# Drive-by Air Pollution Sensing Systems: Challenges and Future Directions

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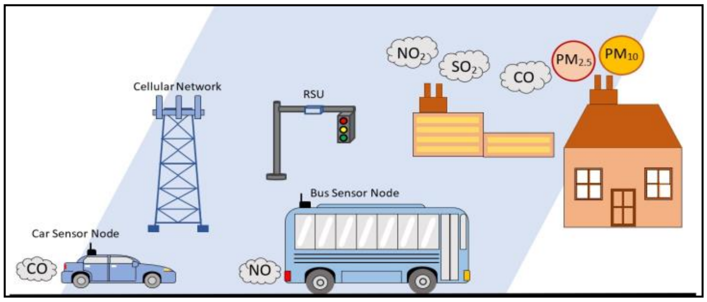


**Abstract: Air pollution has become a significant health, environmental and economic problem worldwide. The conventional approach of deploying fixed high-end air quality monitoring stations provides accurate measurements but can be expensive to deploy and maintain. As a result, the stations are typically deployed in a few strategic locations with various spatial interpolation or prediction models to estimate the air quality values from unsampled points. Recently, drive-by air quality sensing has emerged as a popular approach due to its dynamic nature, high spatial coverage, and low operational costs while providing high-resolution data. At the same time, drive-by sensing has introduced a range of novel research challenges in terms of spatial and temporal coverage, mobile sensor calibration, and deployment strategies. This paper provides a systematic review and analysis of the recent work in this area, focussing on vehicular platforms, deployment strategies, primary challenges, and promising research directions. We have also devised a taxonomy for drive-by air pollution sensing systems after investigating the various challenges and components.**

**Index Terms—Drive-by sensing, Internet of things (IoT), spatiotemporal coverage, low-cost sensor (LCS).**

## I. Introduction

Air pollution has emerged as a global concern due to the rapid increase in urbanization and industrialization, causing severe health issues such as respiratory disorders and cardiovascular diseases and can increase the mortality risk [1] [2][3]. Air pollution sources, such as emissions from burning fossil fuels for transportation, power generation, and heating, are dispersed over a large area. The conventional approach of deploying fixed high-end air quality monitoring stations is expensive due to high equipment and maintenance costs; therefore, they are typically deployed in fewer numbers [4] [5]. Spatial interpolation models are then used to estimate the air quality values from unsampled points [5].

Recently, drive-by sensing has emerged as a popular approach for air quality monitoring due to its dynamic nature, extensive spatial coverage, and reduced operational costs while providing high-resolution data [6][7]. Different vehicles equipped with low-cost sensors have been proposed as mobile platforms for air quality monitoring. Messier et al. [8], used data from sensor-equipped Google Street View cars for mapping air quality in the Greater London area. Biondi, et al. [9], used sensors deployed on buses to acquire air quality data providing a high-resolution air quality map. Gómez-Suárez et al. [10], mounted a low-cost device with optical and electrochemical sensors on bicycles to monitor air quality in urban environments.

At the same time, drive-by sensing has introduced a range of novel research challenges in terms of sensor deployment [11][12], spatiotemporal coverage [13], data collection strategies [14][15][16], calibration models [10] [17], and data analysis [18][19]. For example, the predictable nature of bus routes and schedules presents new opportunities that could be exploited for optimizing spatial coverage. Hence, strategies have been proposed to maximize spatial coverage with a limited number of sensors [20]. Similarly, calibration models can be adapted to the mobility and specifics of public transport due to certain public transit types having predefined and overlapping routes.

Due to various advantages of deploying a drive-by air pollution monitoring system, developing a sustainable approach that is affordable and reliable system is an important task. Communication and sensing technologies, and drive-by sensing platform requirements must be analyzed in-depth to acquire sensible air pollution data. We offer an analysis of the air quality monitoring technologies and drive-by sensing platforms, a summary of the selected articles, an investigation of the primary challenges, an outline of promising future research directions, improve the deployment strategy, and devised a taxonomy for drive-by air pollution sensing systems after investigating the various challenges and components.

The rest of the paper is structured as follows; **Section II** describes the challenges facing wireless sensor accuracy and calibration, sensor communication, and power consumption in a dynamic sensing environment. We also present various air pollutant types and provide their description in Table form.

