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Joint optimization of bus-based mobile sensing and reference sensor deployment for urban air quality monitoring

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Abstract Monitoring air quality is essential for a healthy living environment and can be achieved through various sensor types. While high-cost stationary reference sensors provide precise data, their limited deployment reduces overall coverage. Low-cost mobile sensors (LCSs) can complement stationary sensors, improving both spatial and temporal coverage. However, LCSs suffer from poor accuracy and require frequent calibration. This study presents mathematical optimization models to identify the optimal subset of buses to equip with LCSs and the optimal location of reference sensor stations. The objective is to maximize sensor network coverage while considering budget limitations and ensuring that all mobile sensors are calibrated frequently. The Rotterdam case study demonstrates the effectiveness of the proposed approach in achieving extensive spatiotemporal coverage of residential and industrial areas. The results demonstrate that the joint optimization of mobile and reference sensors enhances both calibration and coverage efficiency.

***Index Terms*— Drive-by sensing, Air pollution, Sensor network design, optimization, calibration**

I. Introduction

Air pollution has become a significant global challenge in many cities, with pollutants such as particular matter ($PM_{2.5}$ and PM_{10}) and ozone (O_3) impacting public health, environment, and economic stability. Comprehensive and accurate monitoring is vital for assessing current conditions and supporting informed decisions to mitigate its harmful impacts [1].

Air quality can be monitored using various instruments, ranging from expensive reference sensor stations that provide highly accurate data to low-cost sensors that offer less precise measurements [2]. However, because of the high costs of equipment and maintenance, sensor stations are typically installed in small numbers. Low-cost mobile sensors can be used as complementary tools to enhance both spatial and temporal coverage. Various types of vehicles equipped with low-cost sensors (LCSs) have been proposed as mobile platforms for air quality monitoring [3]. Among mobile platforms options, Buses are a popular choice for air quality monitoring because they provide wide spatiotemporal coverage and operate reliably. [4]. A key challenge in mobile sensing is to decide which vehicles in a fleet should be equipped with sensors, while balancing objectives such as maximizing coverage and accuracy while minimizing cost [5].

It is key to mention that the importance of data collection can vary across different parts of a city, depending on the specific parameters being monitored. For air quality monitoring, areas with high population density or major emission sources, such as industrial zones, are typically more critical [6] In addition, locations such as hospitals and schools, where vulnerable groups such as young children, the elderly, and individuals with pre-existing health conditions are more likely to be present, are more sensitive to air pollution. Therefore, it is important to evaluate the relative importance of different regions and prioritize them when designing a sensor network [7].

Low-cost mobile sensors may suffer from poor accuracy and stability, requiring frequent calibration to maintain reliable performance. To allow calibration, vehicles equipped with sensors need to occasionally approach to a stationary sensor or another mobile sensor to compare their readings. These meeting points are known as checkpoints. In practice, mobile sensors (MSs) are often calibrated using a method called single-hop calibration. In this method, an MS is placed near a stationary reference sensor to align and correct its measurements [8]. While straightforward, this method can only calibrate sensors that pass close to a reference station. This often requires many reference sensors or a highly connected transportation network in which each

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mobile sensor, such as on a bus, regularly encounters reference stations along its routes. An alternative is multi-hop calibration, where mobile sensors calibrated each other through successive stages [9]. This approach reduces dependence on reference stations and lowers both deployment and operational costs; however, calibration errors increase as the number of hops grows. Since the efficiency of calibration methods depends on the location and number of both stationary and mobile sensors, a key challenge is determining the optimal placement of reference stations and the selection of sensing vehicles.

In this study, we address the challenges mentioned above by proposing a novel approach to designing air pollution sensor networks that integrates both mobile and stationary sensors while accounting for calibration and budget constraints. This study presents two mathematical optimization models for sensor network design based on different calibration methods. Our method is related to recent studies such as [10] and [11] , which also considered mobile and stationary reference sensors with calibration requirements. However, their approaches are mainly route-based, while our study formulates the problem as a bus-based selection problem, which is more practical because sensors are installed on individual vehicles rather than entire routes. We also use real vehicle trajectory and GPS data from the KV6 dataset, which allows sensing and calibration decisions to be based on actual bus movements rather than schedule-based route information. Furthermore, we formulate practical calibration constraints for both single-hop and two-hop calibration settings by considering spatial and temporal distance thresholds for calibration checkpoints between mobile sensors, as well as between mobile and stationary sensors. The models are applied to a case study in Rotterdam. The network is divided into grids, and the importance of each grid is determined by its population. The results show that even with a limited number of mobile sensors, extensive spatiotemporal coverage can still be provided, with higher coverage observed in densely populated grids. To demonstrate the flexibility of the models to different inputs, industrial zones are considered as points of interest, and the results show that the model is able to cover most of those areas as well. Furthermore, this study examines the impact of budget and checkpoint criteria on the performance of the sensor network.

The remainder of this paper is organized as follows. Relevant literature is reviewed in Section II. The elements of the air pollution sensor network design problem, the underlying assumptions, and the details of the mathematical models are presented in Section III. Section IV describes the datasets, case study, and data processing. Section V discusses the computational results. Section VI presents the sensitivity analysis. Finally, the findings are summarized in Section VII.

II. Literature

The relevant literature for this work is reviewed in two main sections. First, studies on drive-by sensing are examined, with particular focus on optimization methods proposed to address its associated challenges. Second, the literature on the calibration of low-cost mobile sensors is investigated. Finally, the most relevant studies are summarized in Table I. The details of these studies are discussed in the following sections.

