Optimization of Bus Routes to Maximize Coverage of Air Pollution Monitors

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Abstract. Air quality monitoring helps assess ambient air quality, the health impacts, and the influence on commuters’ activities. The deployment of a dense network of monitors is cost-intensive and laborious. Therefore, low-cost monitors that can traverse through different routes of the city can be an appropriate solution for higher spatio-temporal coverage. In this study, Delhi is considered the study area due to its exceeding pollutant concentration. Delhi has two large public transit systems: bus and metro rail, serving 1484 km².

A simulation-based approach is proposed to identify the minimum number of routes on which air pollution monitors can be traversed to achieve the maximum coverage. To have a generic approach, commonly used, General Transit Feed Specification (GTFS) data format for public transit is used. For the demonstration, in two scenarios (24h time bin and 1 h time bin), the routes are optimized to place 100 monitors. The simulation algorithm evaluates the routes based on overlaps and probabilities of removal calculated using continuous activation functions such as bipolar Sigmoid function. The results are obtained in the form of the retained routes on which monitors can be traversed.

The minimum number of routes with maximum converge area and least overlapping routes helps monitor the real-time air quality at wide-ranging areas. The results of this study can be helpful to relevant authorities for the implementation of mobile monitoring devices and identifying the source of the air pollution.

Keywords: Air quality monitoring · Mobile sensors · Route optimization.

1 Introduction

Deteriorating air quality with accelerating urbanization and industrialization has caused negative impacts on the environment and human health. Air quality in urban areas represents a major concern regarding the health of urban residents [1]. Vehicular emissions, factories, toxic chemicals, waste and fuel burning, power plants etc., cause air pollution in densely populated cities. The exposure to air pollution varies in cities with discrete activities, and spatio-temporal variations [2,3].

Air quality monitors are predominantly provided for legal and scientific purposes [1]. Monitoring is essential to scientists, researchers, and policymakers to get information, identify the hot spots, design the control/abatement strategies. Additionally, the monitoring can assist the common people in understanding the impacts of varying ambient air quality levels. To prevent the alarming scenarios due to degrading air quality, recognizing the situation in advance with the help of monitoring is advantageous.

Fixed heavy sampler air quality monitors used to be heavy and of higher cost, designed to be located at fixed positions to gather information accurately for one location and then interpolate/predict at other spatial points. The locations of these fixed monitors were determined based on environmental conditions, the need for pollutant information, land use, population density, and the probable use of a monitor. There are both manual and continuous type monitoring systems, and manual monitoring is a long process of estimating pollutants, which takes place in laboratories after collecting samples at the site. In contrast, continuous monitors provide information about all the available pollutants at fixed intervals for the location of monitors. The number of continuous monitors required depending on the population density and area. With the high installation, operation, and maintenance costs of continuous monitors, the network density of the monitors may not be enough to provide accurate and real-time information to common people. For instance, the number of monitoring stations in India is falling short of the required number of stations [4].

Portable sensors replaced the low-density networks of high-cost fixed monitors to overcome the limitations and provide low-cost, energy-efficient monitoring. The lower cost comes at a price of lower accuracy compared to continuous monitors. The portable sensors can provide real-time values and spatial monitoring data. But even with low-cost sensors, for largely populated cities, implementing a dense network is uneconomical due to the high total cost of acquiring a large number of monitors and their cost-intensive operation and maintenance [5].

The fixed monitors provided real-time air quality information, and a network of wireless, portable sensors with a back-end server can convert the real-time data into comprehensible information for users [6]. Crowd sensing-based monitoring was used with low-cost and low-power devices for real-time air pollution data [7]. The placement of monitors needs to focus on citizens’ access to information and ease in assessing exposure. An optimization approach, in which the location of sensors are placements based on individuals’ overall satisfaction, showed that
the individuals’ satisfaction varies with the distance of monitor and frequency at which the information gets updated [8]. A concept of mobility to low-cost wireless sensors is explored in recent years to achieve higher spatial resolution and real-time information of the various toxic pollutants [6]. Studies about selecting these platforms and their routes are being carried out in several places. Mobile monitoring refers to having mobile platforms for placements of monitors which can traverse through places. Different modes for mobile monitoring were used in the past, such as bicycles, buses, personal vehicles, and wheeled rovers [9,10,11,12].

