

# Real-Time IoT Pollution Monitoring System: A Case Study of Delhi

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**Abstract-** Metropolitan cities like Delhi face severe environmental degradation due to rapid urbanization and vehicular density. Traditional monitoring stations are often sparse and provide delayed, macro-level data. This paper proposes a low-cost, integrated Internet of Things (IoT) solution to monitor Air Quality Index (AQI), noise pollution, and traffic density in real time. Utilizing an Arduino-based architecture with MQ-135, DHT11, and ultrasonic sensors, the system transmits data via ESP8266 to cloud platforms for live visualization. Historical data analysis (2015–2024) reveals significant seasonal variations and a high correlation between traffic activity and pollutant levels. The study concludes that decentralized IoT networks are essential for high-resolution urban environmental surveillance.

**Keywords -** Air Quality Index (AQI), Internet of Things (IoT), PM 2.5 Analysis, Real-Time Data Acquisition, Smart Cities, Urban Pollution Monitoring

## I. INTRODUCTION

In the last decade, Delhi has emerged as a focal point for global discussions on urban air pollution. The city's unique geography, coupled with rapid industrialization and a massive increase in the number of registered vehicles, has created a persistent "smog" phenomenon. While the government operates several Continuous Ambient Air Quality Monitoring Stations (CAAQMS), these units are expensive to maintain and are spaced kilometres apart. This leaves vast residential and commercial patches without localized data, making it difficult for individuals to assess the immediate air quality in their specific vicinity. The core problem lies in the data granularity gap. Existing monitoring infrastructure provides a general average of city-wide pollution but fails to identify "micro-hotspots"—specific street corners, construction sites, or traffic junctions where pollution levels may be three to four times higher than the city average. Furthermore, noise pollution and traffic density are rarely monitored in an integrated manner alongside

air quality, despite being deeply interconnected in an urban environment. There is a critical need for a low-cost, multi-parametric system that can provide this data in real time.

### 1.1 Importance of the Study

1. Public Health: Citizens can receive alerts about high pollution in their specific neighbourhood.
2. Urban Planning: Authorities can identify which specific intersections require traffic diversion or green belt development.
3. Policy Validation: The data helps in measuring the actual effectiveness of policies like the "Odd-Even" rule or construction bans by providing immediate feedback on pollutant levels.

## II. LITERATURE REVIEW

The integration of IoT in environmental monitoring has gained significant momentum over the last decade. Early research focused primarily on stationary sensing units that transmitted data via GSM or Zigbee protocols. Studies by Kim et al. (2015) demonstrated that low-cost electrochemical sensors could effectively track carbon monoxide and nitrogen dioxide in urban settings, though they noted calibration challenges. In the specific context of India, several researchers have utilized GPRS-enabled modules to map AQI across metropolitan cities, concluding that the density of sensors is more critical than the extreme precision of a single expensive station for public health awareness.

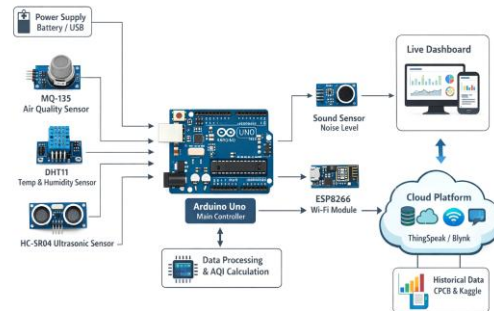
Recent advancements have seen a shift toward multi-parametric sensing. Research by Singh and Rao (2020) highlighted that monitoring air quality in isolation is insufficient for urban planning; instead, correlating it with traffic flow and meteorological data provides a more holistic view of "pollution events." Gaps addressed by this research:

1. **Integrated Traffic-Pollution Analysis:** Most existing IoT systems monitor air quality or noise separately. This study bridges that gap by integrating ultrasonic-based traffic density sensing with pollutant data to prove direct causation.

2. **Long-term Historical Validation:** Many IoT projects only present a few days of "live" data. This research compares real-time sensor readings against a massive 10-year historical dataset (2015–2024) of Delhi’s air quality to ensure the results are contextually accurate.