A. *Drive-by Sensing*

Drive-by sensing, or vehicle-based mobile sensing, is an emerging technique in which vehicles are used to collect data across urban areas in an efficient and cost-effective manner. Advances in wireless communication and pervasive sensing technologies have supported its wider use, allowing extensive spatial and temporal coverage. This approach has a wide range of applications, particularly in urban sensing. As highlighted by [12], existing studies have applied drive-by sensing to areas such as infrastructure condition monitoring [13], air quality monitoring [14], noise monitoring [15], and traffic state monitoring [16].

Mobile sensing platforms are commonly classified into three main categories: fixed-route such as buses and trams [6]; random-route platforms such as taxis [17]; and controllable mobile platforms such as autonomous vehicles [18]. Among public transport options, buses have been widely studied as mobile sensing platforms because they are available in large numbers, provide extensive spatial and temporal coverage, and operate with high reliability [4]. [19] Investigated the contribution of individual buses to city sensing coverage. They developed a metric to quantify this contribution across multiple applications, including waste management, noise monitoring, and air quality monitoring. The results show that the contribution of each bus varies considerably depending on the application.

Another line of research in this field focuses on optimization models for selecting the optimal subset of bus lines or vehicles for different sensing tasks. A comprehensive review on sensing power optimization is provided by [20], which is recommended for further reading on related research. For example, [13] developed an approach for selecting an optimal set of routes that maximize geographical coverage. They formulated problem as a maximum coverage problem and solved it using a greedy heuristic, which was tested on a London bus dataset. [21] proposed an optimization model to enhance spatial and temporal coverage by leveraging bus routes. In another study, [22] treated the problem as vehicle selection rather than route selection. They considered the importance of geographical regions and designed a heuristic algorithm to allocate bus sensors for studying the urban heat island effect. [12] introduced a trip-based optimization framework for sensor deployment in urban bus systems, where spatial grids were used to define coverage. the target area was divided into weighted units to emphasize critical regions, and coverage was determined by grid intersections. To address the temporal dimension, the monitoring horizon was divided into intervals, and coverage was assessed by the presence of sensors within grids at specific times, with temporal weights

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applied to prioritize those times. [6] developed two optimization models for bus selection that incorporated spatio-temporal coverage as well as temporal gaps between successive observation at given locations. These models improve the efficiency of bus-based mobile sensing and strengthen air quality monitoring capabilities.

B. *Low-Cost Sensor Calibration*

Low-cost mobile sensors for air quality can be affected by internal factors like temporal drift and external factors such as changes in environmental conditions (e.g., temperature and humidity). These limitations pose significant challenges to accuracy and reliability, making calibration essential [8]. Calibration involves identifying and correcting systematic biases in sensor readings. Calibration can be performed in two main settings: laboratory calibration and field calibration. Vehicular-based air quality sensors are difficult in a laboratory setting, as this would disrupt regular operation; therefore, they are typically calibrated in the field. In a study by [23], three calibration algorithms with different recalibration periods were examined. Co-located sensor measurements were used to enhance calibration and improve the quality of pollution data. [24] addressed the problem of maximizing the air pollution monitoring. An algorithm was proposed to identify which routes should be selected to maximize the sensor network coverage, while also considering the requirement for periodic calibration. The effectiveness of the approach was assessed using data from Zurich tram network. [25] combined online multi-hop calibration with spatiotemporal route selection to improve data accuracy and coverage. A heuristic algorithm was developed for route selection, enabling comprehensive monitoring and reliable data collection through collaborative calibration. [10] focused on optimizing reference sensor location in multi-hop calibration to maximize the distinct sensing area. They proposed an area-based metric to evaluate coverage. Candidate sites for reference sensors were limited to bus stops. Their work proposed the use of an area-based metric for coverage computation, with reference station placement constrained to bus stops. Using a greedy heuristic, stations were selected, and coverage was defined as the combine unique sensing area of all bus routes connected to those stops. In another study, [11] studied k-hop calibration by selecting an optimal subset of bus routes that maximize coverage. For the chosen routes, the approach determines both the number and locations of reference sensor stations. A metric-based framework and a mixed-integer nonlinear programming (MILP) model were also introduced to capture spatial contributions through route area and temporal contributions through route trips.

While fixed or mobile air pollution sensor network optimization are widely investigated, considering both kind of sensors with calibration concept in one optimization framework has been rarely explored. In this study, we propose a novel approach that consider stationary reference sensors and mobile sensor and simultaneously addresses coverage and calibration under budget limit for air pollution sensor network. The model selects individual buses rather than entire routes and determines the location of stationary sensors using actual bus trajectories. Table I presents the most relevant studies focusing on the air pollution sensor network design optimization.

Table I Relevant studies in air pollution sensor network design

Authors	Type of sensor		Modeling approach	Calibration	Case study
	Reference	Mobile			
[24]		✓	Route-Based	✓	Zurich tram network
[13]		✓	Route-Based		London bus network
[25]		✓	Route-Based	✓	-
[22]		✓	Bus-Based		Athens bus network
[12]		✓	Trip_based		Chengdu bus network
[4]		✓	Active scheduling		Chengdu bus network
[6]		✓	Bus-Based	✓	Shenzhen bus network
[10]	✓	✓	Route-Based	✓	Manhattan bus network
[11]	✓	✓	Route-Based	✓	Toronto, Manchester bus network
This Study	✓	✓	Bus-Based	✓	Rotterdam bus network

III. METHODOLOGY

In this section, we formulate optimization models for the air pollution sensor network design problem, which involves two types of sensors: stationary reference sensors and mobile low-cost sensors installed on buses. The general structure of the proposed formulation builds on the classical maximum coverage problem, where the objective is to maximize covered demand under budget and deployment constraints. However, the calibration-related constraints are specifically designed in this study to represent the requirements of mobile air quality sensing. We formulate constraints for both single-hop and two-hop calibration settings, considering whether mobile sensors can be calibrated by stationary reference sensors or by other calibrated mobile sensors at valid calibration checkpoints.

