). In addition to these pollutants, VOCs like benzene, toluene, ethylbenzene and xylene also play a role in deteriorating the air quality both indoors due to paints, solvents, cigarette smoke, and outdoors due to industrial activities, fuel stations, incomplete combustion of gasoline and diesel vehicles. Research studies show that inhalation of benzene can cause cancer in humans and ethylbenzene are found to be carcinogenic to animals. (Khoshakhlagh A.H *et al.* 2024, Moolla R *et al.* 2015). A study conducted in various indoor environment in Iran found that these VOCs were exceeding the standards set by Environmental Protection Agency based on inhalation exposure time. (Kanmani H *et al.* 2023). The integration of vision and language models for analyzing air pollutant imagery and sensor data can improve detection, classification, and real-time evaluation of air pollutants. (Chen Y *et al.* 2024). Pollutant concentrations vary along line sources and wind paths (Qin P. *et al.* 2024, Wen YB. *et al.* 2022).

Air quality monitoring is crucial for raising awareness and controlling harmful emissions that may pose health risks. (Baklanov A. *et al.* 2016, Ababio B.A *et al.* 2025). Various methods can be employed for this purpose, including real-time monitoring stations, portable equipment, diffusion tubes, and sensors. Fixed monitoring stations can only capture pollutant concentrations at a single point, serving as a representative sample. Portable devices require manual operation and can only be used for limited time periods (Wang Y.Z *et al.* 2025, Huang M. *et al.* 2024). Passive diffusion tubes are suitable for analyzing monthly average concentrations but are restricted to detecting gaseous pollutants. (Ballesta P.P. *et al.* 2023). Trace organic pollutants can also cause degradation of the environment and human health (Gong H. *et al.* 2024). Research on the fluorescence quenching mechanism and pseudo-second-order kinetics model of HMQ composite was conducted by a researcher, potentially leading to the creation of more effective gas sensors for monitoring air quality. The interaction between air pollutants and specific quantum dots or biomimetic materials could potentially enhance the capabilities of current sensors through fluorescence-based detection methods. (Xu F. *et al.* 2024).

Recent research has focused on developing sensors to detect major pollutant concentrations. These sensors utilize micro sensing technology and offer innovative ways to collect air quality data. However, their accuracy must be validated against reference data from monitoring stations or portable equipment before deployment. Low-cost sensors have been used in community-based air pollution studies (Kortoci P. 2022, Thulliez E. *et al.* 2024, Albarracin K.Y.A. *et al.* 2023). Mobile air quality monitoring stations equipped with sensors can provide insights into air pollutants in specific areas (Lee C.C. *et al.* 2020, Miao C. *et al.* 2024).

The reliability of monitoring devices is called into question due to their limitations. Research has shown that long-term spatial data on pollutants and their variations do not significantly correlate with the information generated by these devices (Chojer H. *et al.* 2020, Morawska L. *et al.* 2018, Rai A.C. *et al.* 2017). Despite extensive global research on utilizing low-cost sensors for air quality monitoring significant challenges persist. (Poupry S. *et al.* 2023, Castell N. *et al.* 2017, Deary M.E. *et al.* 2016) One major issue is that fabricated sensors require calibration with standard sensors and often exhibit sensitivity and instability at ground monitoring stations (Jiao W. *et al.* 2016). This can lead to data misinterpretation, necessitating a validation system to verify the accuracy of data collected by these low-cost sensors (Boulic M. *et al.* 2024). Many researchers have noted the drawbacks of using sensors as mobile monitoring stations during post-processing and validation, with consistent sensor performance over time being a primary concern. In Canada, air quality was monitored using a mobile van equipped with sensors, and the data was validated and used to assess population exposure to particulate matter pollutants. Researchers reported a strong correlation between observed and monitored data, which also aligned well with modeled data (Weichenthal S. *et al.* 2016, Sabaliauskas K. *et al.* 2015). Mapping air pollutant spatial data can highlight concentration in specific areas, and reducing these concentrations may mitigate their impact on human health and ensure cleaner air in the future. The development of these sensors has enabled air quality data collection over longer distances by installing devices in mobile vans, bicycles, cars, buses, and taxis (Minet L. *et al.* 2017, Xie S. *et al.* 2024, Clark S.N *et al.* 2024).

Air quality monitoring sensors employ diverse working principles. These include optical particle counters for particulate matter analysis, metal oxide-coated semiconductor sensors, electrochemical devices, photo ionization detectors, and non-dispersive infrared sensors (Borrego C. *et al.* 2016, Seesaard T. *et al.* 2024, Yi W.Y. *et al.* 2015). Sensor integration typically involves combining pollutant-specific sensors with those measuring meteorological parameters, enabling the study of pollutant patterns in relation to factors such as temperature, wind speed, and humidity. The monitoring device can be assembled as a kit, incorporating these sensors alongside a control board integrated with the sensor board for data storage and transmission. After determining the sensor configuration, a validation profile must be established. Optimal calibration involves comparing sensor data with reference measurements from standard monitoring stations. Alternatively, sensors can be validated against well-established, time-tested models that accurately reflect pollutant concentrations based on meteorological data and emission factors. A study showed that a suspended nanomembrane silicon micro ring resonator exhibited high sensitivity when utilized for CO_2 gas detection. (Guo R. *et al.* 2024)

