Connected Emission Control Technologies for Freight Vehicles

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16. Abstract

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About the Pacific Southwest Region University Transportation Center

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The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

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Disclosure

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Abstract

This project explores how connected vehicle technology can be used to reduce the impacts of air pollutant emissions from freight vehicles. Specifically, the objective of this project is to develop new vehicle routing algorithms for determining travel routes for heavy-duty diesel trucks that would reduce the exposure of local residents to air pollutant emissions from these trucks. The core of the methodology is to first estimate the total amount of human exposure to pollutant emissions generated by a truck when that truck travels on a particular road segment. Once this is performed for all road segments, the estimated exposure value can be used in a least cost path algorithm to find a travel route that would minimize the total exposure value for the trip. To evaluate the potential benefits of this air pollution mitigation strategy, simulation-based experiments were carried out using the Reseda-Northridge area of Southern California as a case study. Overall, it was found that as compared to the fastest route, the low exposure route could result in more than 30% reduction in total air pollutant exposure for about 40% of the 400 simulated trips while keeping the increase in trip travel time to no more than 10%.

Connected Emission Control Technologies for Freight Vehicles

Executive Summary

Heavy-duty diesel trucks are significant contributors of nitrogen oxides and particulate matter emissions. As a result, areas with a lot of truck traffic often experience elevated levels of diesel-related air pollution. There has been increasing awareness of this environmental justice issue, which has led to the designation of disadvantaged communities in California. At the same time, the emerging connected vehicle (CV) technology, which enables communication between vehicles and infrastructure as well as among vehicles, has led to innovative applications that promise to improve safety, mobility, and sustainability of future transportation systems. To date, there has been much less attention on utilizing CV technology to reduce criteria air pollutant emissions from vehicles, particularly from freight vehicles. New CV applications can be developed to influence the travel routes of freight vehicles in a way that reduces the impact of air pollutant emissions from these vehicles on local residents, especially those living near roadways.

This project explores how CV technology can be used to reduce the impacts of air pollutant emissions from freight vehicles. Specifically, the objective of this project is to develop new vehicle routing algorithms for determining travel routes for heavy-duty diesel trucks (HDDTs) that would reduce the exposure of local residents to air pollutant emissions from these trucks.

The core of the methodology is to first estimate the total amount of human exposure to pollutant emissions generated by a truck when that truck travels on a particular road segment. Once the estimation is performed for all road segments in a city, the estimated exposure value can be used as the cost in a least cost path algorithm (e.g., Dijkstra's algorithm) to find a travel route that would minimize the total exposure value for the trip. The total exposure value represents how much pollutant generated by the truck is inhaled by local residents. It depends on a number of factors such as how much pollutant is emitted from the truck, how far the pollutant is blown away from the road and in which direction, and how many people live/work/play near that road. The estimation of this value involves a modeling chain that goes from traffic activity to emissions production, to air pollutant dispersion, and finally to human exposure.

To evaluate the potential benefits of this air pollution mitigation strategy, simulation-based experiments were carried out using the Reseda-Northridge area of Southern California as a case study. The area has a road network with a variety of road types (freeways, arterials, collectors, etc.). It also has densely-populated communities with a large fraction of children and seniors who are more sensitive to air pollution. Additionally, several parks, stores, daycare facilities, primary schools, senior centers, and hospitals in this area are located near the roadways. In the evaluation, we simulated 400 different trips traveling from one side of the area to the other

sides. For each trip, we determined the fastest route, and also applied the developed algorithm to find the low exposure route. Then, we calculated the differences in travel time, total exposure to fine particulate matter (PM2.5), and total exposure to reactive organic gases (ROG) between the two routes.

As an example, when comparing the low exposure route to the fastest route of one trip, the travel time would increase by 3% (~40 seconds) while the total mass of PM2.5 and ROG inhaled by residents in the area would be reduced by 87% and 76%, respectively. This suggests that with a small increase in travel time, the truck taking the low exposure route for this trip instead of the fastest route could lead to a significant reduction in the amount of air pollutant inhaled by the residents.

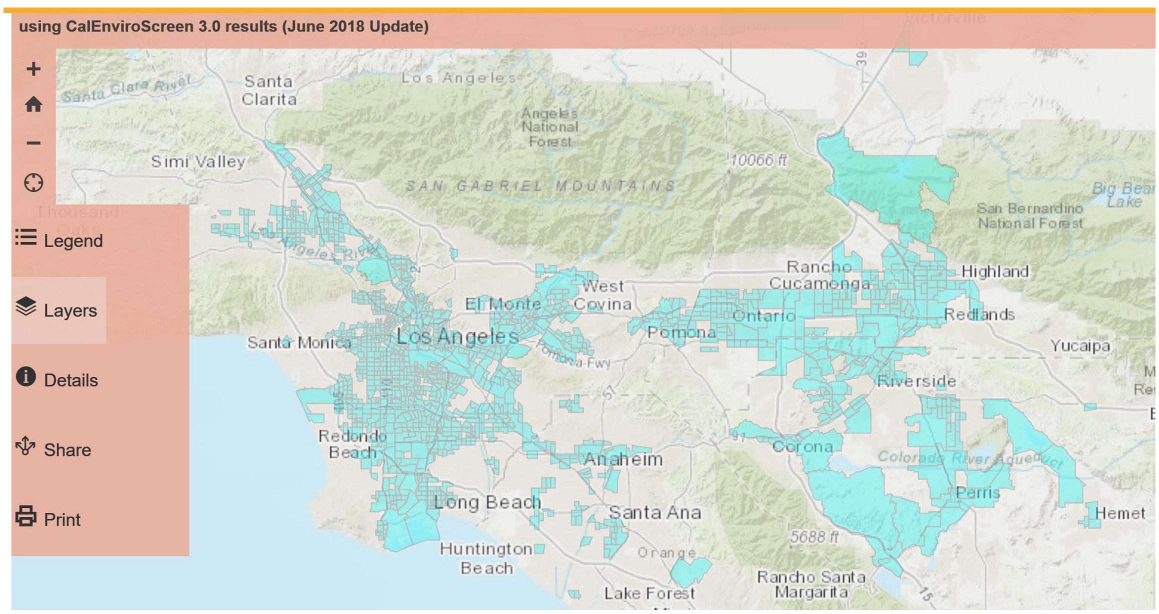
Overall, it was found that as compared to the fastest route, the low exposure route could result in more than 30% reduction in total air pollutant exposure for about 40% of the 400 simulated trips while keeping the increase in trip travel time to no more than 10%. When coupled with clean vehicle technology such as newer diesel engines with lower emissions, a larger reduction in total air pollution exposure can be achieved. This low exposure routing concept is particularly valuable for mitigating the air quality impact of high-emitting vehicles (e.g., HDDTs) in disadvantaged communities as well as near sensitive facilities such as schools and hospitals.

1 Introduction

1.1 Background

Medium- and heavy-duty diesel trucks, the majority of which are used for freight movement, are significant contributors of nitrogen oxides (NOx) and particulate matter (PM) emissions. As a result, areas close to freight hubs such as ports, railyards, and distribution centers often experience elevated levels of diesel-related air pollution. There has been increasing awareness of this environmental justice issue, which has led to the designation of disadvantaged communities (DACs) in California (see Figure 1). These communities are specifically targeted for investments aimed at improving public health, quality of life, and economic opportunity of their residents.

Figure 1. Disadvantaged communities in the southern part of California [1]



At the same time, the emerging Connected Vehicle (CV) technology, which enables communication and information sharing between vehicles and infrastructure as well as among vehicles, has led to innovations that promise to improve safety, mobility, and sustainability of future transportation systems. Several CV applications have been developed under the U.S. Department of Transportation's research programs that target specific benefits such as avoiding vehicle crashes, reducing travel delays, and lowering greenhouse gas emissions. To date, there has been much less attention on utilizing CV technology to reduce criteria pollutant emissions from vehicles, particularly from freight vehicles.

There is great potential in applying CV technology to reduce the environmental and health impacts of freight vehicles on DACs. For example, it is well known that there is tradeoff between fuel efficiency and NOx emissions from diesel engines where air/fuel ratio can be tuned to increase fuel efficiency at the expense of emitting higher engine-out NOx emissions, and vice versa. Thus, it may be possible to dynamically tune the engine, and potentially the aftertreatment system, based on information from CV technology such as vehicle location and/or time of day to meet specific goals. For instance, when a heavy-duty diesel truck enters a DAC, its engine and aftertreatment system would be tuned to emit lower tailpipe NOx emissions so that the impact on the residents is reduced. Once the truck leaves the DAC, then its engine and aftertreatment system would be tuned to increase fuel efficiency so as to limit the fuel cost burden on the truck or fleet owner.