In this system, buses are considered as mobile platforms for the sensing task. Two calibration structures are adopted in our models: single-hop and two-hop calibration. Single-hop calibration ensures that each mobile sensor is directly calibrated against a reference sensor. In the two-hop case, indirect calibration through another calibrated mobile sensor is allowed but limited to a maximum of two hops, since calibration error tends to increase with additional hops. Although accuracy is not explicitly modeled in our formulations, this restriction helps ensure that the data collected by the sensor network remain reliable. Fig. 1, illustrates overall structure of this sensor network system.

In the following sections, the fundamental assumptions and components of the models are explained in Section A. The model based on single-hop calibration is presented In Section B, and the model incorporating two-hop calibration is described in Section C.

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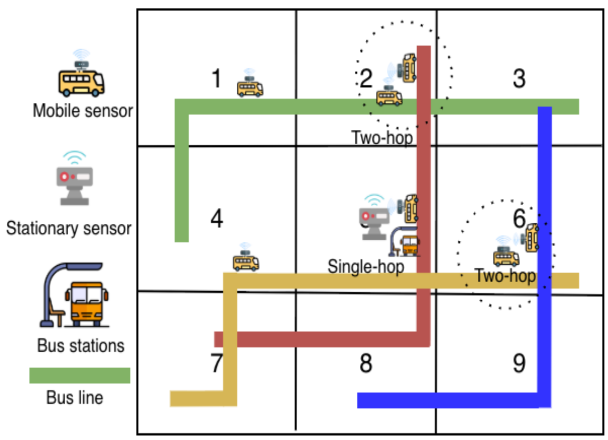

Fig. 1. Proposed structure for air pollution sensor network

A. Assumptions and Components

The main assumptions of the model are described in below:

- It is assumed that all mobile sensors are calibrated immediately upon reaching a checkpoint, either through a stationary sensor or another mobile sensor.
- Once the sensor is calibrated, we assume its readings along its entire route become accurate until the next calibration event.
- It is assumed that all buses follow fixed routes and fixed schedules.
- It is assumed that stationary sensors are only installed at bus stops.
- A spatial and temporal threshold is assumed to define a valid calibration checkpoint.
- Different spatiotemporal weights are assumed for each grid, depending on their importance.

List of notations used in modeling formulation.

Notation	Description
Sets	
A	The set of bus stops
B	The set of buses
H_{gt}	The set of buses passing grid g during timeslot t
P_{ia}	The set of stations a that bus i pass during its trips
V_{ij}	The set of checkpoints of bus i with bus j
Parameters	
ω_{gt}	Spatiotemporal weight of grid g at time t
M	Available budget
c_m	Installation cost of a mobile sensor
c_f	Installation cost of a stationary sensor
Decision Variables	
x_i	Equal to 1 if bus i is selected for sensing task; 0 otherwise
y_a	Equal to 1 if a stationary sensor is installed at station a; 0 otherwise
Auxiliary Variables	
s_{gt}	Equal to 1 if grid g at time t is covered by a mobile sensor; 0 otherwise
n_i	Equal to 1 if bus i is calibrated by a stationary sensor; 0 otherwise
p_i	Equal to 1 if bus i is calibrated by another mobile sensor (bus); 0 otherwise

B. Single-hop calibration Model

In this section, we describe the single-hop calibration model. A mathematical formulation is presented with the objective of maximizing spatiotemporal coverage of the sensor network. Equation (1) expresses objective function, which aims to maximize the total weighted coverage of all grid cells $g \in G$ over all time slots $t \in T$.

$$maximize \sum_{g\in G}\sum_{t\in T}\omega_{gt}s_{gt} \tag{1}$$

$$\sum_{i\in H_{gt}} x_i \geq s_{gt} \qquad \forall g \in G, \forall t \in T \tag{2}$$

$$\sum_{a\in P_{ia}} y_a \geq x_i \qquad \forall i \in B \tag{3}$$

$$\sum_{i\in B} c_m x_i + \sum_{a\in A} c_f y_a \leq M \tag{4}$$

$$y_a, s_{gt}, x_i \in \{0,1\} \qquad \forall g \in G, \forall t \in T, \forall a \in A, \forall i \in B \tag{5}$$

Equation (2) controls that grid g at time t is covered only if there is at least one bus equipped with a sensor ($x_i = 1$) passing through that grid at time t. Equation (3) assures that a bus can be equipped with a sensor only if there is at least one stationary reference sensor installed at one of the stations it passes. Equation (4) is a budget constraint that ensures the total cost of mobile and stationary sensors does not exceed the allocated budget. Equation (5) expresses the type of decision variables.