Mathematical modeling serves as a predictive tool for responses influenced by various factors. In air quality modeling, numerous parameters are considered, including wind speed, wind direction, source location, and elements that significantly affect pollutant dispersion. Research indicates that mathematical equations and software can model air pollution based on its source, categorized as line, point, or area sources. Line source pollution predictions often employ Gaussian-based models, utilizing wind data, emission factors, and various parameters (Brusca S. *et al.* 2016, Yang Z. *et al.* 2020). Deterministic air quality models determine pollution concentrations using source information, emission factors, wind data, and dispersion parameters. The model's integrity relies heavily on the accuracy of input data. Air quality data can be analyzed by a variety of techniques and methods. (Wang Y. *et al.* 2023). A self powered biomimetic mouse whisker sensor (BMWS) studied by a researcher has the possibility to be applied to air quality monitoring since they are more energy-efficient and suitable for long-term remote deployments in urban environments. (Hou X. *et al.* 2023). A researcher suggested a novel method to remove CO_2 from air contaminants by using permeation test with a prepared polymeric nanocomposite membrane. This findings could be used as a mitigatory measure to remove CO_2 from the mixture of atmospheric gases in future. (Delavari M. *et al.* 2024).

This study introduces an innovative, cost-effective miniature air quality monitoring device with high sensitivity and specificity. The device consumes minimal power and responds quickly. Its measured data is integrated and validated using mathematical modeling with predictive capabilities, enabling validation and calibration. The combination of MICS sensors and mathematical modeling enhances accuracy and reliability, facilitating real-time monitoring, forecasting, and air quality management for improved public health outcomes. This paper aims to analyze pollutants using a sensor and validate pollution concentrations using finite line source models.

2. Methodology

2.1. Location of study area

The study area chosen for this work is on the National Highways (NH-48) connecting Chennai and Bengaluru. The road is a four-lane road with extension works carried out for widening the highway to 8 lanes. A stretch of 10 stations were selected in a close interval of 3 to 5 km so that the entire stretch of the Highway stating from Chennai outer to Sriperambudur Toll gate is covered. Major traffic signals and road intersections wherein the anticipated traffic is in a stagnant condition for a considerable amount time were identified as monitoring stations. This road houses two major SIPCOT (Industrial zones) and many educational institutions. The road has a mixed culture of residential, commercial, educational and industrial corridor.

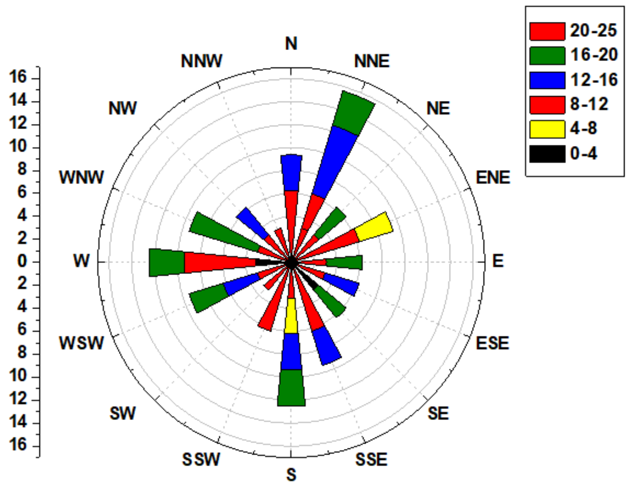


Figure 1. Wind rose diagram showing wind velocity and direction

2.2. Meteorological data

The transport of pollutants is enabled by the wind parameters and dispersion is facilitated by the weather conditions like temperature, relative humidity and rainfall. Wind speed and direction plays a major role in diluting the concentration. The data with respect to wind speed and direction is given as a wind rose diagram in **Figure 1**. The average relative humidity observed in this place ranged from 65 to 72% during summer and 75 to 90 % during winter. The average monthly rainfall along with the maximum and minimum observed temperatures is given in the data presented in **Figure 2**.

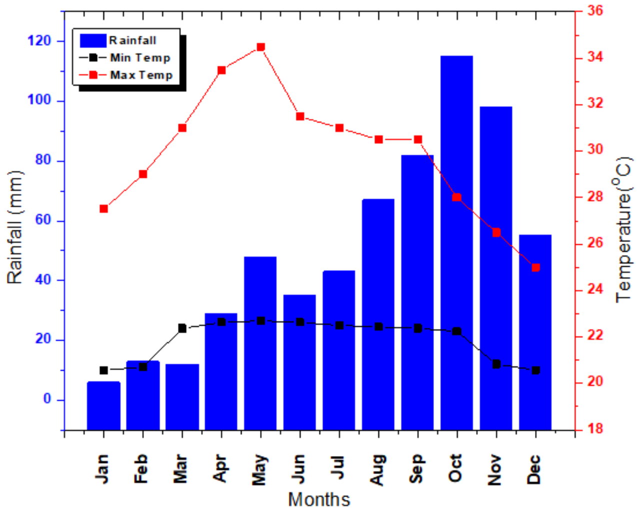


Figure 2. Meteorological data (source: https://weatherspark.com/h/y/110123/2023/Historical-Weather-during-2023-in-Chennai-India)

2.3. Methodology

A sensor kit was fabricated using an aurdino board. The sensor used for monitoring the data is MICS 6814. It is silicon gas sensor consisting of a diaphragm with a sensing layer on top and an embedded heat resistor. It has 3 sensor chips out of which one sensor detects oxidizing gases, the other sensor detects reducing gases and the third sensor detects NH_3. The range of gases that could be detected by the sensors is carbon monoxide (CO) – 1 to 1000 ppm and Nitrogen di oxide (NO_2) - 0.05 to 10 ppm. The other components that were added in the aurdino board are the sensor that can measure temperature and humidity (DHT-11), a Wi-Fi module (NODEMCU) and an Analog to digital converter (ADC 16 BIT). The pollutants considered in this study are NOx and CO as these pollutants can easily be measured using such metal oxide semiconductor sensors and moreover the area under study has these gases as major pollutants. These sensors work by the redox process facilitating the metal oxide to undergo oxidation and reduction as it comes in contact with the gaseous pollutants. Due to this reaction the output is a change in resistance.