Along with these lines, placing monitors on existing mobile platforms such as public transit services is a viable solution to provide real-time data. Still, not all routes of a large city can have mobile platforms at all times. Therefore selecting the optimum routes which provide maximum coverage of a city is essential. Public transit services that move around the maximum area of a city can provide an increased number of data points, thereby enhancing the prediction accuracy in spatial and temporal dimensions. For the selection of a sub-network of the existing public transit network to have sensors as mobile sensing nodes on public transit units, an operation research-based approach was proposed by [13] to provide good coverage of the city using fewer monitors. Checkpoints defined as data points in the same vicinity were also maintained in the sub-network to verify the data. In an experimental study, a low-cost wireless sensors network is created by placing the sensors on public transit buses to collect the real-time air pollution information and have maximum coverage of the city [9]. The routes were selected using a route coverage image analysis algorithm, which estimates the area covered using a combination of buses. Similarly, autonomous wheeled rovers were used to place the monitors for mapping the pollution state and evolution, which resulted in saving cost but at the same time needed robot-operated wheeled rovers to traverse on the routes [12]. Mobile monitoring was used to enhance the spatial-coverage of gaseous pollutants concentration in Canada [14]. Many applications of mobile sensors such as improved health monitoring and transportation systems were shown in previous studies [15]. Mobile monitoring can also identify the specific source of pollution and supply a high spatial resolution for collected data. Apart from real-time information about pollutant concentrations and exposure to humans, the prediction methods also improve with real-time data collected from denser networks. The location of monitors significantly influences the prediction of pollutants in both spatial and temporal dimensions [16,17]. Estimation errors in prediction through various methods were compared for different combinations of suitable locations to select the scenario with a minimum number of locations and the slightest error.

The location of monitors does not directly influence the air quality, i.e., an increased number of data points cannot reduce air pollution. Even so, for accuracy in informed data and enhancing the ambient air quality, the locations of monitors are crucial in finding solutions to curb the pollution. The air quality depends on the available concentrations of toxic pollutants, the meteorological parameters such as temperature, wind speed, wind direction, pressure, relative
humidity, and the amount of time the pollutants stay in the air. While selecting a location for monitor placement, various parameters such as the height of placement, measuring pollutants, obstructing structures, security of equipment, facilities for data communication, and installation and operation cost are analyzed. The optimal deployment should balance risks and profit as all parameters cannot have the same priority. The optimal deployment of sensors can assist in better assessing the coverage area of each vehicle.

A few studies were conducted for location determination for air pollution monitors, but only limited studies explored the optimal placement for mobile monitors, especially in developing countries. With the current study, a metro city of developing countries is considered, with severe air pollution and fewer fixed monitoring devices to cover a large area. A dense network of fixed or mobile monitors traversing in the maximum area is required to achieve maximum spatial and temporal coverage. Few studies have worked on the selection of routes for mobile monitors also. Still, these studies were conducted on smaller areas, and at times the routes were selected based on the availability of mobile platforms.

This study aims to develop a generalized approach to identify the minimum number of devices for maximum spatio-temporal coverage or a given cost/number of devices.

The rest of the paper consists as follows: Section 3 exhibits the characteristics of the study area. The methodology is demonstrated in Section 2 and results are documented in Section 4, and finally, the study is concluded in Section 5.

2 Methodology

Previous studies identified a gap between optimizing the location for fixed air quality monitors and determining the routes for mobile air quality monitors. Limited studies are focusing on the optimization of routes for mobile monitors placed on public transit vehicles. A generalized simulation approach is proposed to bridge this gap and determine the routes through which mobile monitors can be traversed on the condition of covering a maximum area. The study area is selected based on deteriorating air quality, a larger city area, and fewer monitoring stations. Delhi, the capital city of India, is taken as the study area, with the bus transit system as the mobile platform for placing the monitors.

With bus transit, the main objective is to identify the minimum number of routes on which air pollution monitors can traverse and cover the maximum area of the city. For maximum coverage, both spatial and temporal dimensions are incorporated. To have a generalized approach, this study uses General Transit Feed Specification (GTFS) files3, which are commonly available in many cities across the globe. Typically, the GTFS data has details of bus services in the form of agency, calendar, routes, trips, stops, stop times, and shapes. The linkage between different files of GTFS is shown in Figure 1.