In general, all the previously developed CV applications that target lowering greenhouse gas (GHG) emissions can be modified to specifically target reducing pollutant emissions. One such application is eco-routing that determines a travel route between an origin and a destination that would make the vehicle consume the least amount of fuel (see, for example [2, 3]). It not only benefits the vehicle owner by lowering the fuel cost but also benefits the environment by lowering GHG emissions. The eco-routing application can be modified to find a travel route that would make the vehicle emits the least amount of pollutant emissions.

To take it a step further, how the pollutant emissions would disperse from the roadways and be exposed by the residents nearby—especially those that are sensitive to air pollution, such as children, the elderly, and patients—can be taken into account. For example, in Los Angeles, California, more than 30% of the population is living within 50-100 meters of major roads [4]. Research has shown that air pollutant concentrations near the roadways are often 2-4 times higher than at 100 meters away [5]. Thus, new CV applications can be developed to influence the travel routes of freight vehicles in a way that reduces the impacts of pollutant emissions from these vehicles on the local residents, especially those living near the roadways. These new CV applications will require additional information such as meteorological conditions, census demographics, and locations of sensitive sites (e.g., daycare facilities, hospitals), and will involve more complex calculations including air dispersion modeling.

1.2 Objectives

While there have been many research efforts on characterizing the impacts of traffic emissions on human health (see, for example [6-9]), very few of those combine the estimation of pollutant exposure with the development of mitigation strategies. The goal of this research is to develop, and evaluate the potential benefits of, new CV applications specifically aimed at reducing the environmental and health impacts of freight vehicles on DACs. Specifically, the objectives of this project are: 1) to develop new vehicle routing algorithms for heavy-duty diesel trucks that would reduce the exposure of residents in DACs to the harmful pollutant emissions from these trucks, and 2) to evaluate the benefits of the new vehicle routing algorithms in terms of reductions in air pollutant exposure.

2 Methodology

Figure 2 shows the flow diagram of traffic emission exposure modeling method: 1) an emissions model is first used to quantify pollutant emissions from traffic activity; 2) next, a dispersion model is applied to compute the pollutant concentrations in the study area; and 3) a pollutant exposure model is then utilized to account for how much pollutant is actually inhaled by a target population group--in this research, inhaled mass (IM) is used as the metric for pollutant exposure. The final exposure estimates can be generated on a roadway link-by-link basis in a roadway network and used as input to a routing engine as part of the routing cost. Figure 3 maps the critical link-based inputs in each modeling step. Each model and data source that connects the four components in this research are described in the following subsections.

Figure 2. Flow diagram of overall traffic pollutant exposure modeling method

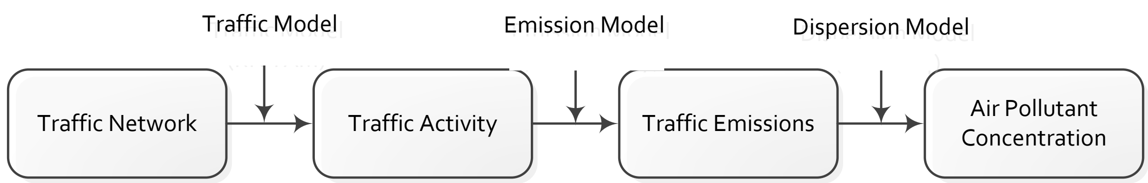
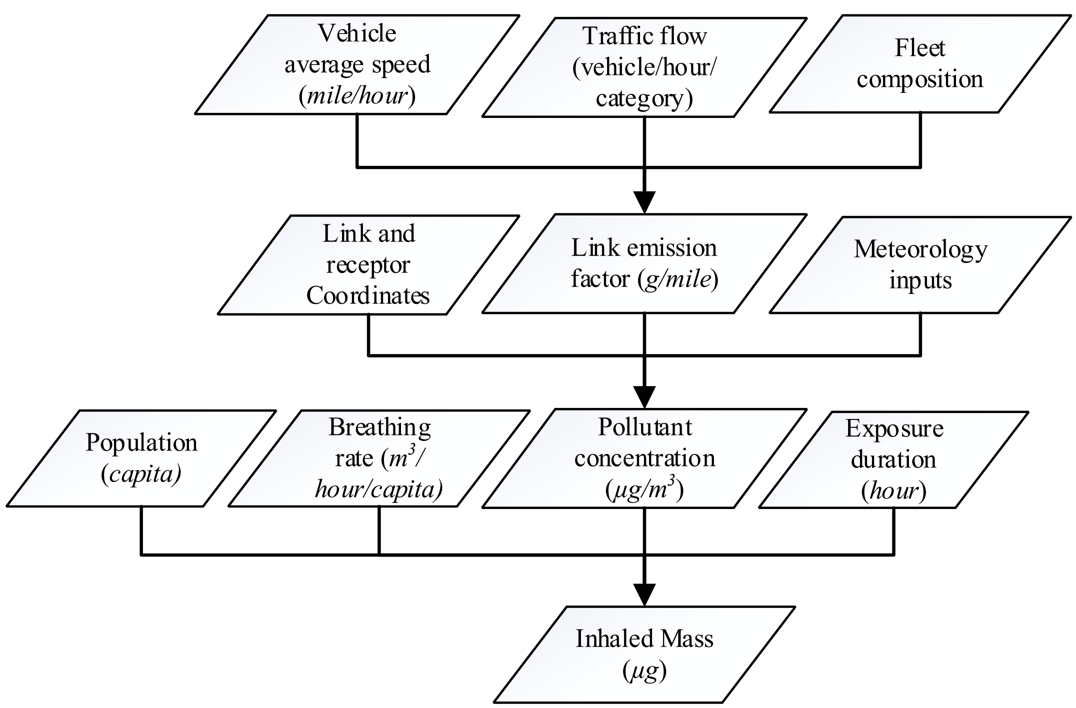


Figure 3. Critical link-based inputs for the overall exposure modeling method



This emission-dispersion-exposure modeling chain has been applied by several researchers using a variety of model combinations. For example, Amirjamshidi et al. [10] investigated the general public's pollutant exposure during peak hour of traffic for the Toronto Waterfront Area. Their results indicate that pollutant exposure is highest in high population density area such as the central business district. In this project, we take a step further by designing the vehicle routing algorithm for reducing pollutant exposure for susceptible population groups in an efficient and dynamic fashion. Considerable efforts of spatial analysis and data processing are made to interface with the various models and data sources.

2.1 Traffic Activity Acquisition

A digital roadway map is at the heart of any routing or navigation application. The map represents geographic features (e.g., location, length, shape), and stores attributes (e.g., road type, lane number, speed limit) of the roadway network. Then, traffic activities on roadways are estimated based on traffic demand and network attributes. For traffic activity parameters, many traffic measurements and models focus on overall traffic speed, traffic flow, and fleet composition. These parameters are available either from real-world measurements (e.g. Caltrans Freeway Performance Measurement System (PeMS) [11]) or transportation models on a roadway link-by-link basis. In this research, we use street map of North America provided by ESRI due to the highly-detailed street information [12]. Posted speed limit values are assigned as average traffic speed in this project.

2.2 Traffic Emission Modeling

To evaluate the mesoscale emission factors (usually in units of gram/mile/link), the link-based traffic activities are fed into an emission model. There are several emission models developed for regulatory or research purposes. Examples include EMFAC (EMission FACtor model) developed by the California Air Resources Board (CARB), which is used for regulatory purposes in California [13], and MOVES (MOtor Vehicle Emission Simulator) by the U.S. Environmental Protection Agency (EPA), which is used for regulation in the other 49 states [14].

For this particular implementation, EMFAC2011 is applied for mesoscale emission factor calculation because it has well-established fleet composition database for California counties and air basins. Emission factors for specific vehicle categories are downloaded from EMFAC2011 online database [15]. Then, link-by-link emission factors are determined based on the overall traffic speed on the links and saved as a new attribute of the roadway network.

2.3 Dispersion Modeling

Next, an atmospheric dispersion model is utilized to estimate the concentration of air pollutants emitted from traffic sources at specific receptor locations. Many dispersion models have been developed and applied for regulatory and research analyses since the mid-to-late 1980s. For instance, CALINE3, CAL3QHC, CAL3QHCR, and CALINE4 are widely used steady-state Gaussian dispersion models. More advanced models, such as CALPUFF and AERMOD, are two EPA-approved models for non-steady state and steady state dispersion modeling, respectively

[16]. They require sophisticated micrometeorology inputs and can be used in complex terrain for emission sources of various shapes, including point sources, area sources, and volume sources.