**Section III** discusses the benefits of employing vehicular platforms as sensor nodes and their implementation protocols. Furthermore, describes their limitations and review prior related work. We will also describe deployment strategies literature to overcome the challenges in **Section II** and **Section III**. Finally, **Section IV**, summarize the work giving our final thoughts.

## II. AIR POLLUTANTS, STANDARDS, AND SENSORS

### A. Air Pollutants

Common air pollutants identified by researchers, namely oxides of sulphur (SOx), oxides of nitrogen (NOx), carbon monoxide (CO), carbon dioxide ($CO_2$), ozone ($O_3$), fine particulate matter (e.g., $PM_{10}$ and $PM_{2.5}$) and VOCs [21]. Artificial sources include emissions from transportation, industrial processes (e.g., factories, power generation, etc.), and land use, such as agriculture and urban development [22]. Transportation-related air pollutants include oxides of nitrogen (NOx), carbon monoxide (CO), hydrocarbons, and fine particulate matter, which are produced by combustion and incomplete combustion of fuel in traffic engines [23].

TABLE I
ILLUSTRATION OF A VARIETY OF AIR POLLUTANTS

| Air Pollutants | Sources | Description | Health Related Issues |
|---|---|---|---|
| Particulate Matter (PM) [24] | Chemical reactions, building sites, combustion of fuel, fires, etc | PM2.5= 2.5μm diameter, PM10= 10μm diameter | Cardiovascular and respiratory diseases |
| Sulphur dioxide ($SO_2$) [25] [26] | Combustion of material or fuel that contains sulphur | Colorless has an odor (irritates) | Respiratory related issues |
| Nitrogen dioxide ($NO_2$) | Combustion, road traffic, and power generation [25] | Colorless, acidic, highly corrosive, and has an odor [26] | Respiratory infection, asthma, and chronic lung disease [26] |
| Ozone ($O_3$) [26] | Combustion, road traffic, bushfires, industrial power generation | Colorless, highly reactive, and has an odor | Causes cardiac and respiratory-related issues |
| Carbon monoxide (CO) | Product of incomplete combustion of fuel, cars, engines, heating stoves, etc. [27] | Colorless, odorless, and non-irritating gas [26] | Causes hypoxia (reduces oxygen in the body) [26] |
| Volatile Organic Compounds (VOCs) | Traffic roadside, factories, indoor emission sources, chemical processes, fuel burning, etc. [28] | Different gasses examples 1,3-butadiene, benzene, styrene, etc. [28] | Respiratory, cardio, and nervous-related issues, and organ damage. [29] |

**Table description:** The Table shows a comparison of various common air pollutants.

### B. Air Pollutants Concentration Standards

The air quality index (AQI) is a numerical index developed to indicate current air pollution levels, specify the impact on public health, and provide cautionary statements [30]. Governments and agencies have set limits on air pollutants to identify their risk factor. To illustrate these differences, we have provided air pollutant concentration limits for three agencies (see Table 2). The air pollution data is reported as averaging time in terms of hourly, annual, or peak season data, as shown in Table 2.

TABLE II
DIFFERENT STANDARDS OF VARIOUS AIR POLLUTANTS

| Air Pollutants | Averaging period | Agencies | | |
|---|---|---|---|---|
| | | United States Environmental Protection Agency (EPA) [21] | European Commission (EC) [31] | World Health Organization (WHO) [32] |
| PM2.5 | 24 hours | 35 μg/m$^3$ | - | 15 μg/m$^3$ |
| | Annual | 12 μg/m$^3$ | 25 μg/m$^3$ | 5 μg/m$^3$ |
| PM10 | 24 hours | 150 μg/m$^3$ | 50 μg/m$^3$ | 45 μg/m$^3$ |
| | Annually | - | 40 μg/m$^3$ | 15 μg/m$^3$ |
| Carbon Monoxide (CO) | 1 hour | 35ppm | - | - |
| | 8 hours | 9ppm | 10 mg/m$^3$ | - |
| | 24 hours | - | - | 4 mg/m$^3$ |
| Ozone (O3) | 8 hours | 0.070 ppm | 120 μg/m$^3$ | 100 μg/m$^3$ |
| | Peak Season | - | - | 60 μg/m3 |
| Nitrogen dioxide (NO2) | 1 hour | 100 ppb | 200 μg/m$^3$ | - |
| | 24 hours | - | - | 25 μg/m$^3$ |
| | Annually | 53 ppb | 40 μg/m$^3$ | 10 μg/m$^3$ |
| Sulphur dioxide ($SO_2$) | 1 hour | - | 350 μg/m$^3$ | - |
| | 24 hours | - | 125 μg/m$^3$ | 40 μg/m$^3$ |
| | 3 months | 0.15 μg/m$^3$ | - | - |

