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Multimodal routing framework for urban environments considering real-time air quality and congestion

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ABSTRACT

The travel choices of citizens can be based on distance, time, exposure, emissions, etc., but the current route planning systems are mostly based only on distance and time. This study develops a route planning framework by integrating the real-time congestion pattern and air pollution levels in the GraphHopper multi-modal routing engine. This study showcases the application for Delhi and Bangalore, India. However, it is transferable to any other city in the world. The route planning algorithms provide alternatives for the fastest, shortest, LEAP (least exposure to air pollution), and the balanced route, considering four travel modes: car, motorbike, bicycle, and foot (pedestrian). GraphHopper libraries involve custom weightings for each of the constraints for route choices, and these weightings are modified to find the optimal route as per users' requirements. The study's novelty lies in integrating real-time congestion patterns and air pollution levels in a multi-modal routing engine. The preference for low travel time and air pollution levels can be altered by adjusting factors in balanced route to suit travelers. Using different travel modes on a specific route found that the exposure reduction ranged from 42.73 % to 71.50 % for fastest to balanced routes and 64.52 % to 82.71 % for fastest to LEAP routes in Delhi. Higher exposure reduction percentages are observed in Bangalore. Using the routing engine can help travelers reduce their exposure by altering travel choices. The interface of the routing engine is made user-friendly and intuitive.

1. Introduction

Air pollution is exacerbated by escalating industrialization and urbanization. Among the sources of air pollution such as power stations, refineries, industries, brick kilns, indoor sources (e.g., domestic cleaning activities), mobile sources (e.g., surface transportation, air, rail), area sources (e.g., crop burning), and natural sources (e.g., forest fires, dust storms, volcano eruptions, etc.), transportation sector contributes significantly higher to air pollution (Karagulian et al., 2015; Guttikunda et al., 2019; Manisalidis et al., 2020; WHO, 2013). In recent decades, air pollution has become a leading cause of health issues and deaths in the whole world (Manisalidis et al., 2020) due to deteriorating urban air quality and greater exposure to ambient air pollution. A total of 12.5% deaths in India (around 1.24 million) occurred due to air pollution in the year 2017, out of which 54% were due to ambient particulate pollutant concentration and 38% were due to household air pollution (Balakrishnan et al., 2019). Air pollution attributable death rate (per 1 lakh population) was observed as 82.09 for India in the year 2018 (WHO, 2022). Higher rates of ischemic heart disease, lower respiratory infections, and chronic obstructive pulmonary diseases were observed in the last three years. For an Indian person, the average life expectancy year lost due to particulate pollution is 6.3 years (Greenstone and Fan, 2020). Among various types of air pollutants, exposure to particulate matter has been the prominent reason for premature deaths and severe health impacts (Apte et al., 2018).

Exposure to air pollution and increased inhalation of pollutants were observed in active transport modes (de Sá et al., 2017). Urban residents are highly exposed to harmful effects of poor air quality even with a short time spent in traffic (Zeng et al., 2016; Sengupta et al., 1996). In a study by Manojkumar and Srimuruganandam (2021) in Vellore, India, it is shown that higher on-road $PM_{2.5}$ exposure is related to traffic intersections, traffic signals, lack of parking space, etc. Simulation modeling was used to analyze the on-road pollution exposure in both scenarios of presence and absence of traffic congestion, and it was found that with congestion, travel time and exposure increases (Zhang and Batterman, 2013; Gurram et al., 2019). Similarly, Agarwal and Kaddoura (2019) showed that a new bicycle track in the middle of a city is likely to increase the exposure significantly. The exertion and higher respiration rates during bicycling lead to increased inhalation

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doses (Bigazzi and Figliozzi, 2014). A hybrid exposure model was developed based on time-activity data to calculate exposure of air pollution in-vehicles and outdoors, where the findings suggested that $PM_{2.5}$ and NO_2 exposure varies mainly with different travel modes (Smith et al., 2016). The evaluation of daily exposure in urban areas in Toronto, Canada showed that active commuters and transit riders are exposed the most (Shekarrizfard et al., 2020). It can be stated that the highest air pollution exposure to people is accounted for during the scenarios where more time is spent in traffic. A statistically significant increase in adverse impacts on people due to travel-related exposure was observed in terms of severe cardiopulmonary health and lung infections (Vilcassim et al., 2019).

Governments, institutes/organizations worldwide are taking steps to control the increasing air pollution. Advancements in vehicle and fuel technologies are primary contributors to such efforts. However, the improvements in urban air quality are insignificant. The deteriorating urban air quality and its harmful effects on human health influence lifestyle changes and travel choices. Travel choices that can help people reduce the harmful effects of air pollution on their health are primarily beneficial for travelers in urban areas. For making informed travel choices, information on various travel choices (e.g., routes, modes, departure times, etc.) are required, which varies based on parameters such as time of the day, travel time, exposure, emissions, congestion, etc. After the improvement in air quality, a significant shift from motorized to non-motorized vehicles as a choice of mode was observed from the revealed preference data in a Chinese city (Li and Kamargianni, 2017). Provision of information about greener (less polluted) routes to school children and the adults with them indicated a higher choice of switching to greener routes (Ahmed et al., 2020). With the rapid growth in the number of trips and time spent on the road, the need to include pollution parameters in the routing engine for various modes emanates. Current online route planning systems (e.g., Google Maps, Apple Maps, tom-tom maps, HERE Maps, etc.) lack in providing exposure-based routing systems or routes with least air pollution. These existing services provide routes based on historical location data or single constraints and do not consider user's requirements (Li et al., 2021). Recently, Google Maps introduced 'eco-friendly' routes, which will generate routes with the least carbon emissions and optimize the routes for lower fuel consumption; this is not the same as the least exposure route (Dicker, 2021).

The routing problem is one of the famous research problems, initially discussed as truck dispatching problem for identification of optimal route between a terminal and number of stations (Dantzig and Ramser, 1959). Optimal routes have been identified using traffic signs for urban flood constraint (Alizadeh et al., 2021). A clean air routing algorithm was developed to determine the shortest health-optimal route based on $PM_{2.5}$ at each intersection of road between origin and destination (Mahajan et al., 2019). The authors compared the traditional shortest route and health-optimal shortest routes and found the relationship between $PM_{2.5}$ exposure and trip length. Themis system of navigation based on current traffic data and future traffic distribution was used to provide route information to drivers in a balanced way (Liu et al., 2016). Themis is a plugin to calculate alternative routes based on travel time and real-time congestion. The unavailability of dynamic routing and a smaller number of participants in field study were the only constraints of the study by Liu et al. (2016). Usage of this system and selection of balanced routing reduced traffic congestion and average travel time at the city level in Beijing, China. Based on spatial monitoring data of NO_2, a web-based routing system was planned for cyclists in Montreal. Length and average traffic pollution on each segment of road between origin and destination were used as factors to determine shortest routes and low exposure routes (Hatzopoulou et al., 2013). It was observed that the cumulative exposure decreased by around 4%, and the predicted decrease in exposure was indicated with little increase in travel distance. NO_x optimized routes were developed using emission factors for diesel vehicles with the modified GraphHopper engine, and it was concluded that all the NO_x optimized routes had higher travel time compared to fastest routes (Engelmann et al., 2019). Along with prevailing navigation systems, an eco-routing system was developed based on the dynamic road network, emission data, routing engine for shortest path estimation, and user interface using Dijkstra algorithm to collect origin–destination data, and provide eco-routes. The most eco-friendly routes referred to least fuel consumption or minimum emissions in form of CO_2, CO, HC, and NO_x, and evaluation of the eco-routes observed 14% fuel-saving and 16% longer travel distances compared to fastest routes (Boriboonsomsin et al., 2012). A land use regression model was used to predict PM_{10} at route level in Dublin, and then the comparison of optimum route choices considering travel time, distance, cost, CO_2 emission, and air pollution doses revealed that travel distance and congestion were directly related with air pollution doses (Alam et al., 2018). Eco-friendly routes contribute to the reduction of fuel consumption and emissions, resulting in benefits to users and the environment. For optimal routing and decision frameworking of electric vehicles, the primal–dual interior-point algorithm was developed considering battery capacity and driveline efficiency of electric vehicles (Yi and Bauer, 2018). Eco-routes for which overall energy cost is minimum were identified through simulation, but no user-based decision-making experiment was conducted.