C. Two-hop calibration Model

The two-hop calibration, objective function (6) as well as the coverage (7) and budget (11) constraints remain the same as in the single-hop calibration model. However, the calibration section involves a different set of constraints.

$$maximize \sum_{g\in G}\sum_{t\in T}\omega_{gt}s_{gt} \tag{6}$$

$$\sum_{i\in H_{gt}} x_i \geq s_{gt} \qquad \forall g \in G \tag{7}$$

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$$\sum_{a \in P_{ia}} y_a \geq n_i \quad \forall i \in B \quad (8)$$

$$\sum_{j \in V_{ij}} x_j n_j \geq p_i \quad \forall i \in B \quad (9)$$

$$p_i + n_i \geq x_i \quad \forall i \in B \quad (10)$$

$$\sum_{i \in B} c_m x_i + \sum_{a \in A} c_f y_a \leq M \quad (11)$$

$$x_i, s_{gt}, y_a, n_i\, p_i \in \{0,1\} \quad \forall g \in G, \forall t \in T, \forall a \in A, \forall i \in B \quad (12)$$

In the two-hop calibration model, mobile sensors can be calibrated either by a stationary reference sensor or by another mobile sensor that has already been calibrated. Equation (8) is for direct calibration and checks whether a bus can be calibrated by a stationary reference sensor. Equation (9) ensures that a bus can be calibrated by other buses only if at least one of them satisfies the following conditions: it has a checkpoint with the uncalibrated bus, it is equipped with a sensor, and it has already been calibrated by a stationary reference sensor. Equation (10) also ensures that a bus can be equipped with a sensor only if it can be calibrated by either a reference or a mobile sensor.

As shown in Fig. 2, the proposed framework follows a general workflow that connects input data, optimization models, and model outputs. The framework first requires spatial information about the study area, bus movement information, and priority locations or weights that define the importance of different grids. These inputs are processed to construct the sets and parameters required by the optimization models, including bus presence in each grid and time slot, the stations visited by each bus, and feasible calibration checkpoints between sensors. The resulting inputs are then used in the proposed optimization models to determine the optimal placement of stationary reference sensors and the selection of buses equipped with mobile sensors under budget and calibration constraints. The main outputs of the framework are the selected stationary sensor locations, selected sensing buses, and the resulting spatiotemporal coverage. The specific datasets used in this study and the corresponding data-processing steps are described in Section IV.

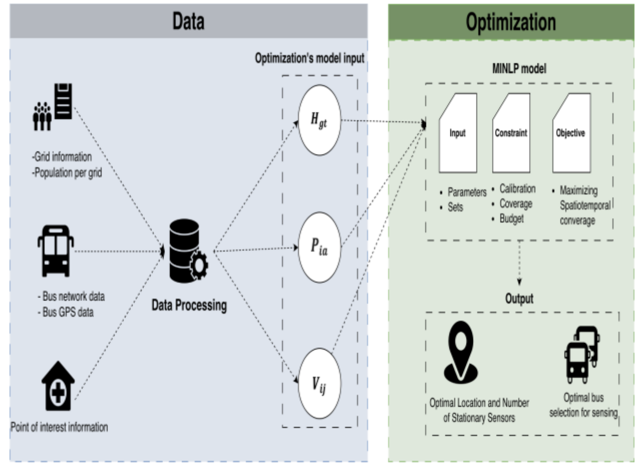

Fig. 2. Methodology framework.

IV. Study area and datasets

A. Study area

In this study, we use Rotterdam as our case study due to its unique urban characteristics and infrastructure. Rotterdam is the second-largest city in the Netherlands, with a population of over 650,000 people, and it hosts the largest port in Europe. As a major city, it includes a mix of residential, industrial, and commercial areas, which results in complex air pollution patterns. In addition, Rotterdam has a large and well-connected public transport system, including buses, trams, and metro lines, which are widely used by its residents. These features, urban density, varied land use, and strong transportation infrastructure, make Rotterdam a suitable and practical case for evaluating the performance of our models.

B. Datasets

Three kinds of data are utilized in this study, and a brief introduction to each dataset is given below.

Bus network and GPS data

The bus network data, which includes information about stations, vehicles and routes, is obtained from the KV6 dataset. This dataset provides vehicle locations (GPS) and punctuality for Buses, Trams and Metro services in the Netherlands (BISON, 2018). In this research, the data is filtered for the city of Rotterdam, focusing specifically on buses. Details about the lines, vehicles and stations are presented in Table II.

Table II Rotterdam bus network details

Total Number of lines	Number of Vehicles	Number of Bus Stops
37	178	801

Real-time positions of buses are extracted from the KV6

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dataset. In this dataset, a vehicle carrying out a given journey sends different types of messages to the KV6 feed under various circumstances: starting a journey, experiencing a delay at the start, traveling along a route, arriving at or departing from a stop, and ending the journey. In this study, the data from April 24, 2022, is used. Each record contains information such as vehicle ID, timestamp, longitude, latitude, message type, and other relevant fields.

Population Data

The population data are obtained from the CBS dataset, which provides annual gridded population data for the Netherlands at both 100 m and 500 m spatial resolutions. In this study, the 2023 dataset is used, and the population data are represented using a 500 m × 500 m grid resolution. This choice is consistent with previous studies on bus-based drive-by sensing for air pollution monitoring; for example, [6] used a 500 m grid resolution, while [12] used a 1 km discretization. Since this study focuses on network-level sensor deployment using scheduled bus movements, the 500 m grid provides an appropriate spatial unit for evaluating spatiotemporal coverage. As the CBS dataset covers the entire country, the data are filtered using the administrative boundary of Rotterdam to retain only grids within the city. It should be noted that some grids in the dataset do not contain population data; therefore, we consider only grids that include valid population information. Fig. 3, shows the population distribution based on a 500-meter square grid for Rotterdam.