**Table 3:** Ppm unit = parts per million by volume, unit ppb = parts per billion by volume, and unit μg/m$^3$ = micrograms per cubic meter of air.

### C. Air Quality Index (AQI)

AQI is for public awareness and recommendations. Different agencies have AQI values and levels, and to illustrate these differences, see Table 3. For calculating the AQI levels, air pollutants concentration data is used; for example, US EPA introduced a linear interpolation equation for calculating AQI levels [33].

TABLE III
AIR QUALITY INDEXES OF DEFRA AND US EPA, COMPARISON

| Air Pollution Banding (DEFRA) [34] | Values | Levels of Concentration (US EPA) [33] | Values of Index |
|---|---|---|---|
| Low | 1-3 | Good | 0-50 |
| Moderate | 4-6 | Moderate | 51-100 |
| High | 7-9 | Unhealthy for sensitive groups | 101-150 |
| Very High | 10 | Unhealthy | 151-200 |
| | | Very Unhealthy | 201-300 |
| | | Hazardous | 301-higher |

**Table description:** Two air quality indices are compared to illustrate the differences in standards. Each range represents different air quality levels, and based on them, air quality descriptions and health risk advisories are provided.

### D. Low-Cost Sensor Technologies

Different low-cost sensors widely used for detecting air pollutants are electrochemical gas sensors, semiconductor or metal oxide gas sensors, non-dispersive infrared (NDIR), and PM sensors. These sensors are affordable, have adequate accuracy and light enough to be portable, and are sensitive to a specific type of air pollutant.

#### 1. Electrochemical Sensors

Electrochemical gas sensors contain electrodes immersed in an electrolyte medium (gel form) which are isolated using a membrane [35], and the oxidation between the electrodes causes current to flow, creating a potential difference which is then measured [36]. Electrochemical gas sensors have advantages are simple and easy to manufacture fast response time, are less affected by environmental factors such as temperature and pressure, and require less power to operate [37]. Electrochemical sensor measurement accuracy can be reduced due to cross-sensitivity from other gases, as the electrical changes when sensing target air pollutant can be similar to other gases; this problem can be avoided by using a supplementary electrode [38].

**2. Semiconductor or metal oxide sensors**

Semiconductor or metal oxide gas sensors contain a surface layer of one or more metal oxides, a sensing chip, and a heater for heating the membrane; when the metal oxide reacts with the target gas, the conductivity increases, which is then measured by the sensing chip [39]. Advantages include fast-response time, long-term stability and lifetime, and adequate sensitivity [40]. Semiconductor gas sensors suffer from interference from other gas compositions in the surrounding atmosphere, temperature fluctuation, and humidity change [41]. Sensor conductivity response is non-linear concerning the target air pollutant [42]. The selectivity problem can be solved using various strategies. For example, physical and chemical gas filters delay or prevent the interfering gas from reaching the sensor surface [43].

**3. Non-dispersive infrared (NDIR) sensors**

Non-dispersive infrared (NDIR) emits IR radiation, and based on the absorption characteristics; the target gas can be identified [44]. NDIR sensor components include an IR source, a sample chamber or gas cell, an optical or light filter, and an IR detector [44]. NDIR sensors measurements are more accurate due to their robustness, good selectivity, and long lifetime [45] [46]. However, readings accuracy due to their high detection limit, spectral interference, and interference caused by humidity and other gas require addressing [47]. Interference from humidity and other target gasses can be reduced using filters, and sensor accuracy can be improved by improving gas chambers, IR detectors, IR emitter sources, and optical filters [47].