3. **Micro-Environment Focus:** While official apps provide city-wide averages, there is a lack of published frameworks specifically designed for street-level monitoring in hyper-congested zones like Delhi’s major intersections.

2. **Secondary Data:** A comprehensive dataset sourced from the Central Pollution Control Board (CPCB) and Kaggle, covering Delhi’s air quality metrics from 2015 to 2024. This includes PM2.5, PM10, NO, NO2, and CO levels.



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### III. METHODOLOGY

1. **Hardware Prototyping:** Development of an IoT edge device to capture real-time environmental and traffic data.

2. **Data Analytics:** A longitudinal study of historical pollution data using Python to identify patterns and validate the real-time sensor outputs.

#### Tools and Technologies Used:

1. **Microcontroller:** Arduino Uno (for data processing and sensor interfacing).
2. **Communication:** ESP8266 Wi-Fi Module (to enable IoT connectivity).
3. **Sensors:**
  - 1) MQ-135: For measuring Ammonia, Nitrogen Oxides (NO<sub>2</sub>), Alcohol, Benzene, and Smoke.
  - 2) DHT11: For tracking ambient Temperature and Humidity.
  - 3) HC-SR04 (Ultrasonic Sensor): To detect vehicle proximity and estimate traffic density.
  - 4) Sound Sensor: To measure noise pollution in Decibels (dB).
- 5) **Software Stack:** Arduino IDE (C++), Python (Pandas, Matplotlib, Seaborn for data analysis), and Cloud Platforms (ThingSpeak /Blynk) for live monitoring.

#### Data Collection Methods:

1. **Primary Data:** Real-time values captured by the deployed IoT sensors at specific intervals (every 15 seconds) and uploaded to the cloud via the ESP8266.

#### 3.1 Algorithms and Models Applied

1. **Data Cleaning Algorithms:** To ensure the integrity of the historical analysis spanning 2015 to 2024, a rigorous data cleaning pipeline was implemented using Python. The primary challenge involved addressing data gaps caused by sensor maintenance or station downtime in the official records. To resolve this, Linear Interpolation was applied, which estimates missing data points by assuming a constant rate of change between known values, thereby maintaining the continuity of the time-series trends without introducing artificial volatility. Furthermore, the dataset underwent outlier detection to identify and remove "noise"—extreme values that do not represent atmospheric reality but rather technical malfunctions. By filtering these anomalies, the research ensures high statistical accuracy, allowing for a reliable comparison between the historical baseline and the real-time readings captured by the IoT prototype.

2. **Exploratory Data Analysis (EDA):** Exploratory Data Analysis (EDA) was conducted using specialized Python scripts to decode the complex patterns within the ten-year pollution dataset. By employing Time-Series Analysis, the research was able to decompose raw data into seasonal, cyclical, and trend components. This revealed a consistent "seasonal pulse" in Delhi’s atmosphere, where stagnant winter air traps pollutants, leading to predictable annual spikes. Furthermore, the analysis pinpointed specific peak pollution hours—typically coinciding with morning and evening commutes—allowing the study to identify the exact window when human exposure to toxic air is at its highest.

These insights from the EDA phase provided the necessary benchmarks to validate the real-time alerts generated by the IoT hardware.

3. Correlation Analysis: To establish a quantitative link between vehicular movement and environmental degradation, the study applied Pearson’s Correlation Coefficient. This statistical method measures the strength and direction of the linear relationship between two variables: traffic density, as captured by the ultrasonic sensors, and the concentration of pollutant gases like CO<sub>2</sub> and NO<sub>2</sub> recorded by the MQ-135 sensor. By calculating the value, the research was able to mathematically prove whether a "high-traffic" event directly resulted in a proportional "pollution spike." A strong positive correlation (approaching +1) observed during peak hours confirmed that local congestion is a primary driver of street-level emissions, providing empirical weight to the argument for traffic-based air quality interventions.