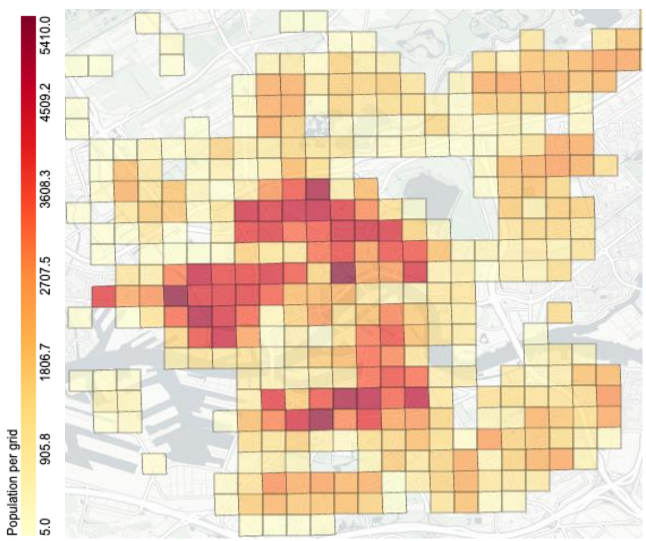

Fig. 3. Population distribution in Rotterdam based on a 500-meter grid

Point of Interest

Industrial zones, which can act as significant sources of air pollution for nearby residential areas, are considered as points of interest in this study. The POI data are obtained from OpenStreetMap. Each POI consists of longitude, latitude, name, and category of the corresponding geographical entity. We focus specifically on industrial zones in Rotterdam located close to residential areas, as it is shown in Fig. 4.

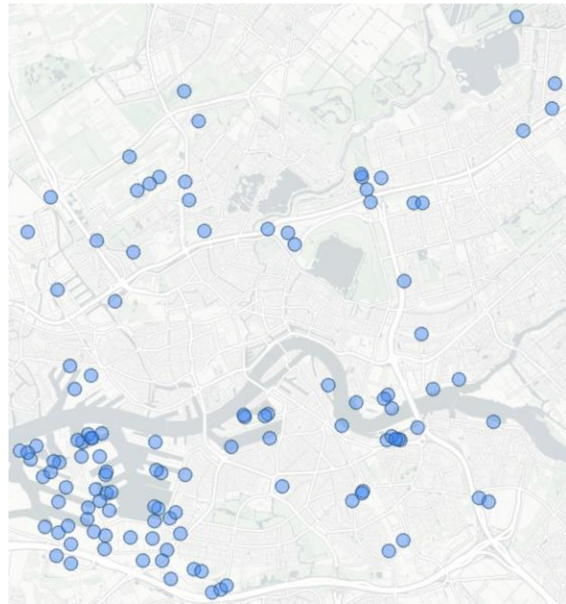

Fig. 4. Selected industrial zones in Rotterdam.

C. *Data Processing*

In the following sections, the data processing steps required for this study are described in detail.

Calculating the set H_{gt}

To build the set $\boldsymbol{H_{gt}}$, grid centers and real-time bus locations are loaded into python. Each grid represented as a square around its latitude and longitude, and each bus location record is treated as point. A spatial-join function is then applied to determine which points fall within which squares. At each time step, this process yields $\boldsymbol{H_{gt}}$, the set of buses present in each grid.

Calculating the set P_{ia}

To construct the set $\boldsymbol{P_{ia}}$, the station information from the dataset (specifically the userStopCode field), is used to identify the stops each bus passes through. From this information, $\boldsymbol{P_{ia}}$ is generated, representing the set of stations visited by each during its trips.

Calculating the set V_{ij}

To calculate the set $\boldsymbol{V_{ij}}$, two criteria are applied for identifying a checkpoint: temporal and spatial distance. For each bus, all GPS records are compared with those of every other bus. When the temporal difference between two records is within a defined threshold, the spatial distance is computed. If this also meets the threshold, the two buses are considered capable of forming a checkpoint.

V. Computational Results

In this section, we conduct experiments to evaluate the

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proposed models using the Rotterdam case study. Section A presents the results for the calibration methods. Section B examines the model performance for points of interest. All models are implemented in Python 3.9.12 and solved with Gurobi 11.0.2 for both linear and nonlinear formulations. Computational experiments run on an Apple M3 system with 16 GB of RAM.

A. Calibration method

In the following sections, the results of the models based on different calibration methods for Rotterdam case are presented. Parameters and inputs value for the models are listed in Table III.

Table III. Model inputs used in the analysis.

Model inputs	Value	Reference
Total number of grids	290	Statistics Netherlands (CBS)
Grid size	500 m × 500 m	[6]
Checkpoint threshold	(50 m, 5 min)	[24]
Total number of industrial zones	120	OpenStreetMap (OSM)
Sensing interval	1 hour	-
Time period	07:00–17:00	-
Total available budget	€ 64,000	Assumption (sensitivity analysis)
Cost of mobile sensors	€ 2,100	[26]
Cost of fix sensors	€ 20,000	[26]

Single-hop

This section presents the results of the single-hop calibration model. The model is applied to the Rotterdam case study, and the results are summarized in Table IV.