**4. Optical particulate-matter (PM) sensors**

Optical PM sensors use the light scattering method; the laser light is scattered by the particles in the sampled air, which is collected at a certain degree by a photodetector, which allows measurement of the particle's size and concentration [48]. The sensor also includes a set of focusing lenses, and a fan allows airflow with particles through the chamber [49]. Optical PM sensor is popular due to their low power consumption, low cost, and quick response [48]. However, the sensor's accuracy can be affected by non-target particles (creating noise), interference from ambient sources, reliability of the parts used, and factors affecting airflow [50].

## E. Data Transmission Technologies

An efficient data transmission method is essential, especially when the application or system requires real-time monitoring. Several communications protocols are used to transfer air quality data for analysis or to communicate between sensors (e.g., during mobile sensor calibration). Typical sensory data communication technologies include Bluetooth, Wi-Fi, LPWAN, and cellular networks (e.g., 4G, LTE, etc.). The continuous movement of mobile sensor nodes makes the network topography dynamic and can cause breakage in their communication links [51]. Good connectivity with high data transfer capacity is essential to prevent high data latency which creates long delays in data transfer.

A cellular network high capacity allows more tasks to be assigned, provides a larger coverage area, and reduces interference from other signals. This makes it a sufficient mode for transferring sensory data. A mobile wireless sensor node entering an area with highly dense WLAN networks can create an overlapping basic service set (OBSS) problem [52]. OBSS creates interference issues such as the deadlock effect and link suppression in a highly dense WLAN, reducing the overall communication performance [53]. Opportunistic routing can increase sensor network efficiency, throughput, reliability increase the networks lifespan [54].

Work described in [16], where a proposal for offloading protocol aiming to reduce 4G costs while maintaining data latency by investigating an opportunistic communication model in which air quality data is transferred via a 4G network or Wi-Fi to adjacent devices deployed along the road. Alternatively, deployment of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) architecture can improve drive-by sensor networks. Infrastructure in the V2I can be a type of road-side unit (RSU) which can be placed in convenient locations along the mobile sensor node route [55]. These platforms can be used as a wireless multi-hop network in which sensory data can be transferred from vehicle-to-vehicle (V2V) to vehicle-to-infrastructure (V2I) or vehicle-to-network (V2N) [56]. (See figure 1). This can reduce cost and power consumption while providing low data latency.

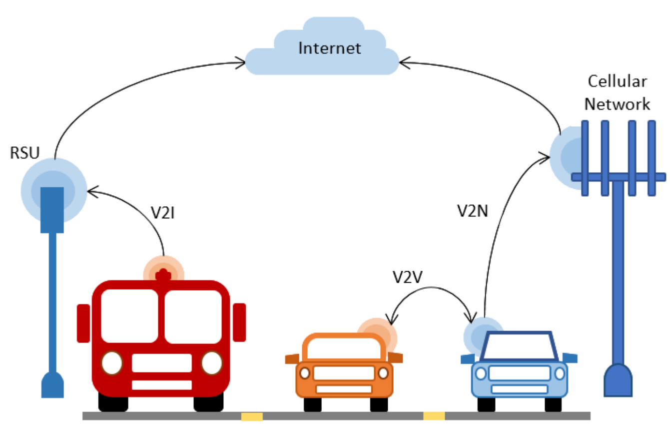


**Fig.1.** Illustrates Vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I) communication and vehicle-to-network (V2N).

## F. Multi-hop Calibration of Mobile Sensors

Errors from internal sources, such as temporal drift, and external sources, such as changes in environmental conditions (e.g., temperature and humidity), present a major challenge for low-cost sensors [57]. Therefore, calibration is the process of identifying and correcting systematic bias in sensor readings.

[58]. The dynamic nature of drive-by air quality sensing makes it difficult to calibrate in laboratories as it will suspend operations. Multi-hop calibration has become a promising approach to calibrate deployed mobile air quality sensors. The approach utilizes rendezvous to calibrate recurring mobile sensors with recently calibrated mobile sensors [59].

Rendezvous situation requires two or more sensors to in the same spatial and temporal vicinity, measuring the same phenomena [60]. Multi-hop calibration allows frequent calibration in a large-scale mobile sensor deployment [59]. This approach requires fewer reference-grade sensors for calibrating un-calibrated mobile sensors, reducing deployment costs. Preventing sensor error accumulation over multiple hops in large-scale mobile sensor networks is a challenge. High-traffic conditions and bias behaviour of drivers could prevent or delay rendezvous between calibrated and un-calibrated mobile sensor resulting in missing a hop causing severe error accumulation.