The profile and architecture diagram of the fabricated sensor kit is given in **Figure 3 (a) and 3(b)** respectively.

Appropriate sensors are selected and calibrated in a controlled laboratory environment using standard reference. Field calibration is done by way of placing the sensors alongside an existing monitoring station to ascertain the accuracy of measured data. Strategic placement is planned considering the pollution sources, population density and geographic features.

Environmental data comprising the meteorological data (Temperature, humidity, wind speed and direction) and supplement data like traffic count and sources of industrial emission are collected. The sensor kit was connected to a laptop and the air pollutant concentrations were measured from 8 am to 8 pm covering the peak hour traffic. The vehicle count was also taken in order to use it for line source model. The line source used in this work for validating the data is Delhi finite line source model (DLSFM). The input data for the models as per the equation was prepared and configured based on the study area and specific pollutants. The data observed using the sensor kit was compared with the model. The air pollutant data is cross validated to evaluate the model accuracy and monitored data. Statistical metrics like correlation coefficients are used to quantify the agreement between the model predictions and sensor observations.

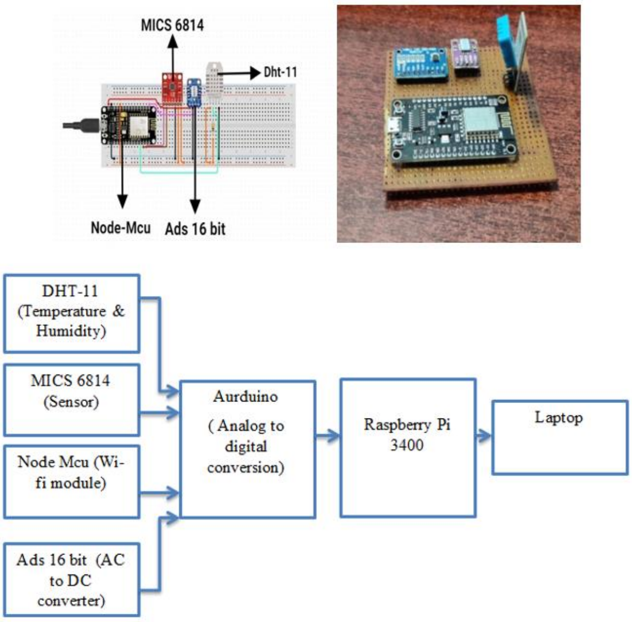


Figure 3. (a) Fabricated sensor kit (b) Architectural diagram of the sensor kit.

3. Results and Discussions

3.1. Monitored data using sensor kit

The data that is monitored using the sensor kit is plotted to show the concentration of the pollutants during summer and winter. The concentration of CO given in **Figure 4** has maximum values in station 5, 6 and 10. The NAAQS value as given for pollution threshold is 2-4 mg/m^3. There has been a marginal increase in CO cumulative concentration beyond 4 mg/m^3 in stations 5, 6 and 10 indicating that it is exceeding the standards.

The station 5, 6, and 10 are locations having higher idling of traffic since they are in zones having traffic signal and road intersections. The idling of vehicles for a considerable amount of time could result in higher concentration of CO concentration. Moreover, the vehicle counts reveals that around 9000 vehicles pass this road in an hour. These monitoring stations are in industrial area that houses automobile industries like Hyundai car factory which has containers for transporting the manufactured cars. The major reason for CO spike is the incomplete combustion of fuels used in these vehicles especially diesel trucks. The other cause associated with increase in CO concentration is from the machineries and equipment's that are used along road-side for construction works like bitumen mixer, paver equipment's, rollers and compactors. Even short-term exposure to CO can reduce the level of oxygen in the blood leading to heart diseases in humans.