Recently, EPA released R-LINE, a research grade dispersion model for near-roadway assessments. It is based on a steady-state Gaussian formulation and is designed to simulate dispersion of line source emissions [17]. R-LINE requires the same surface micrometeorology inputs as AERMOD and performs accurate estimation [18]. In addition, R-LINE has a succinct input configuration, and computes much faster than AERMOD. Therefore, R-LINE is used in this research. The underlying relationship between pollutant concentration and the line source emissions in R-LINE can be expressed as:

$$C(x,y,z) = f(Q, source\ location, meterology\ ) \tag{1}$$

where *C(x,y,z)* denotes the pollutant concentration at a receptor location. *Q* is the traffic emission rate in *g/meter/second*, acquired from traffic emission modeling in the previous step. For *source location*, the coordinates of each line segment's starting and ending nodes are required. Micrometeorology data inputs for R-LINE such as temperature, wind speed, wind direction, surface friction velocity, and Monin-Obukhov length are obtained from the SCAQMD (South Coast Air Quality Management District)'s website [19]. An example R-LINE input control file is illustrated in Figure 4. For more details about the configuration, please refer to the R-LINE user guide [18].

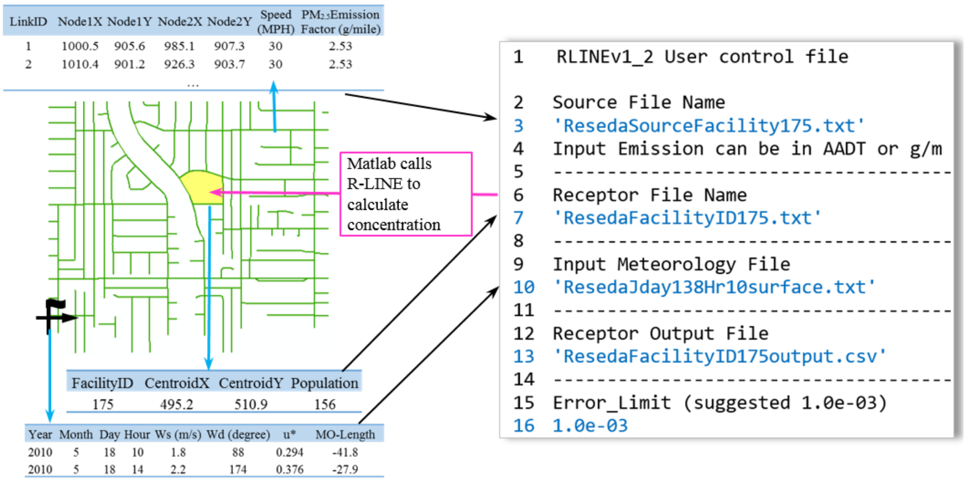
2.4 Exposure Assessment

In this research, pollutant exposure is referred to the amount of pollutant inhaled by a group of subjects. Bennet *et al.* clarified several frequently-used terms applied in exposure study, such as intake and intake fraction [20]. To assess the pollutant intake, *inhaled mass (IM)* is used as a metric and is calculated as:

$$IM = C \cdot Pop \cdot t \cdot BR \tag{2}$$

where *C* is the pollutant concentration ($\mu g/m^3$) in a given microenvironment as calculated by R-LINE. *Pop* is the number of subjects in the microenvironment. *t* is the duration of each trip (*hour*), and *BR* denotes the breathing rate (m^3*/hour/capita*) of the subjects exposed to the pollutant. It is of interest to reduce susceptible population's exposure to traffic-related air pollutants because tailpipe emissions, such as fine particulate matter and volatile organic compounds, are associated with health risks in young children, older adults, patients, and even healthy adults [21]. Therefore, in this research we apply the new routing algorithm to high-emitting vehicles (e.g., trucks) in order to minimize the target population's exposure to certain pollutants for the purpose of protecting their health.

Figure 4. Schematic graph of transition from spatial feature attributes to dispersion modeling implementation



Note: Blue arrows point to pre-calculated attributes of geographic features (e.g. facilities, street links, and weather stations). Black arrows indicate Matlab scripting to select attributes and generate input control files. Pink arrows represent that Matlab calls R-LINE to compute receptor concentration. This schematic graph applies to mobile-source pollutant concentration estimation for all point receptors in this project.

The underlying assumptions and hypothesis are as follows: 1) For now, vehicle acceleration/deceleration/stop and building downwash are not considered; 2) The traffic emissions disperse rapidly into the ambient environment; 3) Only the inhalation exposure mechanism is considered; 4) The dispersed concentrations in indoor and adjacent outdoor areas are the same; and 5) The less inhaled mass is for an individual or a group, the better it is.

2.5 Vehicle Routing Problem

The traditional vehicle routing problem (VRP) initially aimed at finding a travel route with the shortest distance. With the improved sensing technologies that collect real-time traffic speed, vehicle routing algorithms are now able to minimize the total travel time for drivers. In this research, given a pair of origin-destination (OD) points, it is desirable to minimize inhaled mass while constraining the increase of travel time within a practical range for a trip. This is a multi-objective VRP studied by many researchers (e.g., [22]). Several methods for solving multi-objective VPR were summarized by Demir *et al.* [23].

In this research, we use a weighting method that transforms the multi-cost routing into a single-cost routing problem. The inhaled mass is incorporated into the route calculation as in:

$$weighed\_cost_k = \sum_{f=1}^{F}(w_f \times cost_{f,k}) \quad (3)$$

where $weighed\_cost_k$ is the combined cost for link k; w_f is the weight factor for $cost_{f,k}$ (a single cost f for link k). $cost_{f,k}$ can be distance, duration, monetary cost, or, in this research, pollutant exposure. There are a total of F single costs and weigh factors, and $\sum_{f=1}^{F} w_f$=1. Given t_k is the driving time for link k derived from link length and link average speed. When w_f for travel duration is 1, it becomes a simple least duration routing problem. When w_f for pollutant exposure is 1, it means the pollutant exposure is the only cost. Since the two costs have different units and numerical ranges, normalization is applied as:

$$\boldsymbol{IM_k = IM_{orig}/IM_{max}} \tag{4}$$

$$t_k = t_{orig}/t_{max} \tag{5}$$

where IM_{orig} and t_{orig} are the original inhaled mass and duration cost of a link with their original dimension. IM_{max} and t_{max} are the maximum inhaled mass and duration cost of a link in the entire network.

The overall routing algorithm finds a route with the least total cost for a given OD pair where:

$$\boldsymbol{total\ cost = \sum_{i \in L} cost_i} \tag{6}$$

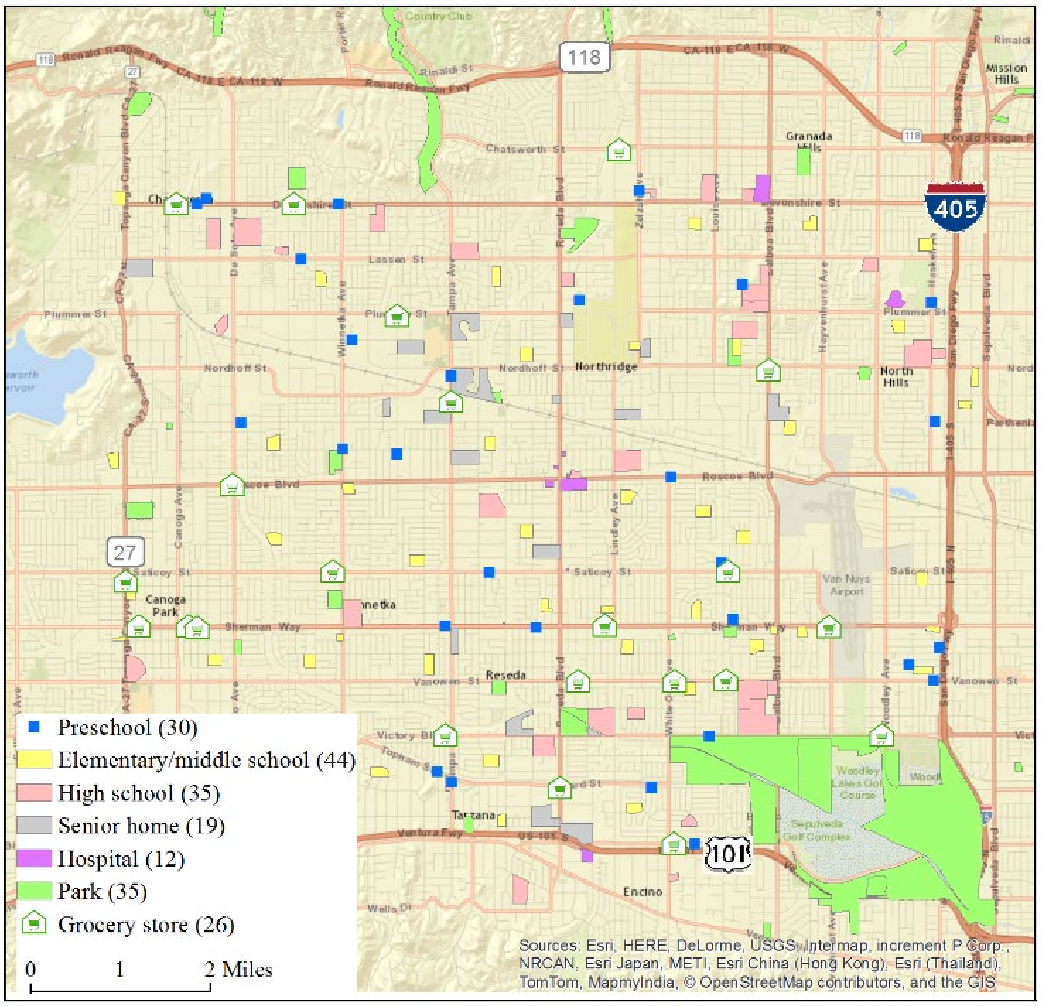
and L is the set of links in the least-cost path computed by the routing algorithm. The total cost is sensitive to w_f. A sensitivity analysis of w_f was presented in a previous work [24]. Based on the sensitivity analysis, we select specific weight factors to balance the tradeoff between travel duration and pollutant exposure. Section 3 provides more details about the experiment.

It is important to note that inputs to the modeling process, including weather, traffic condition, and human activities, are highly dynamic in the real world. In this research, we need to specify time scenarios of these inputs for the calculation of link costs (i.e., pollutant exposure and travel duration). Once link costs and OD pairs are determined for a scenario, low-exposure routes can then be calculated and visualized.

3 Experiments and Results

This section introduces a case study area for our low-exposure road navigation in calendar year 2010. The year 2010 was selected considering the best availability of full range of data at the time of conducting this study. To conduct an experiment on the low-exposure vehicle routing, we consider the roadway network in the Reseda-Northridge area in Los Angeles (LA) County, California, as shown in Figure 5. This area is chosen because the road network represents a variety of road types, including freeways, arterials, collectors, and local roads. In addition, it has a high percentage of seniors and children population. According to the 2010 U.S. Census, this 64-square-mile area is home to more than 531,000 residents. Adults 65 years and older make up 11.8% of the total population, which is 2% higher than the LA County average. Children 5 years old and below make up another 6.3% [25]. Additionally, several residential zones, stores, daycare facilities, primary schools, senior centers, and hospitals in this area are located near the roadways.

Figure 5. Map of the Reseda-Northridge area and facilities within the area



As Figure 5 illustrates, the area is bounded by Interstate-405, U.S. Route-101, State Route 118 and State Route 27. I-405 and US-101 freeways are heavily traveled by both commuters and freight traffic. When heavy-duty trucks enter this area to deliver goods at local stores, they are likely to pass the daycare centers, senior homes, and other facilities which are located right next to the roadways, and their tailpipe emissions could pose potential health risks to the people in those facilities. Therefore, the area presents an interesting case study where the low-exposure vehicle routing can be applied to reduce the susceptible population's *inhaled mass* of traffic-related air pollutants.

3.1 Vehicle Emission Estimation

In this experiment, we focus on air pollution from diesel exhaust. Diesel exhaust is a mixture of gaseous and particle pollutants. A number of health studies have shown that even acute exposure to diesel exhaust can trigger transient irritation and inflammatory symptoms. And chronic exposure of diesel exhaust is likely to cause severe damage to human lung function [26]. In this experiment, fine particulate matter ($PM_{2.5}$) and Reactive Organic Gas (ROG) are chosen as the pollutants of interest in particle and gaseous forms of diesel exhaust, respectively.

The experiment vehicle is chosen as tractor trailer diesel trucks, which are widely used in goods distribution. In the experiment year of 2010, most tractor trailer trucks in LA County are of model year (MY) 2005, according to EMFAC2011's database. These MY 2005 trucks emit 10.5 times more $PM_{2.5}$ and 1.3 times more ROG than MY 2010 trucks, which are required to be equipped with advanced emission control technology. Hence, the low-exposure vehicle routing could be used as an impact mitigation strategy for these older trucks. In our experiment, we examine how old trucks that use low-exposure routes would compare with newer and cleaner trucks using regular routes (shortest duration routes) in terms of pollutant exposure by sensitive population.

3.2 Dispersion Modeling Implementation

As indicated in Figure 2, there are three major inputs for dispersion modeling: receptor locations, roadway links as line sources, and meteorology parameters. Table 1 tabulates the major inputs and their data sources for the dispersion modeling in R-LINE. To understand the transition from the spatial features' attributes to the dispersion modeling, please refer to R-LINE user guide [18].

Table 1. Major Inputs and Data Sources of R-LINE Implementation

Input block	Description
1	File title
Source	User specified text for each run, e.g. '2010ResedaPM2.5_T7MY2005_Hr10'
2	Input source file: Link Index and 3-demention coordinates for both nodes, offset distance, initial σ_z, number of lanes, emission factor, road barrier location and height, suppressed source specification
Source	All facilities' centroids are indexed uniquely, and centroids of residential area buffers are indexed uniquely. Cartesian coordinates of receptors are extracted using ArcMap tool 'Add XY' [27]. Elevations are mapped from USGS DEM database [28]. A link is considered as the center line of a road so offset distance is zero. Road barrier and suppressed road are not considered. σ_z please see R-LINE user guide [18]. Emission factor is calculated in Section 3.1
3	Receptors Index and 3-demention Cartesian coordinates
Source	Receptors Index is nominal. Cartesian coordinates of receptors are extracted using ArcMap tool 'Add XY' and saved in matfiles. Receptors are placed at a typical breathing height of 1.5 m. Receptor elevations are mapped from United States USGS DEM database.
4	Meteorology inputs: date, hour, sensible heat, surface frication velocity, vertical convective velocity, Vertical Potential Temperature Gradient, Monin-Obukhov length, wind speed, wind direction, reference height, temperature, convective and mechanical boundary layer height *etc.*
Source	All the inputs are provided by South Coast Air Quality Management District meteorology data [19]. The meteorology station is Reseda Station which is located in the south of the experiment network.
5	Run specifications, e.g. time average options, analytical or numerical solution *etc.*
Source	This experiment chooses 1 hour average with analytical solution. Lane width is set as 3 meter. Other options please see user guide [18].

3.3 Exposure Assessment and Network Characterization

Recalling Eqn. (2), inhaled mass is a function of pollutant concentration, exposure duration, breathing rate, location of population, and the number of population. In this experiment, hourly averaged pollutant concentration is estimated, and the exposure duration is set to one hour. Pollution distribution becomes an important parameter that affects the collective *IM* that tractor trailer trucks could impose.

Table 2 tabulates the facility types of interest and the estimated number of population. Figure 5 maps the spatial distribution of the facilities. The main reason for selecting these facilities is because of their population's susceptibility to various air pollutants [29, 30]. Other than the selected facilities, residential homes are also included because they should be protected from heavy-duty trucks' diesel exhaust as well. A breathing rate of 15 *L/min* is assigned to all the population [31].