Table IV Single-hop model results

Objective Value	Number of Covered Grids	Number of Stationary Sensors	Number of Active Buses	Grid time-slots Coverage (%)
2877335	189	2	11	55%

As shown in Table IV, the deployment of two stationary sensors and eleven buses results in coverage of 55% of all grid time-slots. Fig. 5, illustrate the grids covered by mobile sensors. To maximize the objective, the model prioritizes buses that traverse densely populated areas, while stationary sensors are located at major bus stops. This configuration demonstrates that the model effectively targets high-demand locations, achieving single-hop calibration with minimum cost and extensive coverage. Fig. 6, presents the coverage frequency across study area. Central and densely populated grids are visited more frequently. This ensures that the sensor network can provides reliable monitoring in these locations.

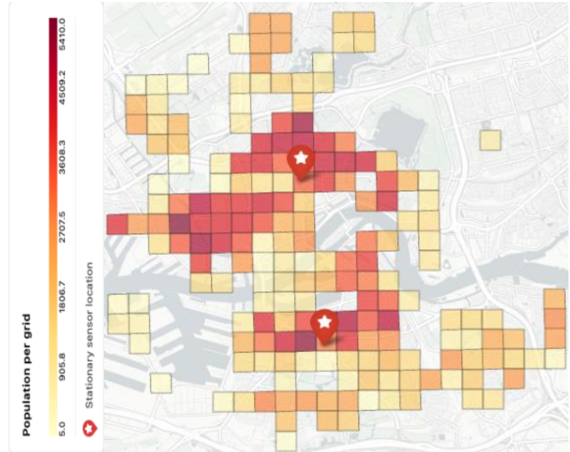

Fig. 5. Sensor network coverage and stationary sensor locations for the single-hop model.

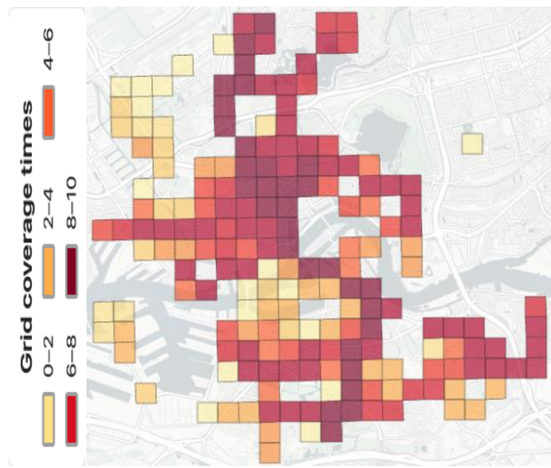

Fig. 6. Grid coverage frequency by the sensor network for the single-hop model.

Two-hop

The results of the two-hop calibration model are presented in this section. The analysis relies in the same parameters used for single-hop model. Table V provides a summary of the results.

Table V Two-hop model results

Objective Value	Number of Covered Grids	Number of Stationary Sensors	Number of Active Buses	Grid time-slots Coverage (%)
3788125	232	1	20	80%

Table V shows that 80% of the available grid time-slots are covered by 20 mobile sensors, each frequently calibrated by either a stationary sensor or another mobile sensor. In the two-hop calibration scenario, mobile sensors calibrate one another, reducing the required number of stationary sensors. Consequently, more budget can be allocated to mobile sensors, increasing both the objective value and grid coverage compared to the single-hop model. As shown in Fig. 7 only one stationary sensor location is selected,

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resulting in expanded coverage areas.

Table VI model results

Calibration Method	Objective Value	Number of Covered Industrial Zones	Number of Stationary Sensors	Number of Active Buses
Single-hop	290	47	2	11
Two-hop	401	61	1	20

Fig. 8 shows the grid coverage frequency for the two-hop model. Compared to the single-hop model, the coverage frequency is significantly improved, with most of the covered grids being monitored more than eight times per day. This indicates that the two-hop approach not only expands the spatial coverage of the network but also ensures more consistent and reliable monitoring across the covered area.

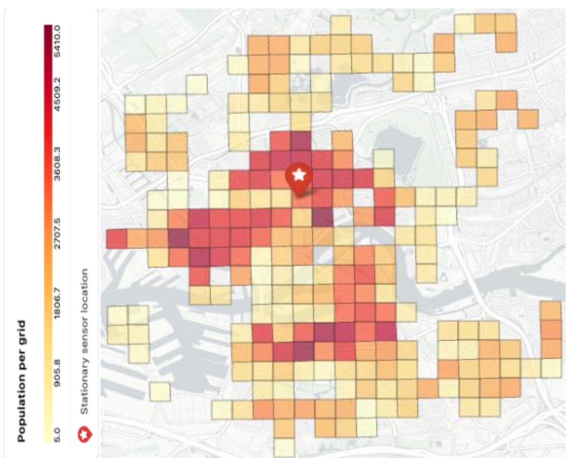


Fig. 7. Sensor network coverage and stationary sensor locations for the two-hop model.