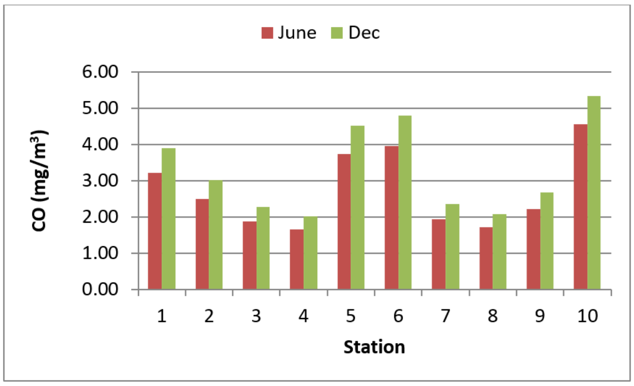


Figure 4. Variation of CO in summer and winter

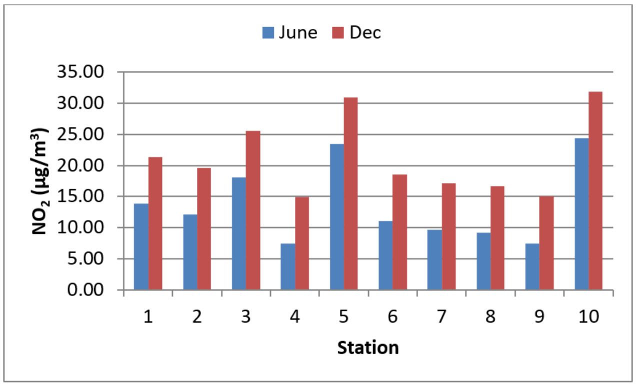


Figure 5. Variation of NO_2 in summer and winter

Similarly, the concentration of NO_2 given in **Figure 5** had maximum concentration in stations 3, 5 and 10. Station 10 is located exactly opposite to the Hyundai car factory. The NAAQS value for NO_2 can be from 40 to 80 µg/m^3. The value measured in all the stations are well below the threshold levels. Pollution from industries and vehicles are the main reason for higher concentration of NO_2. NOx denotes the group of compounds of nitrogen and oxygen. The source of NO_2 is generated from tropospheric ozone, from exhaust of petrochemical process and by burning of fossil fuels. The particles get deposited in wet and dry states in the atmosphere as acidic compounds. NO_2 is considered as a greenhouse gas and is said to create global warming approximately 300 times more than that of CO_2. The concentration of NO_2 in the atmosphere is said to cause acute health hazards in humans like respiratory ailments and low birth weight.

3.2. Modeled data using DFLSM

The model used in the study given in equation (1) was referred from the one used by Khare and Sharma (1999) [27] that was modified from the conventional general finite source model (GFLSM). The major difference in this model is that the error function is eliminated from the base GFLSM. The modeled data was compared with the observed experimental data. The concentration of the pollutants is given as:

$$C=\frac{Q}{2\sqrt{2\sigma y u_e}}\left[\exp\left\{\frac{z-h_o}{\sigma_z}\right\}+\exp\left\{-\frac{1}{2}\left(\frac{z+h_o}{\sigma_z}\right)^2\right\}\right] \quad (1)$$

In the above equation Q represents the emission rate, u is the wind speed, the dispersion parameters are σ_y are σ_z in the horizontal and vertical direction, the receptor distance from the road is y and the height of the receptor is z. The parameters for fixing the receptor were adopted as specified by Gokhale and Khare [28]. In the line source co-ordination system all the parameters, namely, *x*, *y*, *z* can be evaluated from road receptor geometry. This model as given in equation (2) specifies the dispersion parameter as a function of wind-road orientation angle and distance from the source. Height of the receptor relative to the ground is taken as 1.8 m. Horizontal Dispersion Parameter (σ_y) is given as:

$$\sigma_y=\sqrt{\sigma^2{}_{yt}+\sigma^2{}_{ya}} \quad (2)$$

$$\sigma_{yt}=2\sigma_{zt} \quad (3)$$

$$\sigma_{zt}=3.57-0.53U_O \quad (4)$$

Uo is mean wind speed, m/s

$$\sigma_{ya}=\frac{X\sin\lambda}{2.15\cos\lambda} \quad (1)$$

λ depends on stability class and is given by:

λ = 18.33-1.8096 In (x/1000)/57.2958 for unstable (A to C)

= 14.333-1.7706 In (x/1000)/57.2958 for neutral (D)

= 12.500-1.0857 In (x/1000)/57.2958 for stable (E to F)

Here x is in metres and λ in radians

Vertical Dispersion Parameter (σ_z)

The vertical dispersion parameter in is given as

$$\sigma_z=\left(a+bf\left(\theta\right)x\right)^c \quad (6)$$

However, for GFLSM model, the effective downwind distance is given as X/sin θ. a, b, c depends upon stability class. Then 1/sin θ =1/0.2242 for stability class (A-D),= 1/0.1466 for stability class (E), θ = angle between the ambient wind and the road.

The temperature and wind data as given in **Figure 1 and 2** are considered as those occuring on the particular day of measurement. Atmospheric stability is based on Pasquill Gifford stability classes. The traffic data was collected manually and the emission factors were calculated based on the type of vehicle. The mobile source emission factor is defined as the quantity of a pollutant emitted when a vehicle runs a unit length of road and depends upon the type, speed, age, etc of the vehicle. Hence Q is given by : $Q=E_f\times V_h$ Where, E_f is the pollutant emission factor; and V_h is the vehicle density (vehicles/h).

The results given in **Figure 6(a) and Figure 7(a)** are the values of pollutant concentration that was modeled using DFLSM and the concentrations that were observed using the sensor kit. It shows that there are some variations in the numerical values with increase and decrease of 2 to 3 units in both the cases. The correlation coefficient by linear regression between the observed and modeled data is plotted in **Figure 6(b) and 7(b)**. The R^2 value for CO is 0.8 and for NO_2 it is 0.94.

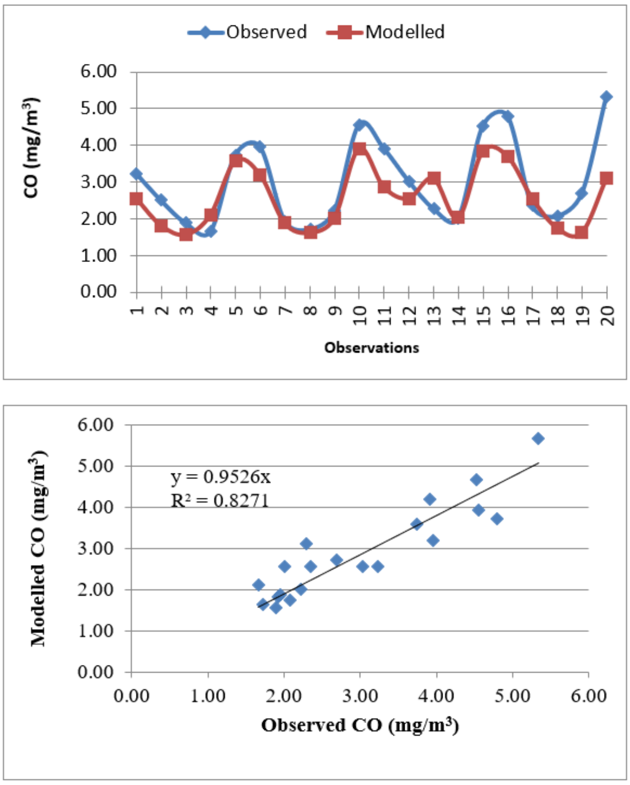


Figure 6. (a) Correlation of observed and modeled data for CO (b) Correlation of observed and modeled data for CO.