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3 See https://developers.google.com/transit/gtfs for details about GTFS.
Various trips of buses take place mostly on the same routes of the network throughout the day. Naturally, to allow ease in passenger exchange, different routes overlap with each other.

It is assumed that a bus assigned to a route does not serve any other route for simplicity. To analyze the bus routes, their overlap spatially and temporally, and the coverage was identified and analyzed using a simulation approach proposed in Figure 2, each step of which is explained in subsequent sections. It is an iterative process and terminates after satisfying given criteria.

### 2.1 Preprocessing of Data

After downloading the static GTFS data for Delhi [18] on 18th April, 2021, various GTFS validation/visualization techniques are used to identify the errors. As shown in Figure 1, the 'stops' and 'shapes' files have the geometries, which are used to visualize the stops and lines. A few stops are wrongly marked and assigned with wrong/incorrect location coordinates (e.g., on a building, off-street). These stops are then fixed in the 'shapes', 'stops', and 'stop times' files. Depending on the errors in the GTFS, this is mostly a manual process. The cleaning of data is essential to prevent errors in further processing.

![Figure 1: GTFS format and inter-connection between files](image_url)
2.2 Initialization

The available data is in the form of different trip IDs for each route and then the respective details of the stops, stop timings, trip details etc. For ease in determining and interpreting the overlaps between various routes, the trips were divided into segments. The idea of the segment is to have at least one data point (i.e., details of the pollutants from the sensor, latitude and longitude, temporal, temperature/ pressure/ humidity/ etc.) per segment. This data point is then either stored in a memory card or transmitted to a server.

Segment creation: A segment is define as

\[ S_{a,b,t} = (s_a, s_b, t) \]

where \( s_a \) and \( s_b \) are the first and second stops; \( t \) is the time bin in which a bus departs from the \( s_a \). Moreover,

\[ s_a, s_b \in S \]

where \( S \) is a set of all stops of the transit network. For a trip, having \( n \) stops, the number of segments will be \( n - 1 \). These segments are generated for each trip of all routes in the GTFS.
Overlap identifier: An overlap identifier is defined for each segment, which depicts the number of overlapping counts on that segment. In other words, overlap count denotes the number of times the data is recorded on that segment.

Further, 

\[(s_a, s_b, t) = (s_b, s_a, t)\]

i.e., an overlap of segments is declared if the latitude, longitude of the stops and a time bin with respect to departure from any stop are identical. In other words, it represents that the two vehicles are moving in the opposite direction on a segment in a time bin. For example, a bus is moving from stop A to stop B. The departure time from stop A is between 10:00 and 10:15 (i.e., 15 min time bin). The average travel time from stop A to stop B is 2 min. Another bus is moving from stop B to stop A, and the departure from stop B is anywhere between 10:00 - 10:15. Clearly, in this case, two data points will be recorded between stop A and stop B and time 10:00-10:15. Thus, the overlap count is one. From this stage, the overlap counts of each segment for respective trips are estimated.

2.3 Probability Calculation

Segmental probability: In general, the higher the overlapping count, the more likely the segment can be removed. Therefore, to estimate the likelihood of excluding an overlapping segment, four different Sigmoid functions (see Equations (1) to (4)) are considered. In simple terms, all functions can be interpreted as increasing the overlap count, decreasing the segments’ need.

\[P(s'_{ab}) = \frac{1}{1 + e^{-x}}\]  
(1)

\[P(s'_{ab}) = \frac{1 - e^{-x}}{1 + e^{-x}}\]  
(2)

\[P(s'_{ab}) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}\]  
(3)

\[P(s'_{ab}) = \frac{x}{1 + |x|}\]  
(4)

where \(x\) represents the overlap counts.

The four functions used for probability determination are continuous activation functions. The distribution of these functions are shown in Figure 3. As the number of overlap counts cannot be negative, the logistic Sigmoid function is not ideal. The bipolar Sigmoid function Equation (2) is employed in this study, due to following reasons:

- the number of overlaps (\(x\)) cannot be negative,
- the value of a function at a given value of \(x\) should be between \([0,1]\), and
- the bipolar Sigmoid function has better performance and comprehensible results than other functions [19], and it is easy to differentiate and gradual in nature.
Joint probability: The joint probability for each route is calculated, as the decision to be made is for routes. The reason behind considering routes is that removing segments will cause discontinuity in the movement of monitors, which is not desirable. Since the $P(S'_{i,j,t})$ and $P(S'_{k,l,t})$ are independent events (i.e., removal of segment $S_{i,j,t}$ does not affect the removal of segment $S_{k,l,t}$). The prime (‘’') denotes the negation or removal of segment. Thus, the joint probability of removing a route ($P(R')$) is given by

$$P(R') = \prod_{\forall S_{i,j,t}} P(S'_{i,j,t})$$

(5)

i.e., product of probabilities of removing all segment of each trip in the route $R$.