Most of the existing routing systems are focused on distance optimization (i.e., shortest by distance), travel time optimization (i.e., fastest), emission optimization (i.e., eco-friendly or green), etc., (e.g., Engelmann et al., 2019; Ahmed et al., 2020). For instance, a few routing engines accommodate the idea of cleaner routes but consider exhaust emissions and fuel consumption only (Boriboonsomsin et al., 2012; Alam et al., 2018; Bandeira et al., 2016; Hatzopoulou et al., 2013). Along with providing the shortest and fastest routes between a pair of origin and destination, routes with least exposure to air pollution are essential. As per the authors' best knowledge, only a few studies attempted to identify the routes with the least exposure (Zou et al., 2020; Sharker and Karimi, 2013). The studies have used historical data to identify the routes, which may not provide accurate real-time routes based on air pollution exposure. Dispensing only the routes with the least exhaust emissions or fuel-efficient routes to all users can cause congestion on initially calculated routes and increase emissions and pollutant concentrations. Those routes will need to be re-estimated if real-time data is not incorporated (Boriboonsomsin et al., 2012). Real-time data for congestion and air pollution can reflect the actual conditions of any urban area. None of the studies have explored the concept of balanced routes based on users' preferences. It is unlikely that a user/traveler would select either the fastest route or the route with the least adverse health effects due to air pollution. For this, firstly, the information should be provided in a user-friendly way, and the users should be willing to shift. The commuters are willing to update their travel choices provided alternative options are available for their travel (Meena et al., 2021). The present study addresses these limitations.

The objectives of the current study include integrating air pollution as an optimizing parameter in multi-modal route planning and providing route alternatives in the shortest, least exposed, fastest, and balanced scenarios. The novelty of this work is the Congestion and Air Pollution Exposure Integrated Router (CERo), which provides Least Exposure to Air Pollution (LEAP) and balanced routes. This study develops a route planning framework by integrating the real-time congestion patterns and air pollution levels in a multi-modal routing engine. This study uses GraphHopper,[1] which is an open-source, multi-modal routing engine. This work presents two case studies of Indian cities due to the ease of data availability. However, the framework is applicable to any other city across the world.

[1] https://github.com/graphhopper/graphhopper/releases/tag/4.0.

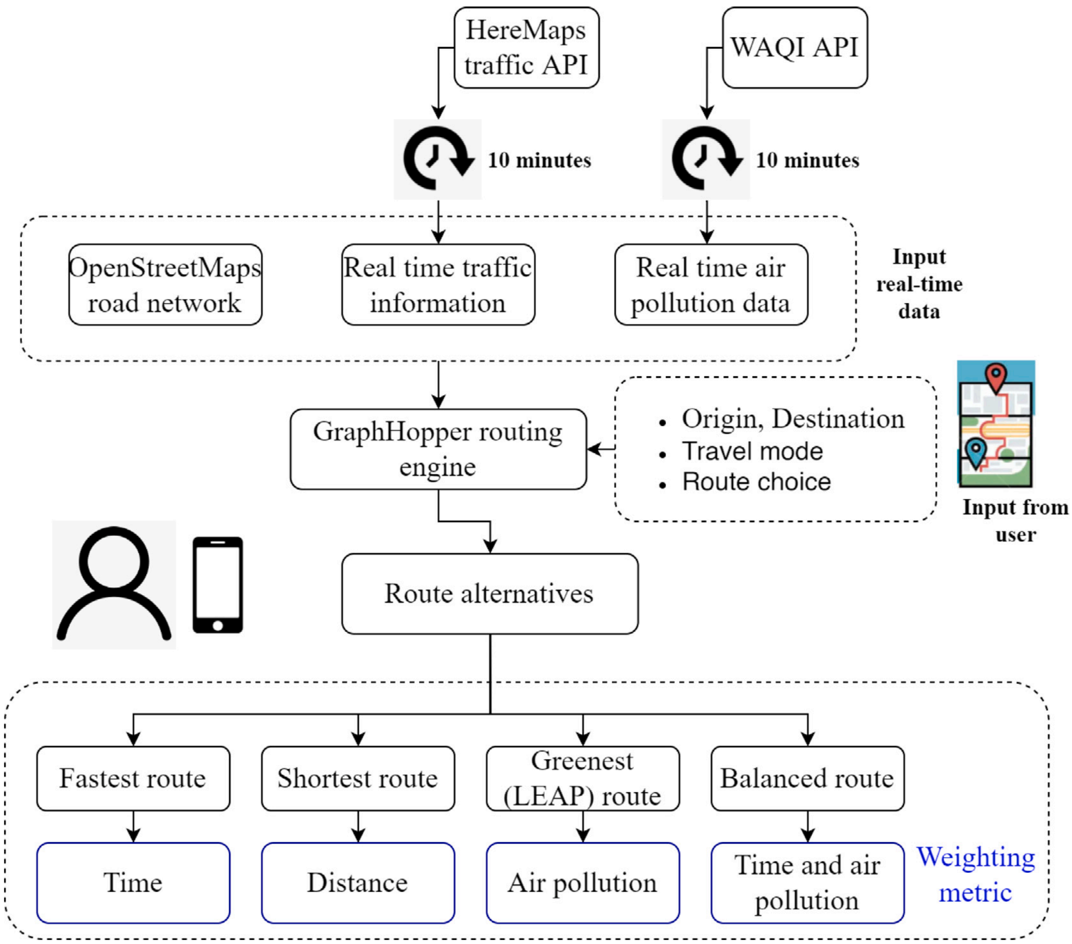


Fig. 1. Simplified schematic algorithm of congestion and air pollution exposure integrated routing system.

The rest of the paper consists as follows: The methodology is demonstrated in Section 2, where the data collected through APIs and GraphHopper engine are discussed. Section 3 exhibits the characteristics of the study area and documents the results. The findings are discussed in Section 4 and the study is concluded in Section 5.

2. Methodology

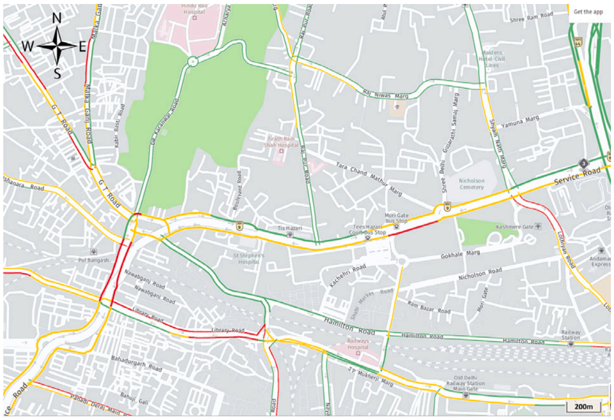
This work attempts to fuse the real-time congestion and air pollution in a multi-modal routing engine to identify the routes which have lesser exposure to air pollution (see Fig. 1). For this, a multi-modal routing engine by GraphHopper is used (see Section 2.1). Real-time congestion patterns are accessed using HERE Maps Traffic Flow API (see Section 2.2) and real-time air pollution data extraction process is explained in see Section 2.3. The integration of these with the routing engine is explained in Section 2.4. Finally, the route alternatives are explained in Section 2.5, and the routing engine and application programming interface (API) to determine these routes are explained in Section 2.6. To show the applicability of developed algorithm, ease in transferability is discussed in Section 2.7.