Table 2. Sensitive Facilities Considered in the Experiment

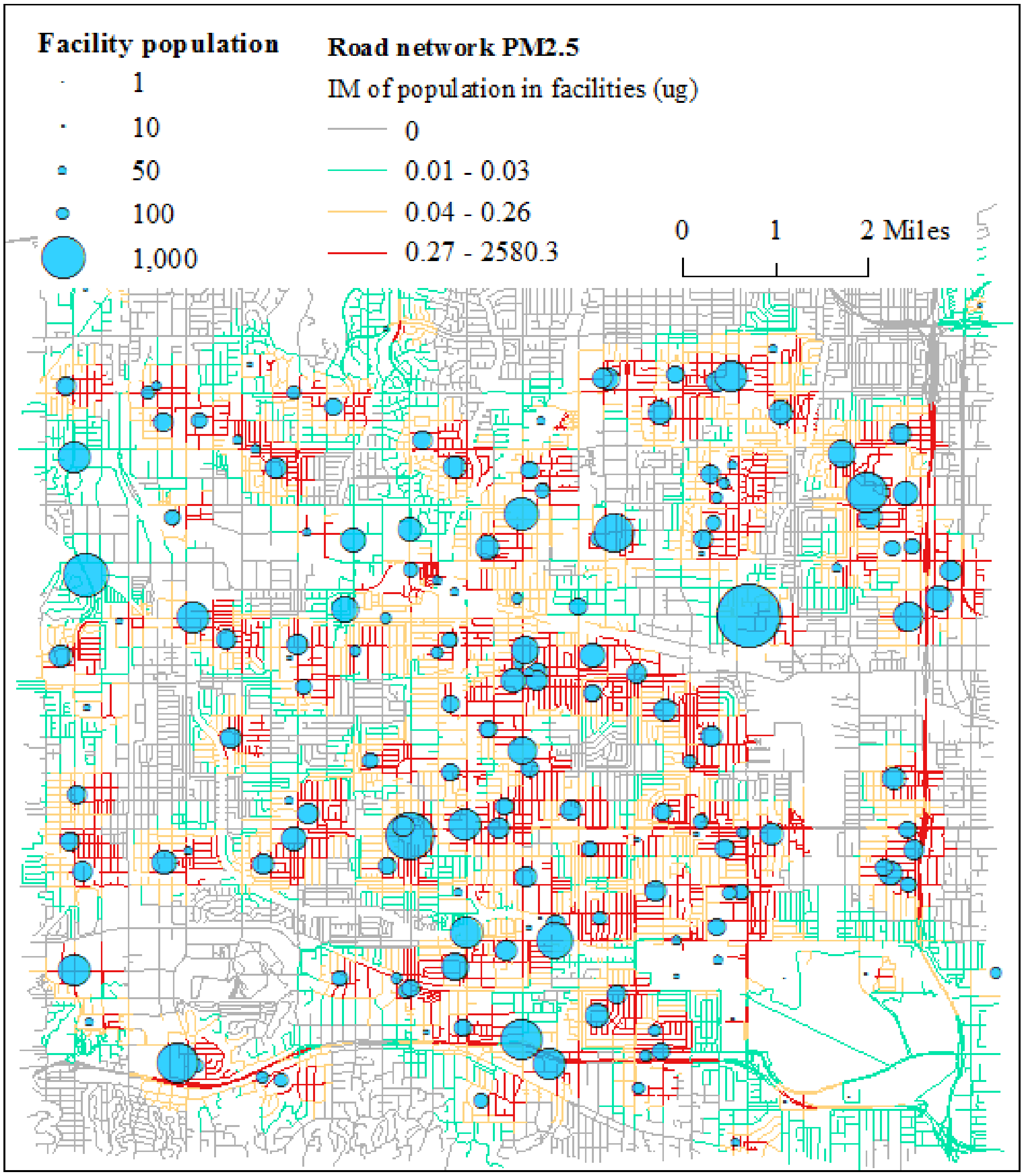
Facility type	Target population	Population data source	Number of facilities	Average population per facility during experiment hour
Preschool	Children 5 years old and below	Census 2010 and US preschool enroollment rate	30	202
Elementary and middle school	Children 6-14 years old	Esri North America Map Series, Census 2010, and California elementary school enrollment	44	254
High school	Teenager 15-17 years old	Esri North America Map Series, Census 2010, and US high school completion rate	35	176
Senior center	65 years old and above	Census 2010 and review websites	19	596
Medical center/Hospital	All age	Esri North America Map Series and Census 2010	12	454
Park	All age	Esri North America Map Series and Census 2010	34	36

Note: Data sources are introduced in [32] and [33]

Population estimation requires multiple steps of data preprocessing. First, local population in different age groups at the block level is extracted from the 2010 U.S. Census data depository and linked to GIS (geographic information system) shapefiles [34, 35]. Next, we use geoprocessing tools in ArcMap to join the nearby census blocks to facilities, and then determine the number of population in an appropriate age range for each facility [36, 37]. Finally, the estimated population value at each facility is calibrated according to California schools' enrollment rates [32] and other available information (e.g., review websites) in order to simulate the real-world situation to the best extent possible.

The pollutant concentration at each sensitive facility contributed by each roadway link is calculated by R-LINE. As air pollutants from one roadway link may reach several facilities, the total inhaled mass for the roadway link is the sum of the *IM* values from all the affected facilities. Figure 6 presents the contribution to $PM_{2.5}$ inhaled mass at sensitive facilities from roadway links in the network. For example, an *IM* value of 1,000 $\mu g/link$ means that there is 1,000 μg of $PM_{2.5}$ inhaled by the nearby sensitive population during the hour when the subject vehicles traverse this roadway link.

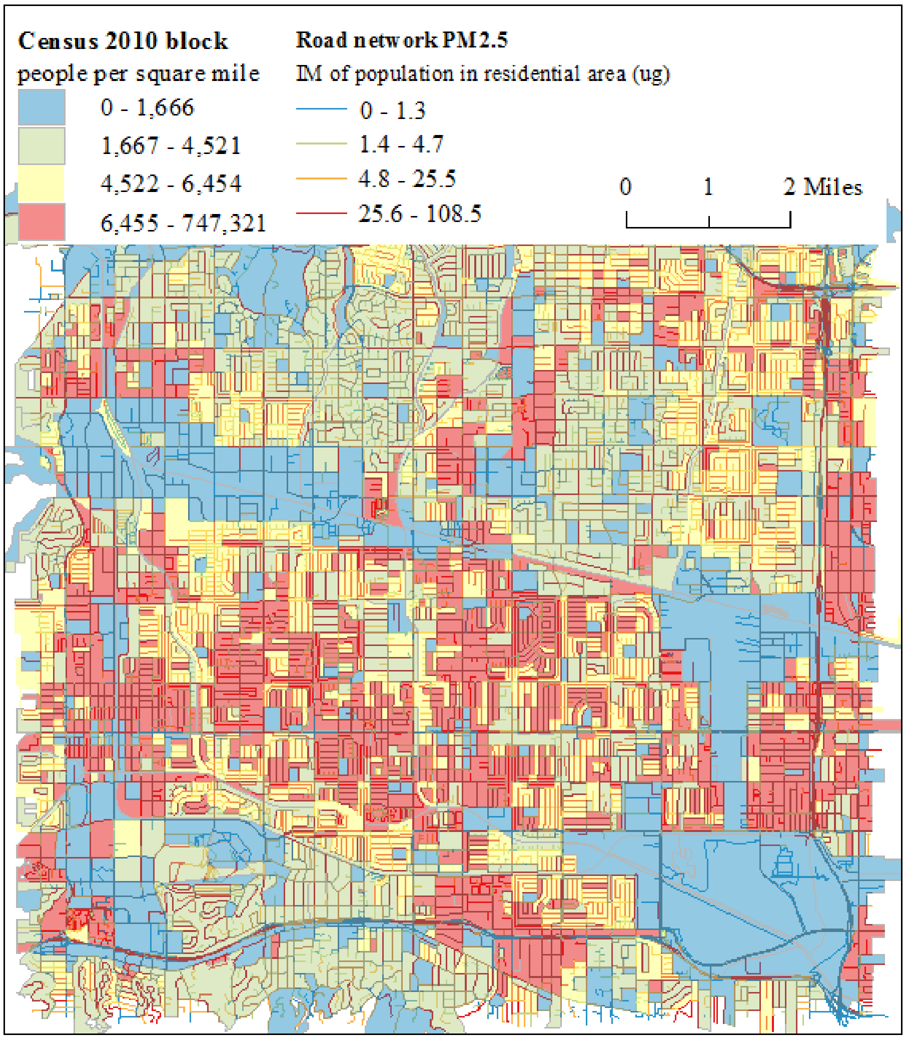
Figure 6. Contribution to sensitive population's PM2.5 inhaled mass (µg/link) from roadway links in the experiment network



Note: *IM* is from one MY 2005 tractor trailer trucks

IM values of the population in residential homes are calculated independently from those of sensitive facilities. First, local population count at the block level is extracted from the 2010 U.S. Census data depository and linked to census block shapefiles [34]. Population density for each census block is then calculated as the total population divided by the area of the census block, which is given in the 2010 U.S. Census data or can be calculated using ArcMap tools [38]. Next, we generate a left-sided 200-meter buffer and a right-sided 200-meter buffer for each roadway link in ArcMap [39]. Pollutant concentration in each buffer is then calculated using R-LINE, assuming that the centroid of each buffer is a receptor, and the roadway link is a line source. After that, we calculate the population within the buffer polygons based on the overlaying census block's population density and the buffer's area, assuming that 20% of the residents are at home, and they are uniformly distributed within each buffer zone. Finally, the left- and right-sided residential *IM* values are calculated using Eqn. 2 and summed to result in a total residential *IM* value for the roadway link, as shown in Figure 7. In general, the *IM* values are positively correlated with the population density in the nearby residential areas.