At point of rendezvous adequate communication technology providing high speed and uninterrupted data transfer between mobile sensors is essential. The driving factors behind selecting appropriate communication protocol between mobile sensors for calibration could be cost, communication range, and power consumption. Although Bluetooth are simpler, consume less power and are less expensive. however, they have short-range and Wi-Fi gateway and cellular network provide a large coverage area and can be used for remote operations [61]. Figure 2 illustrates the multi-hope calibration of mobile sensors, where a few mobile sensors are calibrated by static reference-grade sensors after meeting a rendezvous point. The re-calibrated mobile sensors calibrate the remaining mobile sensors.

## III. Drive-by sensing platform

### A. Public Transit

Public transportation or transit is a mass transport system within the urban area and is used by the public, typically following scheduled routes and timings. Some public transport modes are available in a significant number covering the large urban area. We will describe three types of public transit modes city buses, taxis, and trains or trams.

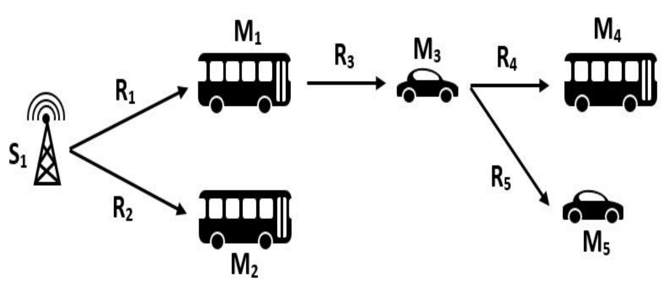


**Fig.2**. Illustrates the multi-hop calibration of mobile sensors ($M_{1-5}$) by static reference grade sensors ($S_1$) after rendezvous ($R_{1-5}$).

#### 1. City Bus

As mobile sensing vehicles, buses have received considerable attention for their availability in significant numbers, high-spatial coverage, and reliable operations [62]. Bus transport has predefined routes and schedules that are typically available publicly, which makes their trajectory predictable [63]. City buses repeat the same route multiple times throughout the day, providing high temporal resolution. Bus routes have overlapping routes, which can result in redundant data collection. The overlapping nature of bus routes can be used for cross-checking individual bus readings and mutual sensor calibration. Bus transit's pre-defined routes and schedules make their mobility less flexible, and sensing campaigns can only be done along fixed routes.

Equipping an entire fleet of buses with sensors increases deployment and operations costs [20]. Significant work was dedicated to maximizing spatial or spatiotemporal coverage with a limited number of vehicles for drive-by-sensing [64]. Ali, et al. [20], analyzed the real bus route dataset and proposed an approach that selects an optimal subset of bus routes to increase spatial coverage. In works [63] [65], where optimal bus set numbers were selected by analyzing the historical trajectories of buses to achieve maximum spatial-temporal coverage. Using the bus as a sensing platform introduces a range of other interesting problems, such as multi-hop calibration of bus-mounted sensors [66], and optimal data transmission.

#### 2. Trains and trams

Trains and trams also have predefined routes and schedule with predictable trajectories and repeat their routes throughout the day, providing high temporal resolution. Their operations are reliable, and they have separate infrastructure; therefore, no urban traffic-related delays provide continuous sampling. Trains and trams also follow fixed route crossing areas along the route, which creates a spatial bias. For example, trains New York City subway and London Tube are subterranean. They will only provide air quality data for underground areas (tunnels and stations) if deployed with air quality sensors.

The OpenSense project deployed in Switzerland placed sensors on public transportation, trams in Zurich, and buses in Lausanne for monitoring air quality in real-time [67]. Deploying supplementary vehicles and sensors equipped with trams and trains can solve the spatial bias issue.

#### 3. Taxi

The taxi fleet covers most urban areas, and their routes are more flexible. In sufficient numbers, they can cover most urban areas with high-resolution sensing in an ideal situation. Taxis do create a spatial bias as they tend to concentrate around areas with high people activity (e.g., shopping areas, airports, etc.), and their behavior is partially irregular [68]. At the same time, taxi mobility also depends on the road-traffic situations, taxi drivers' routing decisions who normally opt for quicker routes, and the client's routing requests making taxi trajectories random and unpredictable [69]. This random mobility leaves some parts of an urban region un-sampled or less-sampled, creating sparse data collection and data coverage time-variation problems [70].