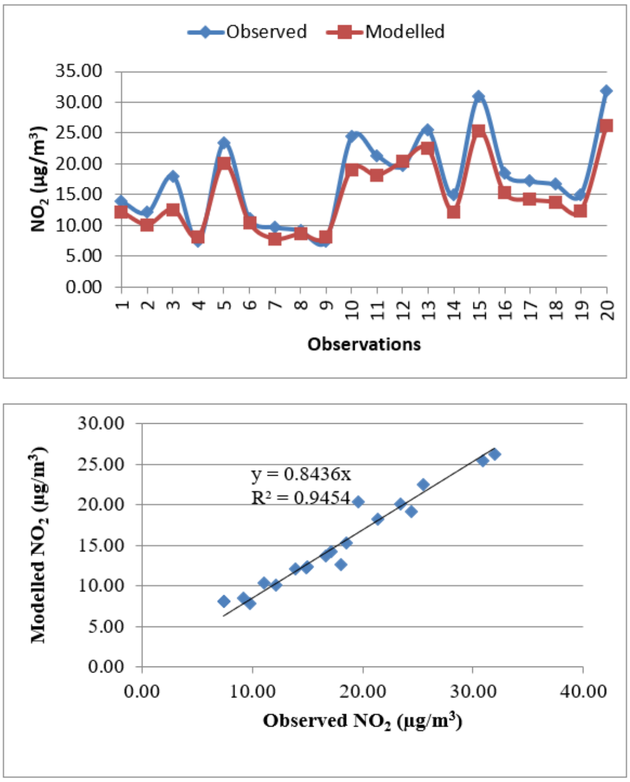


Figure 7. (a) Correlation of observed and modeled data for NO_2 (b) Correlation of observed and modeled data for NO_2.

Comprehensive data collection is the major complexity of the model. Gathering detailed traffic volume, classifying the types of vehicles and estimation of emission factors involves more field monitoring. Accurate meteorological parameters are needed to drive the accuracy of the data. Though the meteorological data keeps varying in a day the average values are considered for calculation. The model's sensitivity to various parameters like atmospheric stability and mixing height requires careful validation. Integrating MICS sensors data with model outputs for validation requires careful analysis and data processing. Continuous calibration of the model against observed data to improve accuracy and reliability is essential.

Exposure of sensors to high levels of pollutants, humidity and temperature variation can cause degradation. Compared to High volume samplers, the data acquired from the sensor kits are thought to have low accuracy and precision. Hence the MICS metal oxide sensor was subjected to a number of periodical calibration and testing methods in order to ensure accuracy in measuring the concentration of pollutants. To evaluate the sensors sensitivity and response characteristics, they were subjected to a range of CO and NO_2 concentrations. This evaluation approach involved introducing and withdrawing the target gases, and the sensors displayed steady and reproducible responses. The sensors were subjected to a known concentrations of CO and NO_2 during the gas sensitivity test, and the voltage level and resistance changes were recorded. This lets us determine how well the sensor performs in various temperature, pressure, and humidity settings and forces us to verify the sensor's linearity and sensitivity. The Response and Recovery Time Testing ensures that the MICS sensor utilized in these studies has a good recovery time and necessitates ongoing monitoring. There is very little interference when these sensors are tested for cross-sensitivity and interference since it is periodically checked once every 3 weeks. If the MICS sensor shows high interference due to environmental conditions such as temperature (20°C-40°C) and humidity (20%-60%) which impacts the sensor output with the standard reference equipment, then a new calibrated MICS sensor is used replacing the defective sensor. Long-term stability tests reveal that the sensors provided reliable readings with low drift over a 24-hour period. According to the findings, MICS gas sensors are suited for real-time monitoring since they have good sensitivity and selectivity for CO and NO_2. Combining MICS sensor data with advanced modeling techniques can help mitigate some of the limitations and enhance the overall quality of air quality assessments.

Further enhancements in MICS sensor technology can focus on improving sensitivity, accuracy, durability while reducing the cost and power consumption. A wholesome air quality assessment assembly can be fabricated using various other sensors and integrating it to be a complete monitoring assembly which can be used in place of high-volume samplers especially in places where high pollution concentration tends to prevail and where human health hazards may occur due to higher concentration of air pollutants.

The highlight of this works involves an innovative approach of using low-cost sensors integrated with line source modeling to assess air quality. This approach renders a cost effective and widespread solution for air quality monitoring especially in urban areas. The integration of sensor networks with line source models allows for continuous data collection and dynamic updating of the models. This ensures more accurate air quality assessments under varying environmental conditions and traffic patterns. The use of low-cost sensors enables deployment across multiple locations, facilitating large-scale air quality monitoring. This provides a more comprehensive view of air pollution distribution compared to traditional, limited monitoring stations. This study also demonstrates a method for validating data from low-cost sensors using line source modeling, addressing concerns about the accuracy and reliability of such sensors. This validation process enhances credibility of data collected through these sensors. Finally, the data collected through this method can significantly aid urban planners and policy makers in identifying pollution hot spots and developing targeted strategies for air pollution mitigation. This has important implications for public health and urban development.