2.1. GraphHopper

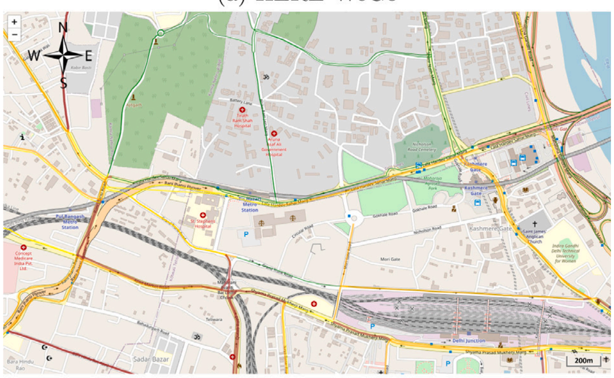
Overview:. GraphHopper[2] is an open-source, fast, memory-efficient routing engine. It supports and uses OpenStreetMap[3] (OSM) to form its underlying graph for the routing application. It can be integrated as a Java Library or a Standalone web server. The source code of GraphHopper is hosted at https://github.com/graphhopper/graphhopper. It is primarily a routing library but provides additional functionalities like map matching, route optimization, isochrone maps, etc.; however, not all of them are open-source. It is selected for the present study since it supports various routing algorithms, e.g., Dijkstra, AstarBi (A* Bi), and is configurable. By default, A* Bi (A* bi-directional) is used for routing in GraphHopper.

Mapping real-world data to edges: Though the use of road networks from OpenStreetMap allows it to get all relevant information associated with the graph's edge, additional efforts are required to integrate the real-world information to the edges (road links). The HERE Maps Traffic Flow API provides the traffic information on the roads (see Section 2.2), which is in terms of latitude longitude for each shape (e.g., a series of road segments) and characteristics of the shape. The mid-point of each segment is identified to integrate these characteristics with the roads in the graph. The traffic flow information of each segment is transferred to edge of the graph. For this, at first, the nearest edge in the graph is identified from the mid-point of each segment (typically a road) using a function in GraphHopper, which returns closet snap from latitude and longitude. This can also be achieved using Map Matching API by GraphHopper, which is not an open-source API. After identifying the closest snap (edge), the traffic flow information is assigned to the edge. A validation of this approach is shown in Fig. 2, in which the Traffic from HERE WeGo[4] is compared with the traffic data visualized on OSM

[2] See https://www.graphhopper.com/.
[3] See https://www.openstreetmap.org/.
[4] Visit https://wego.here.com/traffic.



(a) HERE WeGo



(b) Present Work (CERo)

Fig. 2. Comparison of traffic layers on HERE WeGo and OSM (present work). Note that the HERE weGo shows the traffic conditions depending on the network resolution level, which is not present in the present work.

layer as a part of this work. Clearly, traffic layer on OSM is in sync with the HERE WeGo.

2.2 Real-time congestion data

As described in Section 2.1, road segments, centroid of segment, and real-time traffic information are required to integrate the real-time congestion pattern in the routing. Though any source can be integrated which fetches continuous data using APIs, this study uses HERE Maps Traffic Flow API.[5] HERE Maps provides 250,000 queries every month under the 'Freemium' subscription model. The GraphHopper routing engine can provide shortest route (least distance), fastest (least time), and a few other variants.

Real-time traffic flow (in terms of travel time, travel speed) is required to identify the fastest routes. HERE Maps Traffic Flow API provides various segments (i.e., latitude, longitude) of a road (the geometry of roads) and their attributes. The important attributes are confidence number (CN), functional classes (fc), average speed (su), etc. The former varies between 0 to 1, and if a road has a higher confidence number (≥0.7), it is only considered in the present study. The functional classes specifies types of roads based on traffic volume and speed.[6] In this study, high volume, high/moderate speed roads are used and corresponding values are $1 \leq fc \leq 4$. The average speeds are used in the routing and are associated with the edges of the graph prepared from OSM. The free flow speed on those edges was used where real-time average speed from HERE maps was missing.

2.3 Real-time air pollution data

Degrading air quality in urban areas is becoming a major concern. Consequently, monitoring and mitigating measures are being persuaded. The idea behind the proposal to include the air pollution information in the routing is to give users a chance to shift to a lesser exposed route. Typically, users consider only fastest path to their destination. It is shown that users may opt for least exposed routes, if information is available to them (Meena et al., 2021). Hence, this work introduces air pollution exposure to the routing.

Air quality data is collected from the world air quality index (WAQI). WAQI collects the data from various sources and distributes it using API. The data obtained from WAQI is limited due to fewer static monitors in Delhi (see Fig. 4(b)). However, it is a placeholder, and other sources can be integrated, supporting continuous data fetching using APIs. Though air pollution exposure during travel depends on various factors (Singh et al., 2021), two important factors are exposure duration and concentration of pollutants. For different travel modes, exhale/inhale rates can play a significant role, especially for active modes of transport. Exposure duration and pollutant concentration on each road are required to identify the exposure for different routes. Since the exposure duration is same as travel time, the former can be determined using the same approach as depicted in Section 2.2.

For air quality data at street level (i.e., for every edge in a route), the inverse distance weighting (IDW) method is used to obtain the value at street level based on the measurements from the monitoring stations. Among IDW and Kriging interpolation methods, IDW performs better spatial interpolation for pollutant concentrations (Mittal et al., 2022). IDW provides a quick calculation for the interpolated concentration of pollutants at any point based on the distances from the nearby monitoring stations. For a better estimate, the interpolation data can be replaced with the data from a dynamic air pollution monitoring network (see, Choudhary and Agarwal, 2021; Mittal et al., 2022, for a possible example and use case of dynamic monitoring network). In this study, WAQI API is used, which provides only Air Quality Index (AQI), which is estimated as shown in Eq. (1) (EPA, 1999).

$$AQI = \frac{(I_{bh} - I_{bl})}{(C_{bh} - C_{bl})} * (C - C_{bl}) + I_{bl} \tag{1}$$

where, C is the ambient pollutant concentration, C_{bl} is the break-point concentration less than or equal to C, C_{bh} is the break-point concentration higher or equal to C, I_{bl} and I_{bh} are indices relative to C_{bl} and C_{bh}, respectively. However, for estimation of air pollution exposure, concentration of a pollutant are required, which are estimated using Eq. (2).

$$C = \frac{(AQI - I_{bl})}{(I_{bh} - I_{bl})} \cdot (C_{bh} - C_{bl}) + C_{bl} \tag{2}$$

Hence, the concentration value for an edge is an average of concentration at the start and end of the edge. PM2.5 pollutant type is considered in this study for all the break-point concentrations and relative indices. Further, the exposure duration is estimated using average speed and distance obtained from the HERE Maps Traffic Flow API (see Section 2.2). In this study, AQI data is updated every 10 min.

2.4 Integration of real-time data to routing engine

By default, in GraphHopper routing engine, distance or travel time between origin and destination are used to define the cost function for an edge for shortest and fastest routes. Speeds are taken from HERE maps to estimate the travel time on the edges. The real-time traffic flow, pollutant concentration values and both are associated with an edge and considered for routing process. This study considers the four

[5] Visit https://developer.here.com/documentation/traffic/dev_guide/topics/what-is.html.

[6] See https://developer.here.com/documentation/routing/dev_guide/topics/resource-type-functional-class.html.

different route options; they are shortest, fastest, LEAP, and balanced (see Section 2.5 for details about the routes). The integration of real-time air pollution exposure and congestion pattern is performed to show the influence on the availability of alternative routes as per users' requirements (i.e., fastest-to-low exposure routes) As the real-time data is updated continuously (e.g., every 10 min), it will provide an actual scenario of congestion on roads and the exposure during travel.