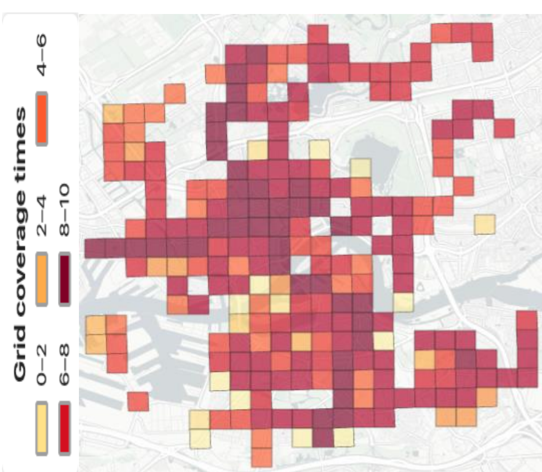
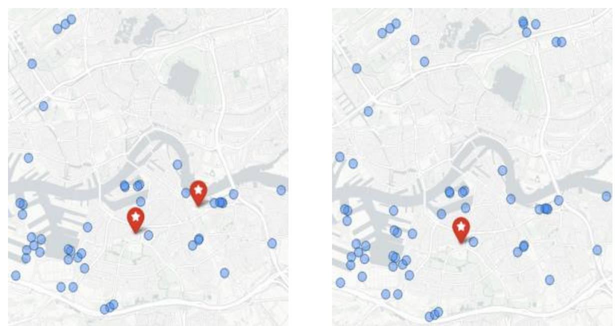


Fig. 8. Grid coverage frequency by the sensor network for the two-hop model

B. Point of interest

In this section, several industrial zones in Rotterdam are considered as points of interest for the proposed model. The effectiveness of the model is assessed with respect to the coverage of these points of interest. The corresponding results are presented in Table VI model results.

Fig. 9 (a, b), shows that the number of industrial zones covered under two-hop calibration (blue dots) is higher than the single-hop case. The locations of stationary reference sensors (white star) differ from those selected when population is used as the input parameter. When population is considered, the model places stationary sensors at bus stops near densely populated areas. In contrast, when industrial zones are emphasized, bus stops closer to those zones are selected for sensor placement.



(a)Single-hop calibration (a)Two-hop calibration

Fig. 9. Industrial zones coverage by the sensor network.

VI. Sensitivity Analysis

In this section, the performance of the model is examined under varying key parameters. Specifically, the results are analyzed with respect to changes in the total available budget and checkpoint criteria.

A. Budget

To evaluate the impact of budget variations on the model's performance, we define seven different budget scenarios. These scenarios are analyzed based on their effects on the objective value, the number of covered grids, and the deployment of stationary and mobile sensors. The results of this analysis are presented in Table VII. The reference scenario described above is shown in italics.

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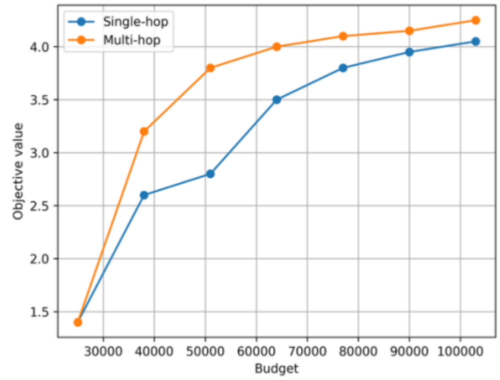
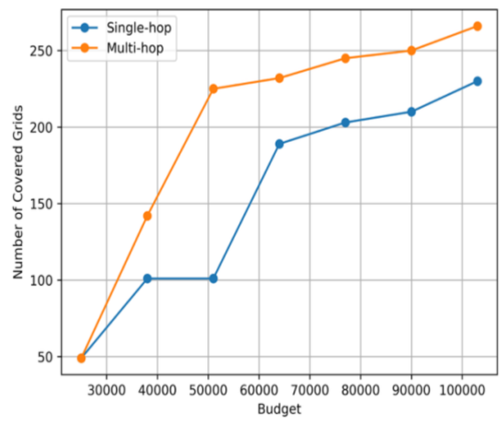
Table VII Single-hop and two-hop calibration results at different budget levels.

Budget	Calibration method	Objective Value	Covered Grids	Stationary Sensors	Active Buses	Coverage (%)
25,000	Single-hop	974085	49	1	2	17.85%
	Two-hop	974085	49	1	2	17.85%
38,000	Single-hop	2167370	101	1	8	39.46%
	Two-hop	2650225	142	1	8	48.73%
51,000	Single-hop	2282540	101	1	14	41.43%
	Two-hop	3426450	225	1	14	69.47%
64,000 (Reference)	*Single-hop*	*2877335*	*189*	*2*	*11*	*55.86%*
	Two-hop	*3788125*	*232*	*1*	*20*	*79.13%*
77,000	Single-hop	3306170	203	2	17	67.06%
	Two-hop	3944235	245	1	26	83.68%
90,000	Single-hop	3453160	210	2	23	69.82%
	Two-hop	4055560	250	2	23	86.57%
103,000	Single-hop	3602745	230	3	20	76.29%
	Two-hop	4174105	266	2	29	90.20%

As shown in Fig. 10 (a, b), increasing the budget improves both the objective value and the number of covered grids, but these two figures describe different aspects of coverage. The objective value reflects the overall spatiotemporal coverage of mobile sensor network which taking grid coverage time per day. While Fig. 10(b) reports the number of distinct grids with at least one observation. Because the two figures measure different characteristics, it is possible for two budget levels to yield the same number of covered grids. However, the objective value can still differ if the additional resources allow mobile sensors to visit more frequently or during more important time periods. This also explains the behavior of the single-hop method when the budget increases from 40,000 to 50,000: the extra budget is used to enhance sensing frequency on the grids that were already monitored, rather than expanding coverage to new areas. Consequently, the number of covered grids in Fig. 10(b) remains unchanged, while the objective value in Fig. 10(a) continues to increase. Across all budget levels, the two-hop calibration consistently outperforms the single-hop method in both coverage and objective value. The impact of budget increases is greatest at lower levels, where additional resources are used for improved sensor deployment and coverage expansion. At higher budget levels, most grids are already covered, and further improvements are less significant.