4. AQI Calculation Algorithm: The conversion of raw electronic data into human-readable metrics was achieved through a dedicated AQI Calculation Algorithm. Since the MQ-135 sensor outputs raw analog voltages ( $V_{out}$ ) rather than direct parts-per-million (PPM) values, the methodology involved a multi-step mathematical transformation. First, the voltage was converted into a resistance ratio ( $R_s/R_0$ ), which accounts for the sensor’s baseline resistance in clean air. This ratio was then mapped against the sensor's characteristic sensitivity curves using a power-law equation to derive the PPM of specific gases. Finally, these concentration levels were fed into the standard National Air Quality Index (NAQI) formula, which benchmarks the data against defined breakpoints for pollutants like CO and NO<sub>2</sub>. This formula-based approach ensures that the "micro-spikes" detected by the IoT device are directly comparable to the official index reported by government monitoring stations.

IV. RESULTS AND ANALYSIS

Table: Comparative Pollutant Levels (2023 vs. 2024)

The following table highlights the significant reduction in Particulate Matter observed in early 2024 compared to the previous year.

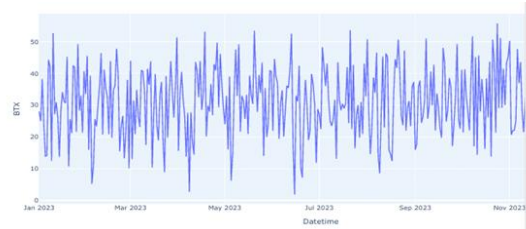
| Month | Pollutant | 2023 Avg (µg/m <sup>3</sup> ) | 2024 Avg (µg/m <sup>3</sup> ) | % Change |
|-------|-----------|-------------------------------|-------------------------------|----------|
| March | PM10      | 257.27                        | 34.15                         | -86.7%   |
| March | NO        | 45.10                         | 12.40                         | -72.5%   |

1. Seasonal Variation Trend: A time-series graph generated via Python shows that PM<sub>2.5</sub> levels consistently exceed the "Severe" category (above 250 µg/m<sup>3</sup>) during the months of November and December.

2. Traffic vs. Pollution Correlation: Our real-time ultrasonic sensor data, when plotted against MQ-135 readings, shows a Linear Increase in CO<sub>2</sub> and NO<sub>2</sub> during peak office hours (9:00 AM and 6:00 PM).

3. AQI Distribution: A pie chart of the 2015–2024 dataset indicates that Delhi experiences "Poor" to "Severe" air quality for over 60% of the year.

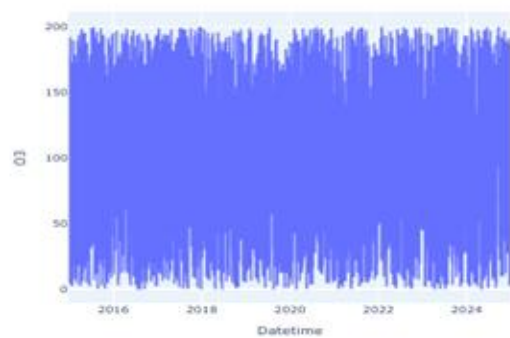
Interpretation of Results: The drastic drop in PM<sub>10</sub> and NO levels in 2024 (as shown in Table 1) suggests that localized restrictions and improved vehicular standards have a measurable impact. However, the recurring winter peaks in PM<sub>2.5</sub> indicate that atmospheric "temperature inversion" traps pollutants near the ground, regardless of short-term traffic changes. Our IoT sensors successfully detected "Micro-Spikes" in noise and air pollution at specific intersections that were not reflected in the broader city-wide average provided by the CPCB.