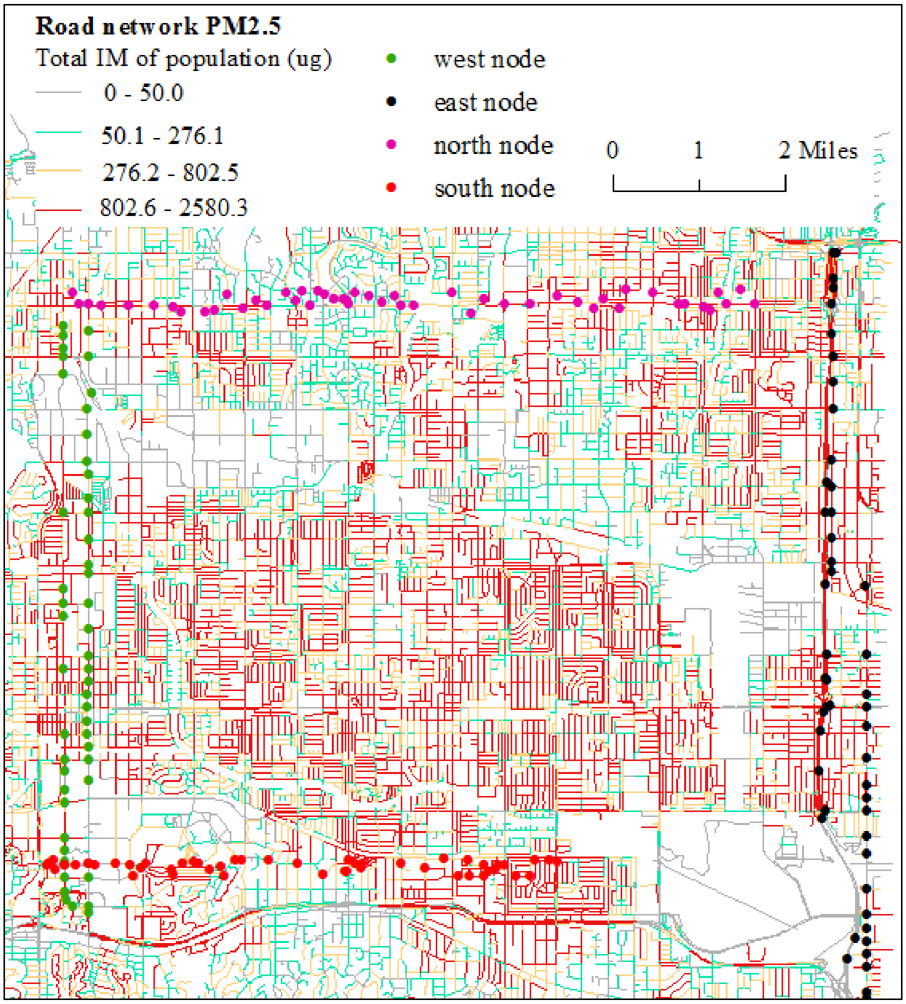
Figure 7 Contribution to residential population's PM2.5 inhaled mass (μg/link) from roadway links in the experiment network



Note: *IM* is from one MY 2005 tractor trailer trucks

The two layers of *IM* are aggregated, and the final *IM* map of the roadway network is shown in Figure 8. Generally, the aggregated *IM* values of the roadway links are sensitive towards critical variables, including traffic activity, dispersion condition, and the number of nearby (sensitive) population. For instance, a roadway link will have a high *IM* value if there are several sensitive facilities and dense residential areas nearby. As for dispersion condition, for example, on a typical Southern California sunny day, the *IM* at 2 P.M. will likely be generally lower than that of 9 A.M. for the entire network because the turbulence in the afternoon tends to be much higher than that of early morning therefore contribute to faster dispersion of pollutants. Meanwhile, the aggregated *IM* values for the roadway network are calculated for both $PM_{2.5}$ and ROG. In the experiment, *IM* calculation for the network should be repeated if any critical variables mentioned in Eqn. (1) changed.

Figure 8. Aggregated contribution to PM2.5 inhaled mass (µg/link) from roadway links in the experiment network and locations of test nodes



Note: *IM* is from one MY 2005 tractor trailer truck. Test nodes are selected approximately 0.2 miles apart from each other in commercial zones

With the *IM* values synthesized for the entire roadway network, it is possible to execute the low pollutant exposure vehicle routing algorithm with a constrained travel duration. Given an OD pair, a least duration route is computed using the Dijkstra's algorithm [40]. Then, a low exposure route is calculated using the weighting method described in Section 2.5. The calculations are performed in Matlab. The tested OD pairs are described in the following section.

3.4 Experiment Scenarios

To compare between the low exposure route versus the least duration route, we set up a few experiment scenarios. As explained in Section 3.1, we choose $PM_{2.5}$ and ROG as the pollutants that we desire to reduce for the selected population groups. The weight factors (Eqn. (3)) for normalized travel duration, normalized $PM_{2.5}$ inhaled mass, and normalized ROG inhaled mass are 0.5, 0.25, and 0.25, respectively.

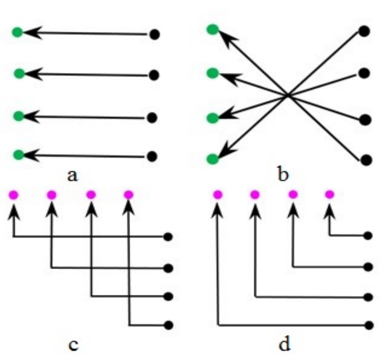
We first consider a baseline scenario A, where a MY 2005 truck is driven to several grocery stores in the area around 10:00 a.m. on a typical work/school day in May 2010. The truck takes the least duration route (LDR). To investigate the *IM* reduction of the low exposure route (LER) as well as of the fleet turnover to cleaner engines, we set up three other scenarios as listed in Table 3.

Table 3. Specifications of experiment scenarios

Scenario	Description	Routing Type	T7 Tractor Model Year
A	Baseline route	LDR	2005
B	Test LER's result	LER	2005
C	Test clean vehicle impact only	LDR	2010
D	Test LER and clean vehicle impacts	LER	2010

To vary trip scenarios, we choose 400 OD pairs to simulate potential driving trips. Figure 8 shows 50 test nodes in each side of the area. These test nodes are used to create 400 OD pairs as illustrated in Figure 9. This setup covers a broad range of route directions for an unbiased evaluation of *IM* versus travel duration tradeoffs. Both the LER and the LDR are calculated for all the 400 OD pairs. Then, the travel duration and *IM* for each OD pair are compared between LER and LDR.