2.5 Determination of alternative routes

This study accesses the GraphHopper storage graph to modify the default edge weight for the possible inclusion of real-time traffic and air pollution data. Edge weights are essential in the developed application so that the custom weights can be included in the back-end routing of the GraphHopper routing engine. This capability to configure GraphHopper routing engine makes it suitable for the present work. Custom weighting is exploited for the three route alternatives in routing applications to provide the LEAP (least exposure to air pollution), fastest, or balanced routes. Though the shortest paths are also included, default routing parameters (i.e., distance) is used in this case. The routing algorithms used the A* bi algorithm to calculate a route based on given constraints or edge weights. Various routes are explained in the following sections.

2.5.1 Fastest route

Typically, fastest route is determined primarily based on the travel time required to reach from origin to destination. This study uses the speeds on the roads from HERE Maps Traffic Flow API, and the same are set to each edge of the graph, which is used to estimate the travel time required to cover each edge distance. As shown in Eq. (3), edge distance, d is taken from OSM graph and speed, v is extracted from real-time HERE maps data.

$$c = t_t = \frac{d}{v} \tag{3}$$

where, t_t is the travel time with penalties such as heading penalty, maximum speed penalty, access-egress penalties etc. Thus, the edge weight is a function of real-time congestion pattern. The boolean reverse variable identifies the direction as the fetched edge speeds can be different in opposite directions.

2.5.2 Shortest route

As shown in Eq. (4), the calculation for the shortest route is based only on the edge distances, i.e., edge cost is edge distance (d). The GraphHopper router uses the edge distance as the weight of the edge in the shortest route weighting. Real-time traffic patterns are not considered for the shortest route alternative.

$$c = d \tag{4}$$

2.5.3 LEAP route

This section explains the process to get the Least Exposure to Air Pollution (LEAP) route.[7] The exposure to air pollution is defined as product of exposed duration and concentration of pollutants. As explained in Section 2.3, the air pollution concentration is estimated and interpolated for each edge in the graph. The concentration is important because algebraic sum of air quality indices cannot be performed to determine the least cost path. The exposed duration on edge is equivalent to travel time on the edge. Thus, the real-time travel time is extracted by diving the edge distance (d) with real-time speeds (v') obtained using HERE Maps Flow API (see Section 2.2) to get the exposed duration. The travel time is considered through a time encoder, not including the penalties used in the fastest route estimation.

$$c = e \cdot t = e \cdot \frac{d}{v'} \tag{5}$$

The product of the air pollution concentration (e) and travel time provides intensity of air pollution exposure, which is linked to the weight of the edge to be considered in the LEAP routes (see Eq. (5)). The air pollution exposure of different edges can be summed to determine the total exposure.

2.5.4 Balanced route

A middle ground is identified between the LEAP and fastest routes to balance travel time to destination and air pollution exposure on the way through the balanced routes. This is closer to estimating the path cost than simply considering only distance or travel time for path cost. Clearly, a balanced route will vary from person to person, depending on the valuation of each of air pollution exposure and travel time. Therefore, this study uses two balancing factors, i.e., time factor (unit less) and pollution factor ($1/\mu g/m^3$ h). The latter factor also cares about the conversion of air pollution exposure to time (or money units or utility). The range for time and pollution factors varies from 0 to 1. Together, a single factor can also be used to convert air pollution exposure ($\mu g/m^3$ h) into time units. Further, a single factor can be made configurable in the application portal so that users can adjust it and get the routes accordingly.

$$c = \frac{d}{v} \cdot f_t + e \cdot \frac{d}{v'} \cdot f_p \tag{6}$$

As shown in Eq. (6), in this approach, the cost function of an edge becomes sum of product of time cost and time factor (f_t) and product of air pollution exposure (i.e., product of concentration of exposure duration) and pollution factor (f_p).

2.6 CERo system and API

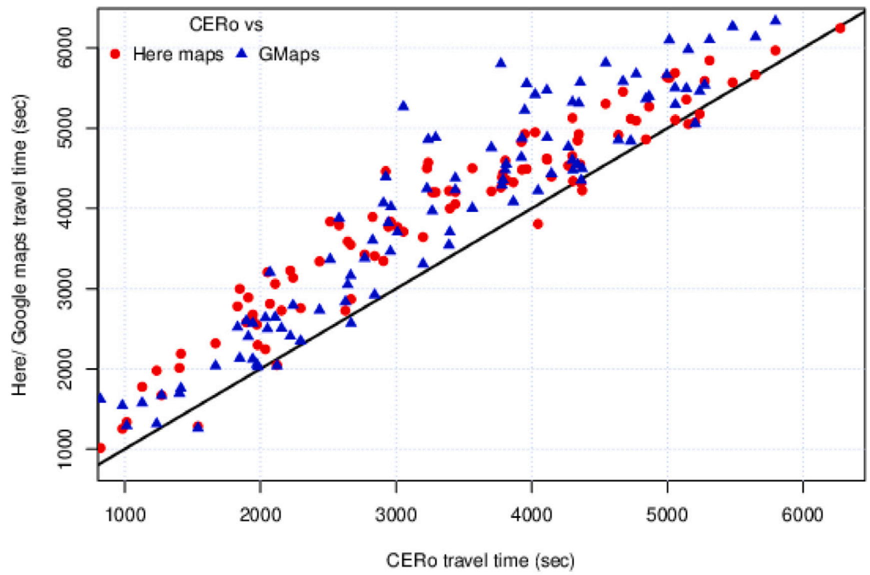
The integrated repo of Congestion and Air Pollution Exposure Integrated Router (CERo) is publicly available at https://github.com/teg-iitr/congestion-emission-routing-system. In addition to a minimalistic, yet simplified web interface, an API is also developed to feed the data directly to the scripts. For this, "mediaType = json" is concatenated at the end of the url, i.e., the details of the routes will be shown in JSON file format.

A comparison of the travel time and distance for 100 random origin–destination pairs in Delhi is shown in Fig. 3. On the x-axis, travel time/distance from CERo (the present study) and on y-axis, travel time from HERE Maps, Google Maps are shown. To get the travel time/distance from HERE Maps, HERE routing API v7[8] is used, whereas to get the travel time/distance from Google Maps, Google Direction API[9] is used. The comparison indicates that CERo system reports slightly lesser travel time than HERE and Google maps. This is a known issue and is present for the routes without real-time congestion patterns. The possible reasons are (a) turn costs are not considered (i.e., deceleration, acceleration at turns), which makes vehicles faster (b) missing max speed tags, (c) method to snap the nearest road from latitude, longitude, etc. On the other hand, the travel distances from Google Maps and Here Maps are in sync with the CERo (see Fig. 3(b)). Since the underestimation of travel time will occur on all routes, it is less likely to affect the comparison among the choices for fastest and LEAP routes. Hence, for the present study, this is considered acceptable.