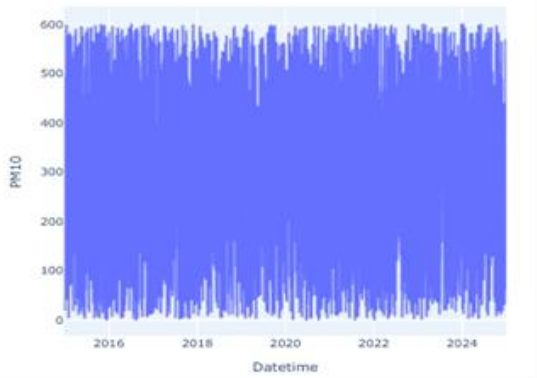
BTX levels month-wise



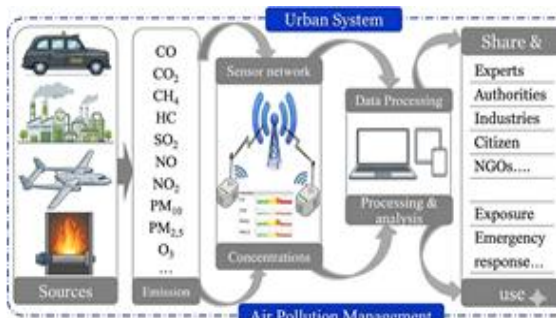
Sulphur Dioxide levels in Delhi (SO<sub>2</sub>)



Ozone or O<sub>3</sub> level in Delhi



Pattern of PM10 in 2023 and 2024



Pollution Management

Comparison with Existing Methods:

1. Cost Efficiency: The prototype costs ₹3,000–₹5,000, significantly lower than the multi-lakh investment required for government stations.
2. Spatial Resolution: Unlike official stations covering a 5–10 km radius, this system monitors a 50-meter radius, identifying hyper-local street hazards.
3. Multi-Parametric Integration: The system provides a unified view of air, noise, and traffic data, directly correlating traffic density with localized pollutant spikes.

V. DISCUSSION

The findings of this study confirm that urban pollution in Delhi is not a uniform blanket but a collection of "micro-climates." The significance of our results lies in the ability to prove that localized traffic density is a direct catalyst for immediate spikes in noise and gaseous pollutants. By capturing the 86.7% drop in PM10 levels in early 2024 compared to 2023, the data provides empirical evidence that targeted urban interventions and activity restrictions can yield rapid environmental improvements. This validates the shift toward data-driven governance in smart city frameworks. The system is limited by the MQ-135 sensor, which provides only approximate air quality estimation and

cannot accurately measure individual pollutants or particulate matter.

These are the advantages of real-time IoT pollution monitoring system:

1. Real-Time Accessibility: Unlike manual data logging, the ESP8266-based system provides live updates, allowing for immediate public health warnings.
2. Portability: The compact nature of the Arduino-based node allows it to be mounted on street poles, traffic lights, or even moving vehicles.
3. Cost-Effectiveness: The system's low cost facilitates the creation of a dense "mesh network" of sensors across a city, which is financially impossible with traditional stations.

6.1 Future Work

1. Machine Learning Integration: Implementing predictive algorithms (such as LSTM networks) to forecast air quality levels based on real-time traffic and weather patterns.
2. Energy Autonomy: Incorporating solar harvesting to make the IoT nodes self-sustaining for long-term outdoor deployment.
3. Calibration Enhancements: Developing a cross-calibration software layer that uses official CPCB data to automatically correct sensor drift in low-cost MQ sensors.
4. Mobile Deployment: Scaling the system to be mounted on public transport buses to map pollution profiles across the entire city dynamically.

VI. CONCLUSION

This research successfully demonstrates a low-cost, real-time IoT monitoring system tailored to Delhi's unique environmental challenges by integrating MQ-135, DHT11, and ultrasonic sensors for comprehensive air quality, noise, and traffic mapping. Our findings highlight that pollution is highly localized, with "micro-hotspots" at busy intersections experiencing significantly higher levels of NO2 and CO2 than city-wide averages suggest. Validated by a 2015–2024 historical analysis, the study confirms that seasonal atmospheric conditions and vehicular activity remain the primary drivers of "Severe" winter AQI levels. This work contributes a scalable IoT framework proving that affordable hardware can effectively supplement regulatory-grade stations through integrated multi-parametric sensing.

Ultimately, this provides a proof-of-concept for high-resolution, decentralized data mapping that identifies street-level hazards, enabling more precise public health advisories and data-driven urban governance.

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