Figure 9. A schematic graph and table to explain the configuration of OD pairs

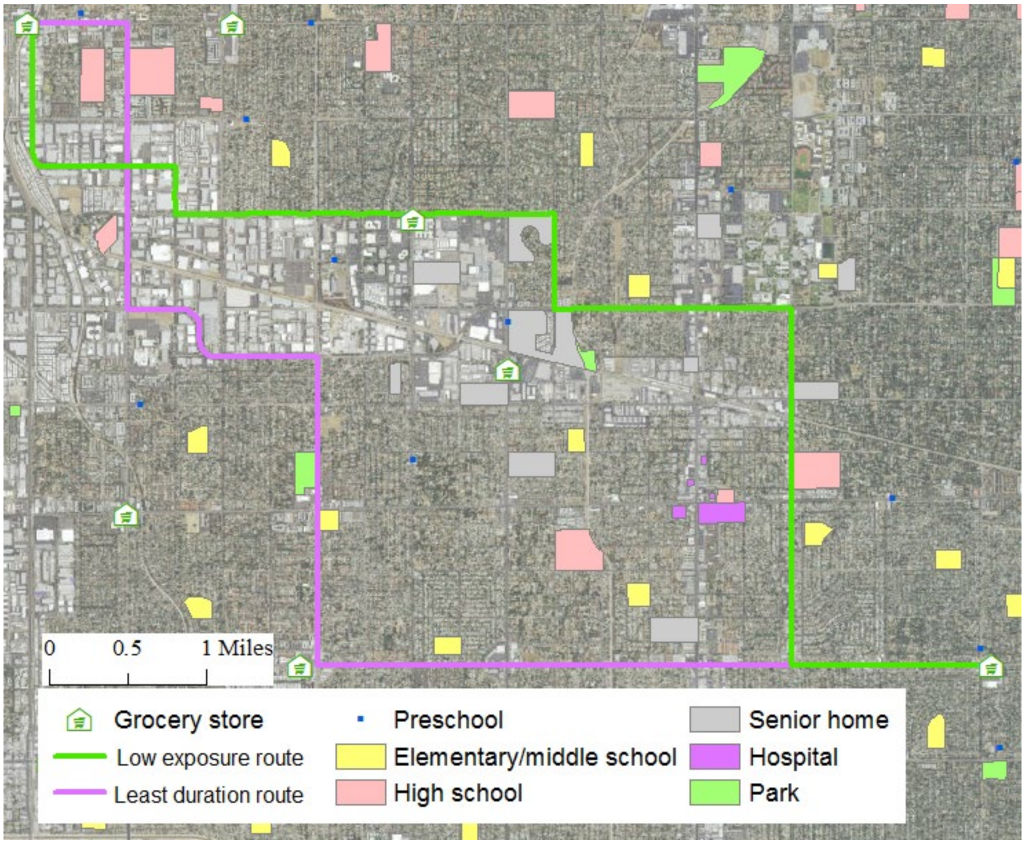


RouteID	Route direction	Route description
1-50	E - W	Parallel, as in Figure a
51-100	E - W	Diagonal, as in Figure b
101-150	N - S	Parallel, as in Figure a
151-200	N - S	Diagonal, as in Figure b
201-250	E- N	Inner corner, as in Figure c
251-300	E- N	Outer corner, as in Figure d
301-350	S - W	Inner corner, as in Figure c
351-400	S - W	Outer corner, as in Figure d

3.5 Experiment Results

In one example trip scenario, the calculated routes are shown in Figure 10 with satellite image overlay. The pink line represents the LDR (Route A in Table 3), and the green line represents the LER (Route B in Table 3). Route C is the same as Route A, and Route D is the same as Route B, hence not shown on the map. The comparison results are summarized in Table 4. It can be seen that choosing the LER for this example trip on a work/school day results in a significant *IM* reduction because it passes fewer sensitive facilities and residential areas.

Figure 10. LER and LDR of an example trip



When comparing Route B to Route A, the travel duration increases 40 seconds (3%) while the IM values reduce by 87% for $PM_{2.5}$ and 76% for ROG, respectively. It suggests that with a relatively small adjustment, the LER can lead to a significant reduction in pollutant intake by susceptible population groups.

When compared with a MY 2005 truck, a MY 2010 truck emits 92% less $PM_{2.5}$ and 70% less ROG (based on EMFAC2011). The proportional reduction in the intake of the target population groups is therefore expected. It is worthwhile to point out that in Scenario C where the MY 2010 truck is equipped with advanced emission controls, the *IM* reduction for ROG (71%) is still less than that of Scenario B (76%). This is because the MY 2005 truck in Scenario B is informed of the population distribution and pollutant dispersion condition when performing the low pollutant exposure routing. It indicates that before high-emitting vehicles are retrofitted or replaced with clean vehicles, the low pollutant exposure vehicle routing offers a possibility to mitigate the impacts of air pollutant exposure by the public. By looking at Scenario D, it is clear that when clean vehicle technology is coupled with the low pollutant exposure vehicle routing, the exposure reduction can be even more significant. In the long run, it is desirable to achieve both pollutant mass and exposure reductions.

Table 4. Comparison results between experiment scenarios

Scenario	Driving duration (min)	PM2.5 IM (ug)	ROG IM (ug)
A (pink, MY 2005 LDR)	20.3	588.2	1238.5
B (green, MY 2005 LER)	21.0	74.7	297.3
Change (%)	3.3	-87.3	-76.0
C (MY 2010 LDR)	20.3	5.8	87.3
Change (%)	0	-92.2	-70.6
D (MY-2010 LER)	21.0	5.8	87.3
Change (%)	3.3	-99.0	-93.0

To better understand the effects of low pollutant exposure vehicle routing, the *IM* and duration results for all the 400 LER are compared with their LDR counterparts. Figure 11 and Figure 12 indicate that both $PM_{2.5}$ and ROG's *IM* can be significantly reduced by the low pollutant exposure vehicle routing. Also, for 30% of the routes, the LER and LDR are identical, resulting zero *IM* reduction. Exposure to the two pollutants shows high levels of reduction. For example, about 40% of the trips have more than 30% reduction in both pollutants.