4. Conclusions

The key conclusions from this research can be summarized as follows:

Combining the real time data from sensor network distribution with line source models significantly improves the accuracy of air quality assessments.

This integration facilitates comprehensive monitoring of pollutant dispersion specifically in urban environment prone to complex emission sources.

The real time data of the sensor network enables continuous data collection thereby allowing for dynamic update of line source models. This ensures the accuracy of models under the varied climatic conditions and traffic fluctuations. Hence a robust air quality information and forecast system can be developed by this integration.

The use of low-cost sensors makes widespread deployment in various stations covering a larger extent facilitating large scale air quality monitoring. The study also demonstrates an alternative low-cost solution in the place of more expensive monitoring stations.

The air quality data provided in this study can help the urban planners and policy makers to identify pollution hot spots and devise appropriate strategies for mitigating the pollution which has significant public health implications.

References

Ababio B.A., Ashong G.W., Agyekum T.P., Yeboah B.A. (2025), Comprehensive health risk assessment of urban ambient air pollution (PM2.5, NO2 and O3) in Ghana, *Ecotoxicol. Environ. Saf.*, 289, 117591, https://doi.org/10.1016/j.ecoenv.2024.117591

Albarracin K.Y.A., Consuegra A.A., Aguilar-Ariaset J. (2023). Particulate matter 10 µm (PM10), 2.5 µm (PM2.5) *datasets gathered by direct measurement, low-cost sensor and by public air quality stations in Fontibón*, Bogotá D.C., Colombia, DIB., 49, 109323, https://doi.org/10.1016/j.dib.2023.109323

Alves A.G.F, de Azevedo Giacomin M.F., Braga A.L.F., Sallum A.M.E., Pereira L.A.A., Farhat L.C., Strufaldi F.S., de Faria Coimbra

Lichtenfels A.J., de Santana Carvalho T., Nakagawa N.K., Silva C.A. and Farhat S.C.L. (2017). Influence of air pollution on airway inflammation and disease activity in childhood-systemic lupus erythematosus. *Clin Rheumatol* 2018; 37: 683–90. https://doi.org/10.1007/s10067-017-3893-1

Baklanov A., Molina L.T., Gauss M. (2016). Megacities, air quality and climate, *Atmospheric Environment*, 126, 235–249, https://doi.org/10.1016/j.atmosenv.2015.11.059

Ballesta P.P., Bau A., Field R.A., Woolfenden E. (2023). Using the POD sampler for quantitative diffusive (passive) monitoring of volatile and very volatile organics in ambient air: Sampling rates and analytical performance, *Environment International*, 179, 108119, https://doi.org/ 10.1016/j.envint.2023.108119

Borrego C., Costa A.M., Ginja J., Amorim M., Coutinho M., Karatzas K., Sioumis Th., Katsifarakis N., Konstantinidis K., De Vito S., Esposito E., Smith P., Andre N., Gerard P., Francis L.A., Castell N., Schneider P., M. Viana, Minguillon M.C., Reimringer W., Otjes R.P., Von Sicard O., Pohle R., Elen B., Suriano D., Pfister V., Prato M., Dipinto S., Penza M. (2016). Assessment of air quality microsensors versus reference methods: the EuNetAir joint exercise, *Atmospheric Environment*, 147, 246–263. https://doi.org/10.1016/j.atmosenv.2016.09.050

Boulic M., Phipps R., Wang Y., Vignes M., Adegoke N.A. (2024). Validation of low-cost air quality monitoring platforms using model-based control charts, *Journal of Building Engineering*, 82, 108357, https://doi.org/10.1016/j.jobe.2023.108357

Brusca S., Famoso F., Lanzafame R., Mauro S., Garrano A.M.C, Monforte P. (2016). Theoretical and experimental study of Gaussian Plume model in small scale system, *Energy Procedia*, 101, 58–65, https://doi.org/ 10.1016/j.egypro.2016.11.008

Castell N., Dauge F.R., Schneider P., Vogt M., Lerner U., Fishbain B., Broday D., Bartonova A. (2017). Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates?, *Environment International*, 99, 293–302, https://doi.org/10.1016/j.envint.2016.12.007

Chen Y, Li Q, Liu JY. (2024). Innovating Sustainability: VQA-Based AI for Carbon Neutrality Challenges, *Journal of Organizational and End User Computing*, 36(1). https://doi.org/10.4018/JOEUC. 337606

Chojer H., Branco P.T.B.S., Martins F.G., Alvim-Ferraz M.C.M., Sousa S.I.V. (2020). Development of low-cost indoor air quality monitoring devices: Recent advancements, *Science of The Total Environment*, 727, 138385, https://doi.org/10.1016/j.scitotenv.2020.138385

Clark S.N., Kulka R., Buteau S., Lavigne E., Zhang J.J.Y, Riel-Roberge C., Audrey S. Weichenthal S., Ryswyk K.V. (2024). High-resolution spatial and spatiotemporal modelling of air pollution using fixed site and mobile monitoring in a Canadian city, *Environmental Pollution*, 356, 124353, https://doi.org/10.1016/j.envpol.2024.124353