Taxis' random mobility issue is a considerable challenge in relation to spatial and temporal coverage. Xu et al. [70], designed an adaptive hybrid model-enabled sensing system (HMSS) to achieve optimal sensing coverage quality and fine-grained air pollution estimation to address the challenge of sparse and time-varying data coverage. Around 53.5 million data samples were collected in 14 days using 47 portable air pollution monitoring sensor devices for system performance assessment. They were deployed in two cities to conduct both controlled and uncontrolled tests. An alternative approach to overcome the taxi's mobility issues is to equip sensors onboard taxis and supplementary vehicles.

## B. Municipal Transport

Apart from mass transit for public use, there are other transportation services in urban areas. These service transports are typically used for maintenance purposes, such as dump trucks for solid waste transportation, vans for deliveries, ambulance patient transport service, etc. Spatial coverage depends mostly on the type of public service vehicle; police patrol vehicles provide good coverage, while emergency vehicles such as fire trucks and ambulances do not, as they are only operational in emergency situations. Delivery vans cover most of the commercial and residential areas and their routes. Public service vehicles have biased behavior, and their routes are not predefined and depend on the driver's decision. Their operations are not continuous, as when their services are completed, their operations are also suspended. Their low number provides low spatial coverage and leaves large gaps in sensing data.

Work described in [71], proposed a context-aware locally adapted deep forest (CLADF) model where $NO_2$ measurement collected from low-cost sensors equipped on 17 postal vans in Antwerp, Belgium, was taken for conducting extensive validation experiments. Their sampling routes were relatively random, and the sampling campaign is generally conducted from 6:00 to 23:00 on weekdays and Saturdays. During the daytime, the sampling intervals were 10 seconds, and at night-time, 10 minutes when the vans were parked.

## C. Private Transport

Private transportation, as opposed to public transit, refers to the type of transportation for personal or individual use that is not available for public use. There are several private vehicles or conveyances for air quality sensor placement.

### 1. Dedicated Vehicles

Private transportation is more flexible as the routes are not predefined or fixed, and dedicated private vehicles can be modified to suit sensing requirements. For example, google street view cars which are dedicated and modified vehicles also used for air pollution monitoring, in works like [8] [72] [73]. Other vehicle types can also be used, such as work in [74], deployed low-cost sensor device on the laboratory van through the cable hole on the vehicle's roof for monitoring urban air pollutants. With dedicated vehicles, air quality sensing operations can have fewer time constraints, extensive spatial coverage, and diverse manageable movement.

Deploying a dedicated vehicular sensing platform increases deployment and maintenance costs. Dedicated vehicles also require a dedicated operator (driver), e.g., cars, vans, and bicycles. Deploying dedicated air quality monitoring vehicles in a significant number is a challenge due to their high deployment costs. Deploying sensors on less expensive vehicles, such as bicycles, UAVs, etc., can lower the overall costs.

### 2. Personal Vehicles

Personal vehicles, including cars, SUVs, bicycles, etc., have flexible movement, provide adequate spatial and temporal resolution, and have low-cost deployments and operations. Personal vehicles are used and owned by private individuals, and routes and schedules are dependent on the owner's behavior. This behavior creates a spatial bias and can create random vehicle mobility. Deploying personal vehicles for air quality sensing creates several challenges, such as bias movements and adequate providing spatiotemporal coverage. Sensor-equipped personal vehicles in large numbers could provide high-spatiotemporal coverage.

Gómez-Suárez, et al. [10], researchers mounted the low-cost sensor on bicycles for monitoring air quality in urban environments. Wesseling, et al. [75], used measurements from 500 sensors mounted on bicycles in Utrecht, the Netherlands, to estimate the $PM_{2.5}$ levels that the cyclists are typically exposed to. The HazeWatch project described in [76], low-cost gas sensors equipped cars to collect air pollution concentrations (e.g., CO, $NO_2$, and $O_3$) data for analysis in Sydney.