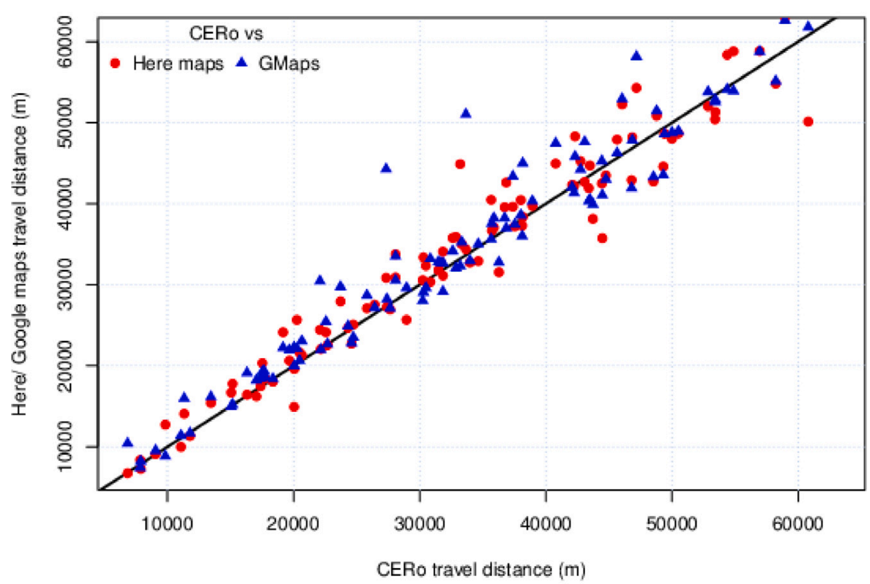
[7] A LEAP route is not the same as the green or eco-friendly routes, which are indicators of least exhaust emissions or fuel consumption.

[8] See https://developer.here.com/documentation/routing/dev_guide/topics/introduction.html.

[9] See https://developers.google.com/maps/documentation/directions/overview.



(a) Comparison of travel times



(b) Comparison of travel distances

Fig. 3. Travel time and distance comparison of 100 origin–destination pairs in Delhi. The data is collected using HERE Maps routing API, Google Maps Direction API and CERo API (i.e., present work) on February 17, 2022.

2.7 Ease in transferability

The whole framework is designed in a way that approach is applicable to any other scenario. Firstly, an OSM file is required to compute the routes using GraphHopper engine. The OSM files are available for all cities across the world. The CERo system directly considers real-time congestion and air pollution data using external APIs that needs a bounding box to identify the region. A rectangular bounding box is defined using lower-left and upper-right coordinates. These coordinates must be inside the OSM file to find the routes. For instance, to get the congestion patterns from HereMaps API, following URL is used:

```
https://traffic.ls.hereapi.com/traffic/6.2/flow
.xml?apiKey= + apiKey + &bbox= + boundingBox.minLat
+ "," + boundingBox.minLon + ";" + boundingBox.maxLat
+"," + boundingBox.maxLon + &responseattributes=
sh,fc&units=metric
```

Here, the API key is the secure key to access the portal and can be obtained by creating a freemium account in HEREmaps. The response attributes ‘sh’ represents shape and ‘fc’ represents functional classes. The former will push the lat, long in the output and the latter will provide the types of roads. Using this url, the average speed on each edge is collected in this study.

Table 1
Comparison of different routes shown in Fig. 5 from CERo system. The numbers are showing trip distance, travel time and exposure to air pollution respectively.

Route	Car	Motorbike	Bicycle	Foot
Fastest	11.14 km, 18.4 min, 97.67 $\mu g/m^3$ h	11.12 km, 6.57 min, 59.67 $\mu g/m^3$ h	11.06 km, 27.3 min, 84.67 $\mu g/m^3$ h	10.08 km, 44.15 min, 58.83 $\mu g/m^3$ h
Shortest	10.34 km, 20.9 min, 44.67 $\mu g/m^3$ h	10.34 km, 8.18 min, 44.67 $\mu g/m^3$ h	10.5 km, 26.84 min, 44.67 $\mu g/m^3$ h	9.26 km, 65 min, 42.5 $\mu g/m^3$ h
LEAP	17.5 km, 32.7 min, 21.17 $\mu g/m^3$ h	17.5 km, 12.06 min, 21.17 $\mu g/m^3$ h	17.5 km, 43.5 min, 21.17 $\mu g/m^3$ h	17.02 km, 100 min, 10.17 $\mu g/m^3$ h
Balanced	13.19 km, 25.32 min, 27.83 $\mu g/m^3$ h	18.32 km, 12.34 min, 25.17 $\mu g/m^3$ h	13.32 km, 33.97 min, 30.67 $\mu g/m^3$ h	11.23 km, 60 min, 34.17 $\mu g/m^3$ h

WAQI API is used for air pollution, which can be replaced with any other API having pollutant concentration values from static monitors or mobile monitoring networks. For WAQI API, following url is used:

```
https://api.waqi.info/v2/map/bounds/?latlng=
+ bounds + &token= + token
```

Similar to the API for HereMaps, the WAQI API key is stored in form of token, and the bounds include the bounding box of an area. In both of these external APIs, any area's bounding box can be fed with other information to change the study area and to check the applicability of the proposed framework for any area.

3 Case studies

Two Indian cities, Delhi and Bangalore, are explored in the paper to show the application of the routing system in urban areas where real-time congestion and air pollution data are available.

3.1 Delhi, India

The routing engine proposed in the current study is applied to Delhi, India. With urbanization and increasing population, traffic congestion is also increasing in Delhi, which leads to higher air pollution exposure to citizens. Fig. 4(a) shows the real-time traffic data in Delhi, India. Delhi has the maximum number of air pollution monitors at the city level in India. The real-time continuous air pollution data is available from around 30 air pollution monitors located across the city. Fig. 4(b) shows the location of static air pollution monitors for which the data is available on World Air Quality Index.[10]

The results showed that the distances for LEAP routes are longer compared to the fastest, shortest and balanced routes if alternative routes are possible between given origin–destination. For car, motorbike, bicycle and pedestrian, Table 1 show the fastest, shortest, LEAP, and balanced routes from the School of Planning and architecture, Delhi, to Sarojini Nagar, Delhi. The time and pollution factors are taken as 0.5 for the current study, indicating a traveler's equal preference for travel time and air pollution exposure. It can be observed that the LEAP route takes longer time compared to the fastest route, whereas the balanced route is somewhere in between the fastest and LEAP. These results are based on the data fetched on April 2nd, 2022 at 16:00, for four alternative travel modes.

While comparing the routes provided for different modes in both LEAP and balanced scenarios, Fig. 5 shows that pedestrian routes are longer compared to routes for car. Since travel choices depend on several static and dynamic characteristics, shortest, fastest, LEAP, and balanced routes may be different in different study scenarios. It was observed that the exposure reduction for different modes on a particular route ranged from 42.73% to 71.50% for fastest to balanced routes and 64.52% to 82.71% for fastest to LEAP routes. For now, car, motorcycle, bike (bicycle) and pedestrian (foot) modes are supported. Fig. 6 shows different route alternative for car as travel mode between Indira Vihar to Sarojini Nagar, Delhi. This also confirms that the balanced routes are in between fastest and LEAP routes in terms of travel time to destination and the air pollution exposure. The real-time congestion pattern and air pollution information are fetched at a given interval. This application framework uses an aggregated index for pollutant concentrations which gives an idea of overall air quality on the routes. The damages to the health for the travelers are not explored in the present study, which can be performed by including the inhalation rates for drivers/riders/travelers.

3.2 Bangalore, India

The proposed routing algorithm is applied to Bangalore, a mega city in Southern India, to make the proposed routing algorithm more reliable and transferable to other cities. The urban area of Bangalore is 850 km^2 which has 10 air quality monitoring stations as shown in Fig. 7. In the last few years, the air quality has been deteriorating in Bangalore due to increased traffic congestion and the number of motorized vehicles.