Conde PG, Farhat LC, Braga ALF, Sallum AEM, Farhat SCL, Silva CA. (2018). Are prematurity and environmental factors determinants for developing childhood-onset systemic lupus erythematosus? *Modern Rheumatology* 2018; 28: 156–60. https://doi.org/10.1080/14397595.2017.1332508

Deary M.E., Bainbridge S.J., Kerr A., McAllister A. and Shrimpton T. (2016). Practicalities of mapping PM10 and PM2.5 concentrations on citywide scales using a portable particulate monitor, *Air Quality, Atmosphere & Health*, 9(8), 923–930, https://doi.org/10.1007/s11869-016-0394-3

Delavari M., Beyranvand F., Jahangiri M., Abdipour H. (2024). Increasing the Permeability of Carbon Dioxide and Nitrogen Gases Through a Polymer Membrane Consisting of a Modified Polyether Block Amide and Experimental Design, *Journal of Polymers and the Environment*, 32, 4822–4841, https://link.springer.com/article/10.1007/s10924-024-03247-z

Gong H., Hu J., Rui X., Wang Y., Zhu N. (2024). Drivers of change behind the spatial distribution and fate of typical trace organic pollutants in fresh waste leachate across China, *Water Research*, 263, 122170, https://doi.org/10.1016/j.watres.2024.122170

Guo R., He Q., Zhang Z., Xu Y., Zhang S., Lang Q., Xiao S., Han P., Wang J, Ding T, Liu T., Tsang H.K., Goda K, Cheng Z. (2024). High-Q silicon microring resonator with ultrathin sub-wavelength thicknesses for sensitive gas sensing, *Applied Physics Reviews* 11, 021417. https://doi.org/10.1063/5.0189343

Hou X., Xin L., Fu Y., Na Z., Gao G., Liu Y., Xu Q., Zhao P., Yan G., Su Y., Cao K., Li L., Chen T. (2023). A self-powered biomimetic mouse whisker sensor (BMWS) aiming at terrestrial and space objects perception, *Nano Energy*, 118, Part A, 109034. https://doi.org/10.1016/j.nanoen.2023.109034

Huang M., Li X., Yang M., Kuai X. (2024). Intelligent coverage and cost-effective monitoring: Bus-based mobile sensing for city air quality, Computers, *Computers, Environment*, Urban Syst., 108, 102073, https://doi.org/10.1016/j.compenvurbsys.2024.102073

Jiao W., Hagler G., Williams R., Sharpe R., Brown R., Garver D., Judge R., Caudill M., Rickard J., Davis M., Weinstock L., Zimmer-Dauphinee S., and Buckley K. (2016). Community Air Sensor Network (CAIRSENSE) project: evaluation of low-cost sensor performance in a suburban environment in the southeastern United States, *Atmospheric Measurement Techniques*, 9(11), 5281–5292, DOI: 10.5194/amt-9-5281-2016

Kamani H, Abdipour H, Mohammadi L and Rayegannakhost S. (2023). Health risk assessment of BTEX compounds (benzene, toluene, ethylbenzene and xylene) in different indoor air using Monte Carlo simulation in zahedan city, Iran, 9(9), e20294, https://www.cell.com/heliyon/fulltext/S2405-8440(23)07502-3

Khoshakhlagh A.H, Yazdanirad S, Moda H.M., Gruszecka-Kosowska A. (2024). The impact of climatic conditions on the carcinogenic and non-carcinogenic risk of BTEX compounds: A systematic review and meta-analysis. *Journal of Hazardous Materials Advances*, 16, 100470, https://doi.org/10.1016/j.hazadv.2024.100470

Kortoci P., Motlagh N.M., Zaidan M.A., Fung P.L. (2022). Air pollution exposure monitoring using portable low-cost air quality sensors, *Smart Health*, 23, 100241, https://doi.org/10.1016/j.smhl.2021.100241

Lee C.C., Tran M.V., Choo C.W, Tan C.P, Chiew Y.S. (2020). Evaluation of air quality in Sunway City, Selangor, Malaysia from a mobile monitoring campaign using air pollution micro-sensors, *Environmental Pollution*, 265, part-A, 115058, https://doi.org/10.1016/j.envpol.2020.115058

Lin L., Yang H., and Xu X., (2022). Effects of Water Pollution on Human Health and Disease Heterogeneity: A Review, *Frontiers in Environmental Science*, 10, 880246, https://doi.org/10.3389/fenvs.2022.880246

Miao C., Peng Z.R., Cui C., He X., Chen F., Lu K., Jia G., Yu S., Chen W. (2024). Quantifying and predicting air quality on different road types in urban environments using mobile monitoring and automated machine learning, *Atmospheric Pollution Research*, 15(3), 102015, https://doi.org/10.1016/j.apr.2023.102015

Minet L., Gehr R., Hatzopoulou M. (2017). Capturing the sensitivity of land-use regression models to short-term mobile monitoring campaigns using air pollution micro-sensors, *Environmental Pollution*, 230, 280–290, https://doi.org/10.1016/j.envpol.2017.06.071

Moolla, R., Curtis, C. J., & Knight, J. (2015). Assessment of occupational exposure to BTEX compounds at a bus diesel-refueling bay: A case study in Johannesburg, South Africa. *Science of The Total Environment*, 537, 51–57. doi:10.1016/j.scitotenv.2015.07.1