2.4 Removal prioritization and termination

Removal prioritization: Removing routes from the existing network, which are overlapping, and if removed, do not significantly impact the coverage. At first, a route with the highest joint probability, estimated using Equation (5), is removed in each of the iterations. However, it is also possible that multiple routes have the same probability (e.g., 1 for entirely overlap routes). In such cases, different factors can be used to further order them for removal priorities. Some of the examples are trip time, trip length, population density, area, etc. In this study, a route is prioritized to remove based on less valuable time, i.e., idling. After every trip, a terminal time is provided to match the schedule, change the shift, etc. Thus, more trips are equivalent to frequent breaks for terminal time and are less desirable to place a monitoring device. This process of removing routes is continued till the termination criteria are reached.
Summary statistics: The objective is to reduce the needed number of devices that provide real-time values with high spatial resolution. Thus, to compare the different possibilities, a validator function is defined as follows:

\[ OR = \frac{\sum \ell_o}{\sum \ell_S} \]  

where, \( OR \) is the overlapping ratio, \( \ell_S \) is the length of a segment and \( \ell_o \) is shown in Equation (7).

\[ \ell_o = \begin{cases} \ell_S & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases} \]  

At the end of every iteration, overlap counts for each segment, number of remaining trips/routes, overlapping ratio, etc., are written out for comparison and analysis purposes.

Termination criteria: In this step, termination criteria are defined to stop the iterative process. Some of the examples for termination criteria are:

- the process can run for ‘n’ iterations.
- if the joint probability calculated for removing routes is greater than a threshold probability, the routes are removed. The threshold probability can be configured by a user (e.g., 0.8) depending on the total cost of the monitoring stations.
- routes can be removed until only 100 routes are left.

The number of monitors is taken as 100 to provide a generalized optimization method. The routes that remained post-termination will provide the maximum coverage based on the given conditions.

3 Study Area and Data

Delhi is known for its higher pollution levels throughout the year; therefore, providing real-time monitors covering all parts of the city can benefit Delhi citizens. Therefore, in this study, Delhi is selected as the study area to optimize the bus routes for the placement of air pollution monitors that provide maximum coverage. The area of Delhi is 1480 km\(^2\), and the population is over 16 million [20], in which only 38 monitoring stations were established by the state and central pollution control board authorities.

For public transit services, Delhi has metro rail and bus transit services. Metro rail is at underground, at grade, and elevated levels. In this study, the bus transit system of Delhi is considered for the study, which has a wider network spread in all zones (see Figure 4). For details of bus transit Delhi, the General Transit Feed Specification (GTFS) data that includes the schedules and locations of all the transit routes and stops of the public transit services is taken as secondary data [18]. The GTFS data of Delhi has details of bus services in the
Figure 4: A map of Delhi, India, showing bus depots, network of bus lines and positions of monitoring stations.

form of agency, calendar, routes, trips, stops, stop times, and shapes (see Figure 1). The data belongs to the agency of Delhi Integrated Multi-Modal Transit System Ltd. In Figure 4, the location of Delhi in India, the bus network of Delhi along with 23 bus depots, and the existing static monitors are shown. There are a total of 3210 bus stops spread in all zones of Delhi. There are 533 unique routes in the network, each with varying trips from 16 to 161.

The extent of overlap may vary from city to city. For Delhi, Figure 5 shows the overlapping segments for the whole day (i.e., 24 h time bin). The red colored lines show segments with maximum overlap, whereas the blue lines show segments with least overlap. Clearly, central Delhi and some routes in the west have the highest overlap.

4 Results

In this study, two scenarios are considered for Delhi.

1. Scenario A: 24 h time bin
2. Scenario B: 1 h time bin

The former case is expected to have at least one data point on each segment in a day, whereas for the latter, it is one data point per segment in a 1 h time bin.