### 3. Un-manned Ariel Vehicles (UAV)

Unmanned aerial vehicles (UAV) are flexible, low-cost vehicle, pathway is managed by an on ground controller. Vehicles on ground with flexible routing and schedule movement is still limited to the road paths and tracks, however UAVs have not such limitations. They have no road traffic related issues and can travel to their destination directly or taking paths that are required providing data from hotspots. UAVs are better suited for targets air quality monitoring such as work described in [77], where air pollutants data was collected using UAVs from landfill sites in real-time. UAVs can also be used for high altitude air quality sensing and areas or locations that are hazardous or dangerous to human well-being.

Measurements from sensors deployed on UAV or drone can be affected by the wind generated from the rotors [78]. This problem has been addressed in work [79], by analysing the structure of a UAV. Another problem is the communication range of the UAV and the controller. Once out of range the controller will lose control. UAVs limited deployment and difficulties measuring ground level air quality levels create a challenging environment. In Figure 3, we illustrate a taxonomy that categorizes the main components of drive-by air pollution sensing systems.

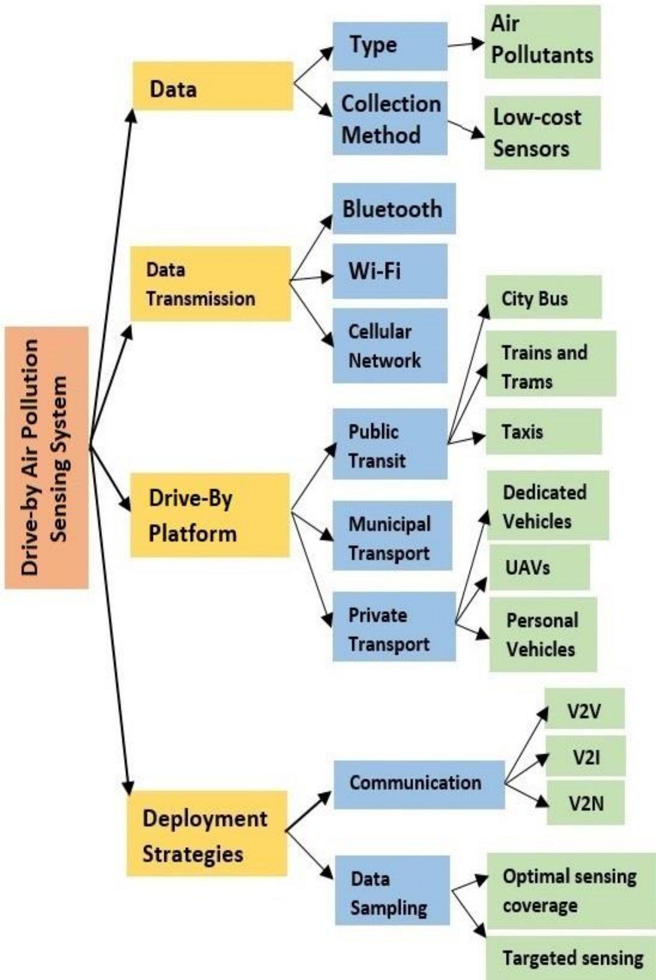


**Fig.3.** Taxonomy for deployment strategies for drive-by air pollution sensing systems.

## IV. CONCLUSION AND FUTURE WORK

Drive-by air pollution monitoring has gained significant attention over recent years. Due to mobility, a relatively small number of sensor devices can monitor air pollution over vast geographical urban areas. However, a number of challenges need to be resolved in terms of deployment strategies, calibration, communication, and other issues.

In this review paper, we analyzed various solutions to these problems. We first presented a summary of major air pollutants, sensor types to detect them, and relevant important air pollution standards. We then analyzed the relevant work on mobile air pollution monitoring categorized by major urban transport modalities, such as buses, taxis, and utility vehicles. We highlighted the benefits and limitations of each transport mode and the challenges and lessons learned in those projects. This is followed by a review of relevant work on calibration and data communication for drive-by air monitoring. Our review shows that there are currently various solutions at analytical, data analysis and practical deployment levels. Nevertheless, a number of open problems exist, in particular related to calibration of mobile low-cost sensors, data communication, and robustness of route planning and deployment strategies to traffic congestion. We hope that the review will help in future research toward more robust, accurate, and secure drive-by air pollution monitoring systems.

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