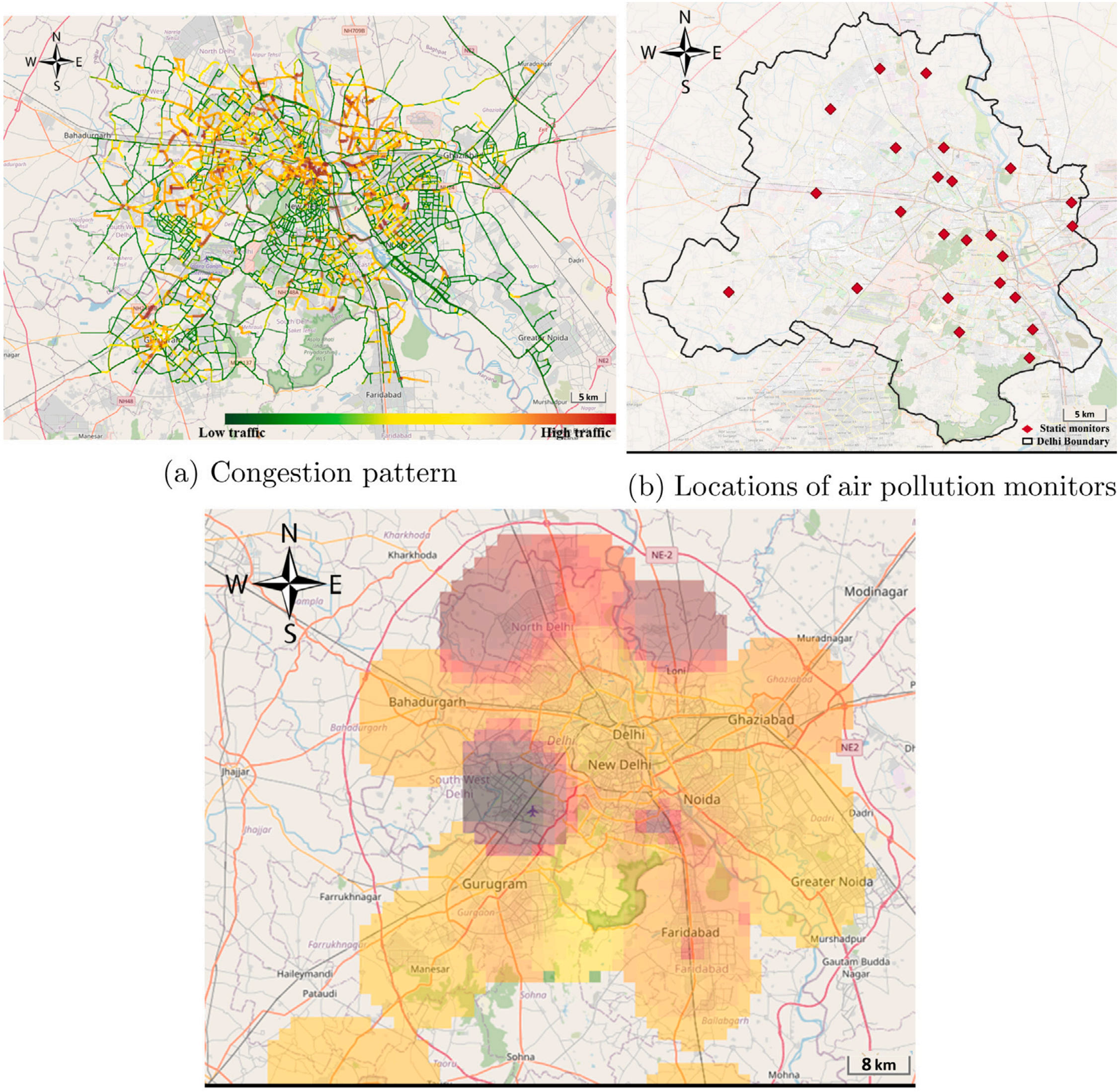
The Fig. 8 shows the route alternatives ad related details of the routes between ISRO, Bangalore, and Jagjeevanram hospital, Bangalore. The data was fetched on July 22nd, 2022. For the balanced routes, pollution and time factors are considered as 0.5, giving equal preference to lower travel time and air pollution exposure for the travelers. The results show that balanced routes have exposure levels and travel time between the ranges of LEAP and the fastest routes. Due to the rainy season and better local environment compared to Delhi, the exposure levels are lower than Delhi for a similar distance.

Table 2 shows that exposure in the car is lowest for the fastest route alternative among all other modes. The exposure in the fastest and shortest routes is almost 10 times that in LEAP routes. The exposure level is lowest for pedestrians compared to other travel modes, but it does not seem a feasible distance for a pedestrian. While among motorized vehicles, the exposure is the same. The shortest routes are based on distance, and due to heavy traffic on the shortest routes, the travel time is high, leading to high exposure. It was observed that the exposure reduction for different modes on a particular route in Bangalore ranged from 82.08% to 96.7% for fastest to balanced routes and 91.3% to 98.0% for fastest to LEAP routes.

4 Discussion

Generally, the exposure to air pollution on a route can increase with travel time and with higher ambient air pollution (Singh et al., 2021). The exhaust air pollution will increase with distance and travel time, which in turn also increase the ambient air pollution, implicitly. In this study, a framework is proposed to determine alternative routes based on shortest distance, lowest travel time, least exposure to air pollution, and balance between time and exposure. Clearly, if congestion is higher, it will reflect in both exposure duration (same as travel time) and ambient air pollution. The framework is applied for two case

[10] https://aqicn.org/data-platform/.



(a) Congestion pattern

(b) Locations of air pollution monitors

(c) Spatial map of air quality index (AQI)

Fig. 4. Study area: Delhi, India. Spatial maps showing congestion and Air pollution patterns in Delhi on February 15, 2022 at 11:00 am.

Table 2
Comparison of different routes shown in Fig. 8 from CERo system. The numbers are showing trip distance, travel time and exposure to air pollution respectively.

Route	Car	Motorbike	Bicycle	Foot
Fastest	10.76 km, 19.21 min, 23 μg/m^3 h	13.54 km, 8.33 min, 42 μg/m^3 h	10.88 km, 36.02 min, 24 μg/m^3 h	12.1 km, 59.58 min, 52 μg/m^3 h
Shortest	10.41 km, 23.63 min, 30 μg/m^3 h	10.41 km, 19.07 min, 29 μg/m^3 h	10.41 km, 34.92 min, 29 μg/m^3 h	10.24 km, 96 min, 33 μg/m^3 h
LEAP	12.11 km, 30.65 min, 2 μg/m^3 h	12.09 km, 14.7 min, 2 μg/m^3 h	14.41 km, 53.08 min, 1.6 μg/m^3 h	14.89 km, 102.2 min, 1 μg/m^3 h
Balanced	13.54 km, 26.55 min, 4 μg/m^3 h	13.01 km, 13.97 min, 2.2 μg/m^3 h	13.7 km, 44.76 min, 1.9 μg/m^3 h	13.12 km, 99 min, 1.7 μg/m^3 h

studies of Delhi and Bangalore. It was observed for multiple sets of origin–destination that the LEAP routes are longer than other routes, and the balanced routes give exposure between the LEAP and fastest, which can be helpful for the residents to escape the adverse effects on health.

Though this study, at this stage, does not estimate and provide the direct health damages for the users, it will be helpful for the users in making the decisions about the trip to prevent the possible damages. The amount of pollutants concentration inhaled can be estimated using exposure, type of pollutant, and the inhalation rate of a particular person. Inhalation/exhalation rates can also be considered to determine the effects on health due to exposure during travel, which will be critical for cyclists or pedestrians. Exposure to particulate matter and gaseous pollutants during travel and traffic-related pollution has shown changes in cardiopulmonary functions, lung capacity, and respiratory functions in young people (Vilcassim et al., 2019; Brunekreef et al., 2009).