Morawska L., Thai P.K, Liu X., Asumadu-Sakyi A., Ayoko G., Bartonova A. Bedini A., Chai F., Christensen B., Dunbabin M., Gao J., Hagler G.S.W, Jayaratne R., Kumar P., Lau A.K.H, Louie P.K.K, Mazaheri M., Ning Z., Motta N., Mullins M., Mahmudur Rahman Md., Ristovski Z., Shafiei M., Tjondronegoro D., Westerdahl D., Williams R. (2018). Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone? *Environment International*, 116, 286–299, https://doi.org/10.1016/j.envint.2018.04.018

Pandey A., Brauer M., Cropper M. L., Balakrishnan K., Mathur P., Dey S., Beig G. (2021). Health and economic impact of air pollution in the states of India: the Global Burden of Disease Study 2019, Lancet Planetary Health, 5(1), e25–e38. doi:10.1016/s2542-5196(20)30298-9

Poupry S., Medjaher K., Beler B. (2023). Data reliability and fault diagnostic for air quality monitoring station based on low cost sensors and active redundancy, Measurement, 223, 113800, https://doi.org/10.1016/j.measurement.2023.113800

Qin P., Ricci A., and Blocken B. (2024). Modeling traffic pollutants in a street canyon by CFD: Idealized line sources versus multiple realistic car sources, *Science of The Total Environment*, 2024, 955, 177099, https://doi.org/10.1016/j.scitotenv.2024.177099

Rai A.C., Kumar P., Pilla F., Skouloudis A.N., Sabatino S.D., Ratti C, Yasar A., Rickerby D. (2017). End-user perspective of low-cost sensors for outdoor air pollution monitoring, *Science of The Total Environment*, Vol.607–608, 691–705, https://doi.org/10.1016/j.scitotenv.2017.06.266

Sabaliauskas K., Jeong C.H., Yao X., Reali C., Sun T., Evans G.J. (2015). Development of a land-use regression model for ultrafine particles in Toronto, Canada, *Atmospheric Environment*, 110, 84–92, https://doi.org/10.1016/j.atmosenv.2015.02.018

Seesaard T., Kamjornkittikoon K., Wongchoosuk C. (2024). A comprehensive review on advancements in sensors for air pollution applications, *Science of The Total Environment*, 951, 175696, https://doi.org/10.1016/j.scitotenv.2024.175696

Thulliez E., Portier B., Bobbia M., Poggi J.M. *et al.* (2024). Deployment of low-cost air quality sensors in Rouen: A dataset of one year of hourly concentrations of gas pollutants, DIB., 55, 110768, https://doi.org/10.1016/j.dib.2024.110768

Wang M, Wang J, Wang P, Wang Z, Tang S, Qian G, Liu T, Chen W. (2025). Multi-pass cavity-enhanced Raman spectroscopy of complex natural gas components, *Analytica Chimica Acta*, 1336, 343463. https://doi.org/10.1016/j.aca.2024.343463

Wang Y., Huang L., Huang C., Hu J., Wang M., (2023). High-resolution modeling for criteria air pollutants and the associated air quality index in a metropolitan city, *Environment International*, 172, 107752, https://doi.org/10.1016/j.envint.2023.107752

Wang Y.Z., He H.D., Huang H.C., Yang J.M., Peng Z.R. (2025). High-resolution spatiotemporal prediction of PM2.5 concentration based on mobile monitoring and deep learning, *Environmental Pollution*, 364, 125342, https://doi.org/10.1016/j.envpol.2024.125342

Weichenthal S., Ryswyk K.V., Goldstein A., Shekarrizfard M., Hatzopoulou M. (2016). Characterising the spatial distribution of ambient ultrafine particles in Toronto, Canada: a land use regression model, *Environmental Pollution*, 208, 241–248, https://doi.org/10.1016/j.envpol.2015.04.011

Wen J, Jingwei Zhang, Hao Zhang, Nan Zhang, Ruoyan Lei, Yujia Deng, Quan Cheng, He Li and Peng Luo. (2024). Large-scale genome-wide association studies reveal the genetic causal etiology between air pollutants and autoimmune diseases, *Journal of Translational Medicine*, 22 (392). https://doi.org/10.1186/s12967-024-04928-y

Wen YB, Huang ZR, Tang YF, Li DR, Zhang YJ and Zhao FY. (2022). Air exchange rate and pollutant dispersion inside compact urban street canyons with combined wind and thermal driven natural ventilations: Effects of non-uniform building heights and unstable thermal stratifications, *Science of The Total Environment*, 851, 158053, https://doi.org/10.1016/j.scitotenv.2022.158053

Xie S., Chen X., Fan J., Liu Y., Du K., Xi M. (2024). Mobile monitoring of air pollutant concentration in the park of Urumqi, China, ATMOS ENVIRON-X., 24, 100297, https://doi.org/10.1016/j.aeaoa.2024.100297

Xu F., Bai W., Zhang J. and Jin L. (2024). The synthesis and application of MRI-fluorescence dual mode materials with absorption ability on quantitative analysis of malachite green, *Physica Scripta* 99 105575. https://doi.org/10.1088/1402-4896/ad7d4a

Yang Z., Ya Q., Buser M.D., Alfieri J.G., Li H., Torrents A., McConnella L.L, Downey P.M., and Cathleen J. Hapemanet C.J. (2020). Modification and validation of the Gaussian plume model (GPM) to predict ammonia and particulate matter dispersion, *Atmospheric Pollution Research*, 11(7), 1063–1072

Yi W.Y, Lo K.M., Mak T., Leung K.S, Leung Y., Meng M.L. (2015). A Survey of Wireless Sensor Network Based Air Pollution Monitoring Systems, *Sensors*, 15(12), 31392–31427, https://doi.org/10.3390/s151229859