In an ideal situation where the information about the vehicles is available, the approach should be applied to remove the vehicles while having maximum coverage. In this study, the approach is applied to routes only. Thus, if all segments must be covered, the number of required monitoring devices will be the
same as the number of routes. However, the number of devices is limited to limit the capital, maintenance, and operational costs. Therefore, in both scenarios, it is determined how many routes will remain (i.e., overlap) if only ‘n’ monitors are available. This will become the termination criteria (see Section 2.4) for both scenarios.

For the demonstration purpose, we consider the termination criteria of determining the routes to place 100 monitors while keeping the maximum coverage for the two scenarios.

4.1 Scenario A: 24 h time bin:

A simulation is set up for the termination criteria of having 100 routes for mobile monitoring for 24 h time bin. As the number of routes is assumed to be equal to the possible number of monitors required, there is a requirement of 533 monitors in the existing scenario. Figure 6a shows the bus network of Delhi at iteration zero, i.e., when no routes were removed. After 433 iterations and removal of routes based on overlaps, the retained routes have probabilities almost equal to zero. After removing 433 routes, the retained routes for placing the monitors are shown in Figure 6b. Clearly, by placing only 100 monitors, a very high coverage can be maintained for pollution monitoring. Further, Figure 8 shows that the maximum overlapping ratio (for all 533 routes) is about 0.66, whereas the overlapping ratio for 100 monitors drops to 0.33.
4.2 Scenario B: 1 h time bin:

Similar to 24 h time, a simulation is set up in which segments are constructed for 1 h time bin. Since a route is removed in every iteration, 100 routes are retained after 433 iterations, where the monitors can be placed.

For comparison purposes, all routes for iteration 0 and retained routes in iteration 433 are plotted for time bin 08:00-9:00 (i.e., peak hour). In absence of
the transit demand, the frequencies of buses on all routes at different times of the day is used to identify the peak hour, i.e., higher frequency would require to cater the transit demand during the 1 hour time bin. Figure 7a shows all routes and Figure 7b shows the 100 retained routes. Clearly, for 1 h time bin too, the coverage is very high, and the overlapping ratio (Figure 8) drops to 0.32 from 0.60.

![Figure 8: Overlapping ratio for scenarios A and B](image)

Though the output of the two scenarios looks similar, they are optimized for different time bins. The total number of trips corresponding to 100 retained routes is 8665 for scenario A and 9083 for scenario B. This happens due to the difference in the overlap identifier for different time bins. It is likely to maximize the data points for the corresponding time bin.

5 Conclusions

With the growing need to comprehend the behavior of air pollution, its sources, spatial and temporal distribution with varying meteorological and traffic parameters, the impending need of understanding the monitoring system is also increasing. For a developing country such as India, pollution is one of the leading reason for various health issues and deaths. The existing monitoring system of Delhi has only 38 monitors covering its large area and providing information to individuals.

Mobile monitors are a possible replacement for fixed expensive air pollution monitors. This paper considered the problem of selecting public transit routes
in a city to accomplish maximum coverage through air pollution monitors, i.e.,
having the maximum number of data points spatio-temporally. A generic simula-
tion algorithm was developed working on the General Transit Feed Specifications
(GTFS) data to remove overlapping routes from the network. The proposed ap-
proach is transferable to any other city since GTFS is a commonly used data
format for transit supply. In this study, a demonstration was given with a target
to retain 100 routes through simulation to provide 100 mobile monitors over the
bus network of Delhi, which can provide maximum coverage. Two scenarios with
different time bins, 24 h, and 1 h, were observed, and 100 routes were rationalized
for both scenarios. The number of routes required for traversing can be derived
using the proposed method for any given number of monitoring devices. From
the results, it was observed that with a limited number of monitors traversing
through the city, a larger area can be covered, i.e., a large number of data points
can be achieved. Thus, the proposed approach addresses the optimal application
of a dense monitoring network with least capital cost for portable devices and
maximum coverage.

In the future, instead of routes, the actual number of vehicles can be identified
for placement of monitors, using the information of vehicles running in real-time.
It is likely to be more realistic but will be specific to limited number of cities.

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Author Contributions

The authors confirm contribution to the paper as follows: Conception and design
of study: AA, RC; Literature review: RC; data collection and model development:
RC, AA; analysis and interpretation of results: RC, AA; draft manuscript prepa-
rati on: RC, AA. All authors reviewed the results and approved final version of
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