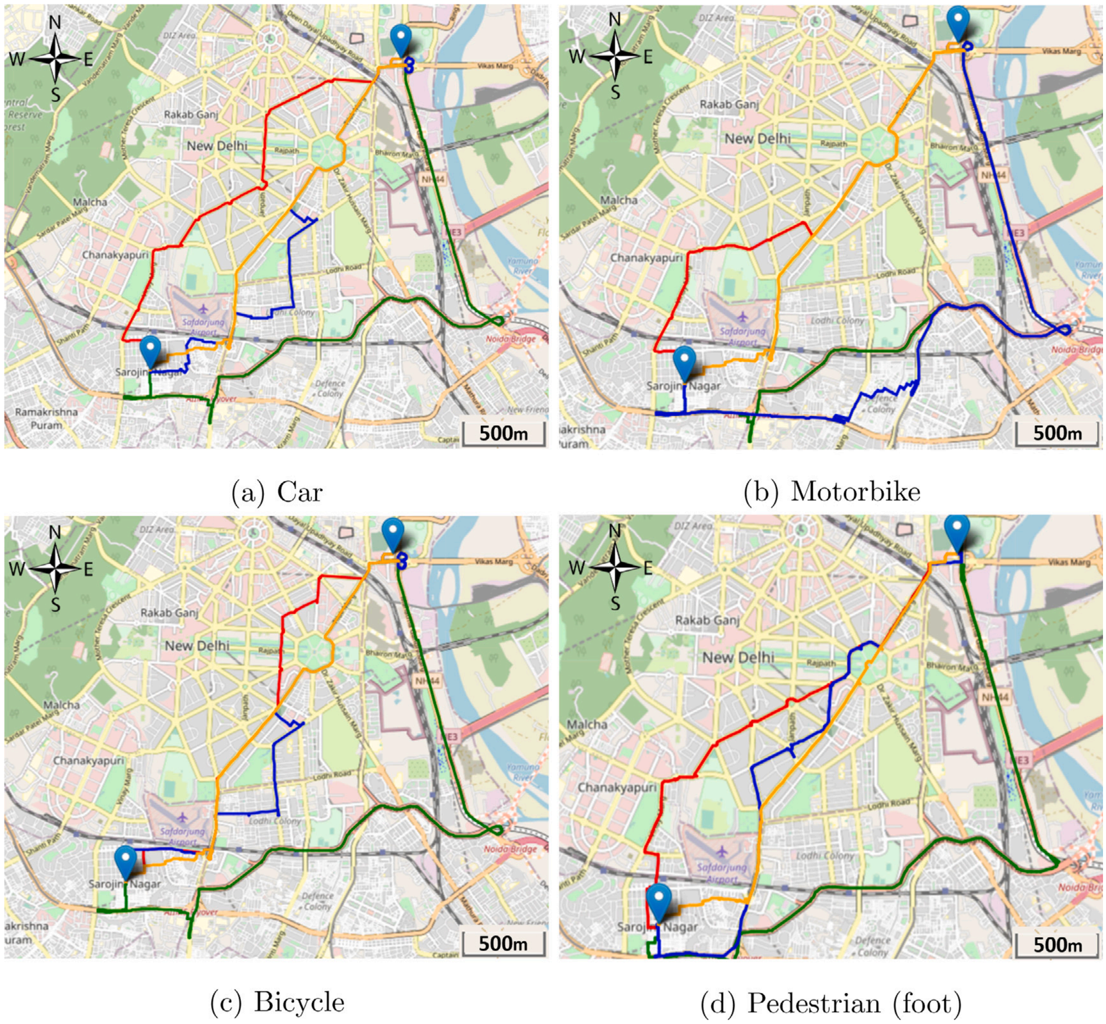


Fig. 5. Route alternatives for car, motorbike, bicycle and foot/pedestrian modes from School of planning and architecture, Delhi to Sarojini Nagar, Delhi. The colors are representative as Red: fastest, Orange: shortest, Green: LEAP, and Blue: balanced route.

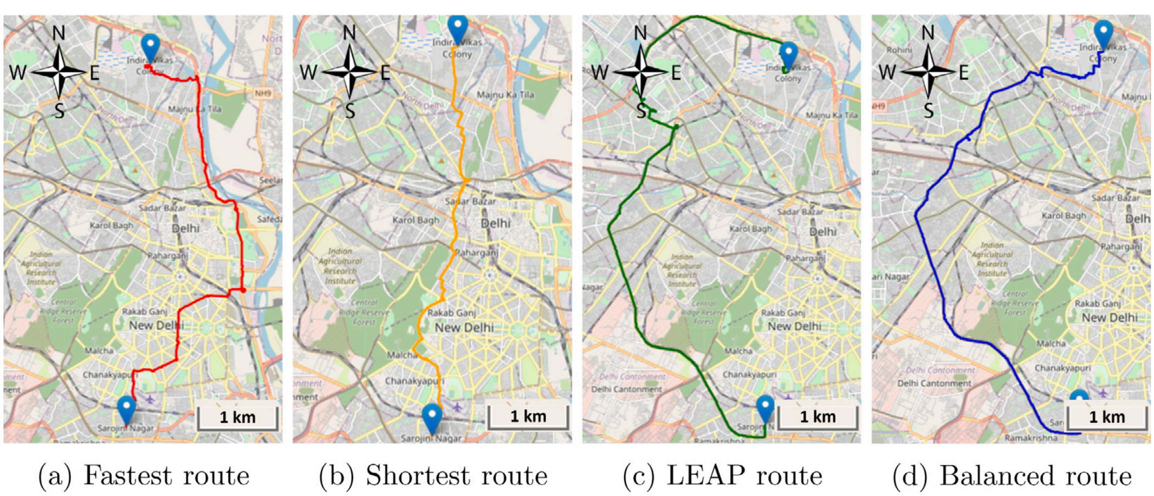
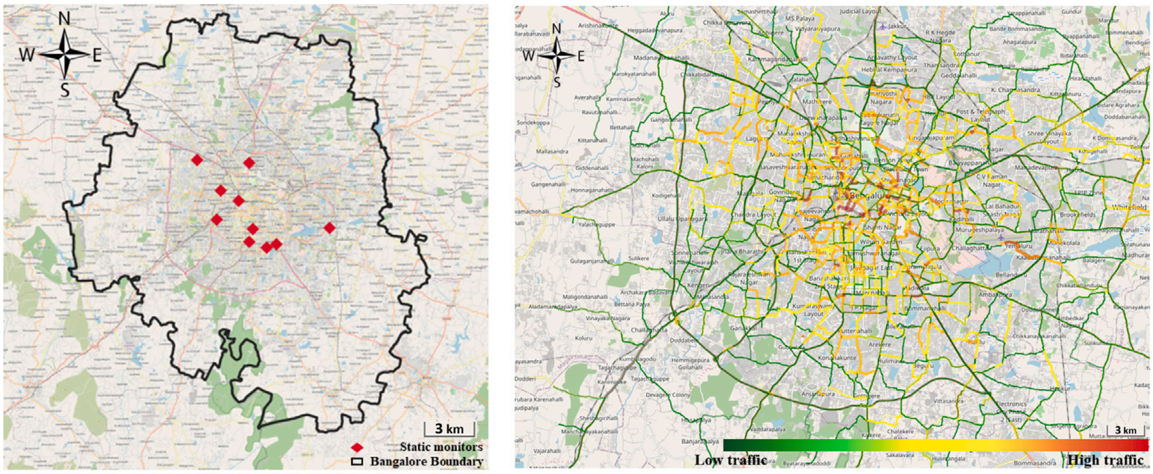