Figure 11. PM2.5 IM reduction for 400 OD pairs

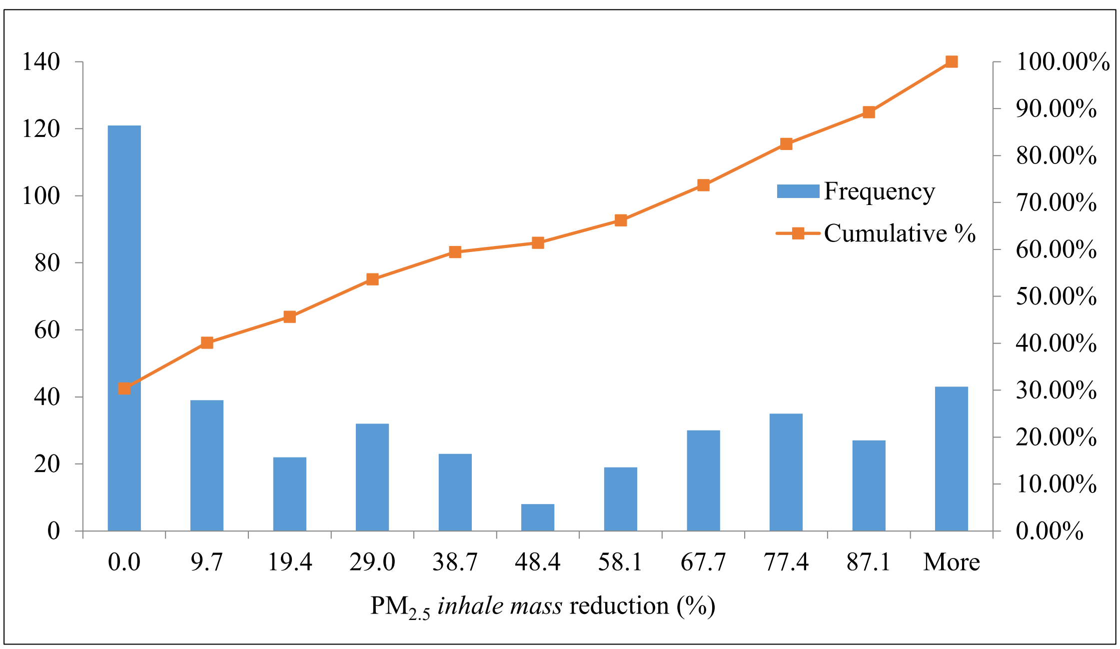


Figure 12. ROG IM reduction for 400 OD pairs

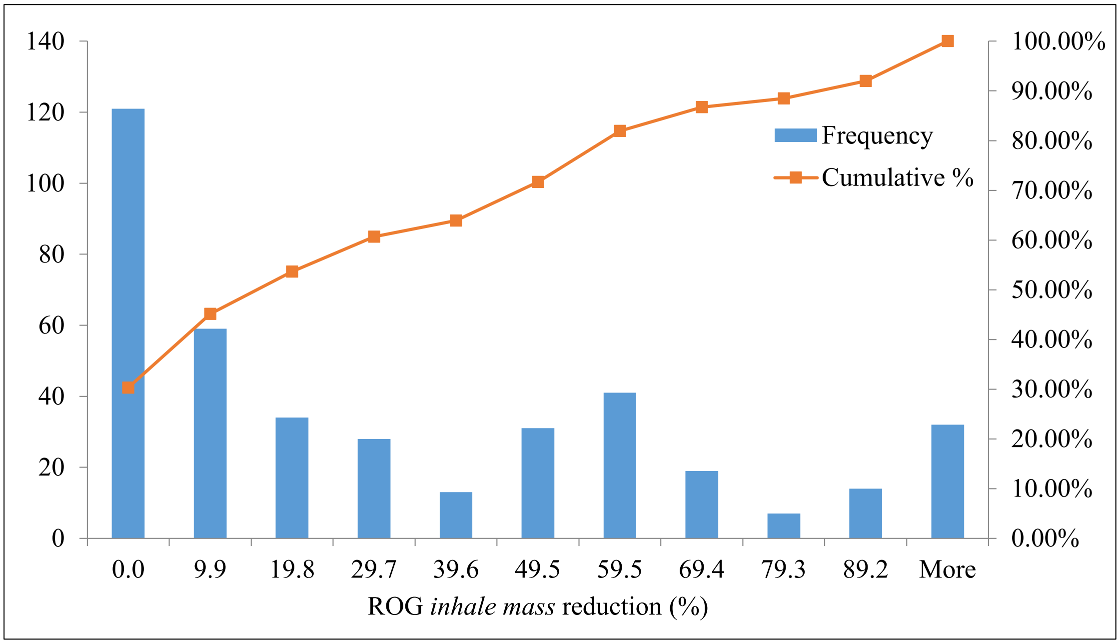


Figure 13. Driving duration increase for 400 OD pairs

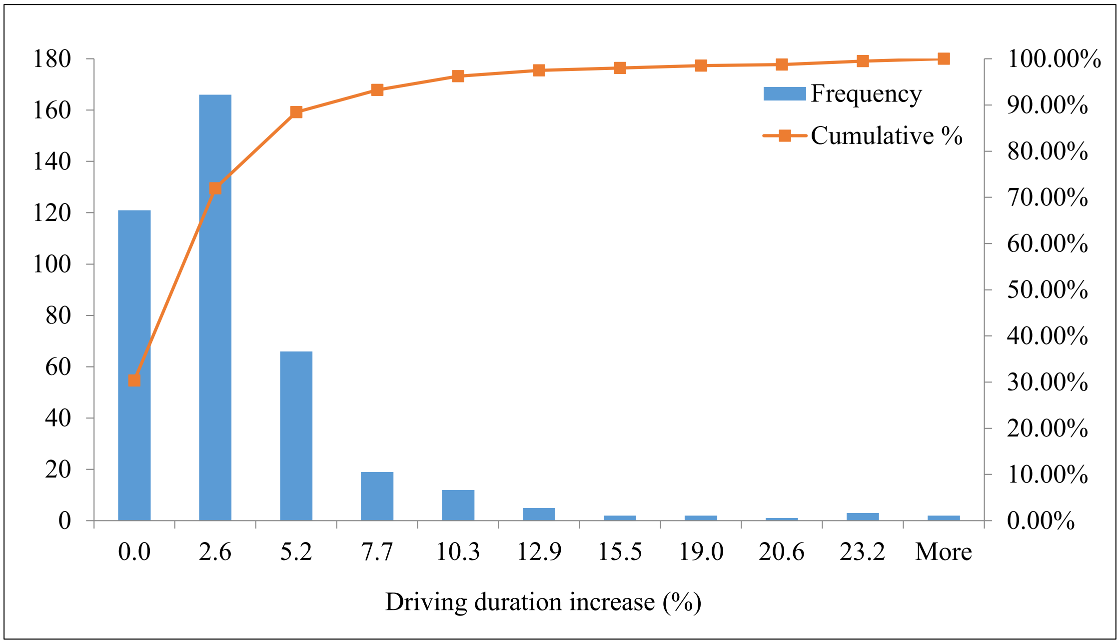


Figure 13 shows that 96% of the LER driving duration increase are no more than 10%. For LER with prolonged driving time, we can adjust the weighting factors and iterate LER calculation until it reaches a desired balance between driving time and *IM* reduction.

When examining the routes of the 400 trips with respect to the locations of OD nodes and the proximity to sensitive facilities/residential areas, it is found that network topology plays an important role in the changes in driving duration and *IM*. For example, when an OD pair is close to a freeway, the LER tends to avoid freeway links with dense population around and instead choose non-freeway roads with fewer sensitive facilities and residential homes, which usually have a lower speed limit. Hence, OD pairs close to freeways are more likely to be associated with significant *IM* reduction and moderate driving duration increase. In contrast, for OD pairs that are further from freeways, the LER's driving duration increase could be either very small or very large. Additionally, the *IM* reduction depends on the relative locations of sensitive facilities, residential areas, and roadways. Generally, in a diverse roadway network such as in this case study; there are often alternative routes for high-emitting vehicles to travel so that their emission impacts on the local population could be mitigated.

4 Conclusions and Future Directions

In this project, new vehicle routing algorithms are developed to determine travel routes for heavy-duty diesel trucks that would minimize the exposure of local residents to air pollutant emissions from these trucks. The algorithms are based on a modeling chain that goes from traffic activity, to emissions production, to air dispersion, and finally to human exposure. Using population activities and atmospheric conditions data, high-emitting vehicles (e.g., heavy-duty diesel trucks) can be directed onto travel routes that would cause the least health impacts on sensitive population groups such as children, seniors, and patients.

To the best of our knowledge, this research is the first effort that evaluates the use of connected vehicle technology as related to navigation as a mitigation strategy for reducing human exposure to harmful traffic-related air pollution. To examine the potential benefits of this air pollution mitigation strategy, a series of simulation modeling experiments are carried out in a case study roadway network in Southern California. It is found that low exposure routes are sensitive to several factors, such as vehicle characteristics, atmospheric conditions, and population activities. It is also found that the total pollutant exposure by target population groups can be greatly reduced with small adjustments to route choice. Compared to the least duration route, the low exposure route can lead to more than 30% reduction in pollutant exposure for about 40% of the 400 simulated trips while keeping the increase in trip duration to no more than 10%. When coupled with clean vehicle technology, a larger pollutant exposure reduction can be achieved.

Therefore, using information about population activity and atmospheric conditions, it is possible to route high-emitting vehicles (e.g., heavy-duty diesel trucks) in a way that lowers the total exposure of local residents to air pollutants from these vehicles. This concept is particularly valuable for mitigating the air quality impact of high-emitting vehicles in disadvantaged communities as well as near sensitive facilities such as schools and hospitals.

Future directions for this research include the use of real-time traffic and population activities data, refinement to emission modeling, and dynamic routing implementation. Specific improvements are as follows:

- In the case study, population activities are static estimates. Also, traffic and weather parameters are obtained from historical databases. In the era of Big Data, it would be possible to realize the collection of these various datasets in real time. In future research, we plan to consider dynamic location information of people such as National Human Activity Pattern Survey. The effects of low exposure routing with respect to different time periods and seasons are also important factors for real-world applications.

- In the current work, pollutant emissions are modeled at the mesoscale based on link average speed. In the future, microscopic traffic simulation and/or probe vehicles can be used to better represent the modal operation (acceleration, deceleration, cruising, and idling) of vehicles on the roads. In addition, road grade and vehicle weight data can also be incorporated in conducting microscale, power-based emission modeling to improve the accuracy of emission estimates and subsequent pollutant exposure assessment. Furthermore, fuel consumption, carbon dioxide emissions, and economic impacts should also be evaluated.

- With the use of real-time data, the route calculation must become dynamic. More efficient algorithms for routing such as the A* algorithm can be applied to make the low pollutant exposure navigation more practical. Different penetration levels of CAVs will impact the traffic interaction, hence emissions and exposure assessment. Therefore, studying the effects of penetration levels of CAV is an intriguing future direction as well.

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Data Management Plan

Products of Research

Data used in this research include digital map, vehicle emissions on roadways, meteorological parameters, sensitive facility locations, and census demographics for the study area.

Data Format and Content

- street_attributes.xlsx – Attribute table of the street links corresponding to the R-LINE source input. The data fields are described in the headers.
- sensitive_facilities.xlsx – Table of sensitive facilities. The data fields are described in the headers.
- 2010sfc.txt & 2010pfl.txt – Surface and profile meteorological parameters for R-LINE. For data field description, please refer to the AERMOD/AERMET manual at https://www3.epa.gov/scram001/7thconf/aermod/aermetugb.pdf.

Data Access and Sharing

All data can be accessed through DRYAD (https://doi.org/10.6086/D1PT0J).

Reuse and Redistribution

All data can be reused but not redistributed.