(a)



(b)

Fig. 10. Comparison of single-hop and two-hop calibration methods under different budget levels: (a) objective value and (b) number of covered grids.

As shown in Fig. 11(a,b), increasing the budget influences the deployment of both stationary sensors and active buses. In the single-hop calibration, calibration is only possible through stationary sensors, which leads to a higher number of such sensors as the budget increases. In contrast, the two-hop approach allows calibration through other mobile sensors, reducing the need for stationary units. This difference is clearly reflected in the results: the two-hop method deploys fewer stationary sensors but makes greater use of active buses, especially as the budget increases.

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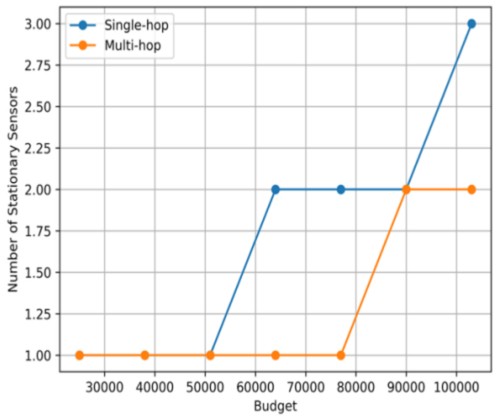
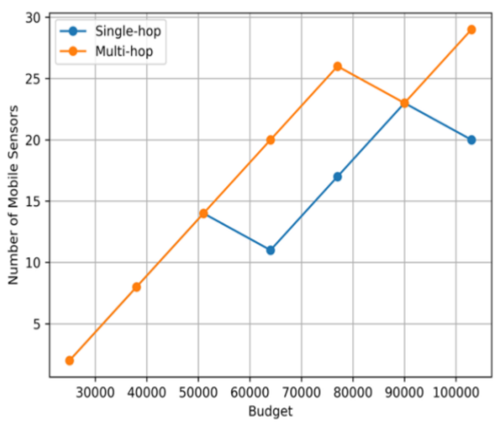


(a) Stationary sensor



(b) Mobile sensor

Fig. 11. Deployment of stationary sensors (a) and active buses (b) under different budget levels for single-hop and two-hop calibration models.

B. *Checkpoint*

Determining the spatial and temporal distance for calibration checkpoint depend on the process of interest. For example, the change of ozone concentration over short distance is insignificant in contrast to the concentration variability of fine particles. In this section we define different scenarios based on different value of spatial and temporal distance for checkpoint. All these scenarios are implemented on two-hop calibration model.

Table VIII Two-hop scenarios with different spatial and temporal checkpoint distances

Scenario	Calibration: Spatial distance (m)	Calibration: Temporal distance (min)	Objective Value	Covered Grids	Stationary Sensors	Active Buses	Coverage
1	10	3	3297755	207	1	20	64%
2	30	4	3739000	233	1	20	77%
3	50	5	3774035	236	1	20	78%
4	80	8	3784765	232	1	20	78%

As shown in Table VIII, across different scenarios, the number of active buses for sensing tasks and the number of stationary sensors remain constant. However, the specific buses selected vary between scenarios, while the location for the stationary sensor remains the same. By increasing the spatial and temporal distances, the objective value improves. This indicates that with wider spatial and temporal constraints, more buses have opportunities to calibrate each other. Consequently, the model selects buses that contribute more effectively to the objective function. This finding aligns with theoretical expectations, as looser constraints increase the likelihood of calibration opportunities.

VII. Discussion and Conclusion

This study investigates the design of an air pollution sensor network that integrates both mobile and stationary reference sensors. While most previous studies focus on route selection, they emphasize spatial coverage but neglect bus mobility, often resulting in suboptimal sensing performance caused by coarse deployment granularity. To address this, we develop a mathematical optimization framework that selects an optimal subset of buses and identifies the best locations for stationary reference sensors, using bus trajectory data and schedules. The objective is to maximize the spatiotemporal coverage of the network under budget limitations. The model also supports both single-hop and two-hop calibration strategies, ensuring that all mobile sensors are sufficiently frequently calibrated through interaction with either stationary reference sensors or other mobile sensors. This process improves data accuracy and demonstrates the reliability of the proposed approach.

The novelty of the study lies in the fact that, to best of our knowledge, no previous study on air pollution sensor network design optimization has simultaneously addressed both bus selection and the placement of reference sensors, which demonstrates the novelty of this research. The models are applied to a real-world case study of the Rotterdam bus network. The results indicate that extensive spatiotemporal coverage of the city can be achieved only with a limited number of mobile sensors, highlighting the efficiency of the approach. Furthermore, the findings for industrial zones indicate that the models are adaptable to different inputs and can deliver strong performance.

The findings of this study show that strategically integrating mobile and stationary sensors can significantly improve urban air quality monitoring while maintaining both accuracy and cost-effectiveness. Nevertheless, some limitations remain. Future research could address uncertainties related to changes in bus routes or schedules to enhance network resilience. In addition, future studies could investigate calibration settings with a larger number of hops and explicitly incorporate data accuracy and calibration error propagation into the optimization model. Future research could also examine the sensitivity of the proposed framework to different spatial discretization levels, including finer or adaptive grid structures. Exploring alternative mobile platforms, such as taxis or micromobility services, together with incorporating low-cost fixed sensors, could further increase spatiotemporal coverage and robustness.

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