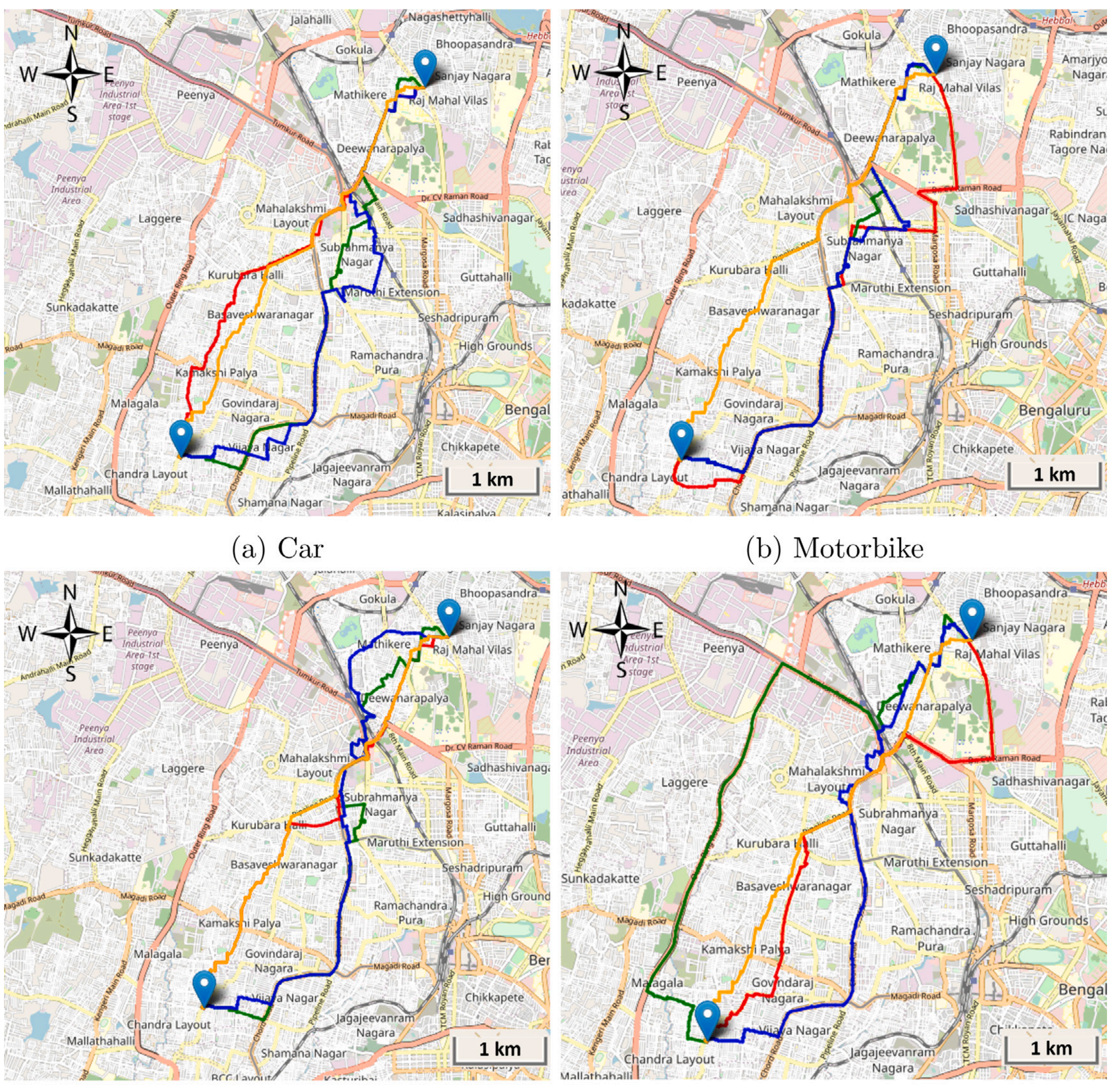
Fig. 6. Different routes for car as travel mode from Indira Vihar to Sarojini Nagar, Delhi.

Using LEAP routes can lead to a low impact on health, but these are generally of longer distances than the fastest and shortest routes; therefore, users may ignore these. The balanced routes are provided based on the travel time and exposure as constraints for route selection to overcome this. The weights of these two parameters can be adjusted using balancing factors based on the conditions, such as trends in pollutant concentrations and travelers' preferences. In practice, the priority of time or exposure depends on the travelers. A traveler may have different priorities for different trip purposes. Thus, it can be



(a) Location of air pollution monitors (b) Congestion pattern

Fig. 7. Study area: Bangalore, India. Spatial map showing congestion pattern in Bangalore on July 15, 2022 at 11:00 am.



(a) Car (b) Motorbike

(c) Bicycle (d) Pedestrian (foot)

Fig. 8. Route alternatives for car, motorbike, bicycle and foot/pedestrian modes from ISRO, Bangalore to Jagjeevanram hospital, Bangalore. The colors are representative as Red: fastest, Orange: shortest, Green: LEAP, and Blue: balanced route.

configurable so that the user can enter the priorities between the two (time and exposure) and get the desired alternatives.

One of the limitations of this study includes the underestimation of travel time in GraphHopper maps (see Fig. 3). This means the travel times are marginally underestimated in the proposed framework and, thus, the exposure values. The GraphHopper routing engine underestimates the travel time because it does not consider traffic lights, crossings, and max speed tags and takes the speed limit on edges as the actual speed. Acceleration/deceleration rates can be added on edges, or other routing engines can be employed to overcome this in the future.

Another limitation lies in updating data from APIs, for which the current frequency is set at 10 min. In other words, the actual congestion patterns and air pollution conditions may change during these 10 min. In the proposed framework, the frequency can be increased for fetching the data from the source provided the data is available for congestion as well as for air pollution. From the previous trends of air pollution concentration, as shown by Mittal et al. (2022), the pollution does not change suddenly unless any unexpected event occurs, such as a fire, blast, etc. Therefore, the frequency for data updating in case of air pollution data can be kept the same in the future to save computational resources.

The spatial interpolation technique is used in this study to estimate the pollutant concentration at the street level using the data from static monitors located sparsely over the city. As static monitors are few considering the city area in India, the dynamic monitoring networks can be beneficial in obtaining high spatial resolution data. Even in dynamic monitoring, spatial interpolation may be required to obtain the data at the street level, but any interpolation technique can provide good results with a higher number of data points. In areas where dynamic monitoring networks are not available or feasible, improved interpolation techniques such as artificial neural networks, neural graph networks etc., can be used. The pollutant concentrations in the current study are obtained by using the air quality index, breakpoint concentrations, and relative indices. If the data for pollutant concentrations are directly available, that should be preferred over the conversion, as that will provide direct observation and actual data on the ground.

5 Conclusions

Increasing air pollution and its harmful impacts on human health and the environment leads to the need for research on how exposure to air pollution can be reduced. In the Indian scenario, air pollution is causing a significant amount of health issues and deaths. As maximum exposure is observed while traveling, changing travel choices can help reduce the exposure. Information about exposure on available alternative routes is required for informed travel choices. In this work, a multi-modal routing engine is developed using GraphHopper routing engine based on OSM, air quality data, and real-time traffic congestion data. The available alternative modes include car, motorbike, bicycle, and pedestrian, and the facilitated route choices are fastest, shortest, LEAP, and balanced routes.

The proposed framework can give routing results quickly, and the interface is user-friendly and intuitive. With this initiative, residents of a city could reduce their exposure to air pollution. Furthermore, instead of aggregated pollutant concentration, specific pollutants with a higher concentration on roads can be considered for route planning. The flexible and adaptable nature of GraphHopper API can help easily change various parameters to identify best route planning approach. The results are true for another case study (Bangalore city) also, therefore, the proposed framework is transferable to any other city given the traffic data and air pollution data is available. In the future, the authors would like to replace the interpolated air pollution data (using IDW) with the data fetched from the dynamic monitoring network (Mittal et al., 2022), which is likely to provide better estimates for the LEAP and balanced routes. The proposed framework can also be used for experimental design to study the route and mode choice, incorporating air pollution exposure's effects on travel choices.

CRediT authorship contribution statement

Rashmi Choudhary: Conception and design of study, Literature review, Algorithm and model development, Analysis and interpretation of results, Draft manuscript preparation. **Siftee Ratra:** Algorithm and model development. **Amit Agarwal:** Conception and design of study, Literature review, Algorithm and model development, Analysis and interpretation of results, Draft manuscript preparation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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