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Vehicle Routing to Mitigate Human Exposure to Traffic-Related Air Pollutants

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***Abstract*—Intelligent Transportation System (ITS) technology often aims at improving traffic safety and mobility. In recent years, a number of ITS applications have also been developed to reduce environmental impacts from greenhouse gases and pollutant emissions. Typical eco-friendly ITS applications (e.g., eco-routing) focus on reducing overall vehicle emissions. However, pollutant emissions from vehicles would cause more adverse impacts on public health where there are more population living closer to the emission sources (i.e., roadways). To date, eco-friendly ITS applications have not been developed from a *pollutant exposure* point of view. In this paper, we introduce a new vehicle routing method that goes beyond minimizing overall pollutant emissions; instead, we aim to minimize pollutant exposure to the localized population along the roadways. As part of the method, the human *inhaled mass* of pollutants is modeled and used as part of the routing cost. Modeling results show that the *inhaled mass* of fine particulate matter for the selected susceptible population can be reduced by approximately 30% - 80% on a typical workday with the implementation of the proposed vehicle routing method.**

***Index Terms*—route plan, mobile-source, emission, pollution, exposure**

I. Introduction

Over the last decade, several eco-friendly intelligent transportation system (Eco-ITS) applications have emerged are geared towards improving energy efficiency and reducing environmental impacts of transportation. Examples of Eco-ITS applications include eco-signal operations, low emission zones, eco-integrated corridor management, and eco-traveler information systems (see, e.g., [1]). In addition, new eco-routing algorithms have been developed to give travelers an alternative means of routing in order to minimize fuel and emissions (see [2, 3]). Eco-routing has been shown to be effective, but it is focused specifically on individual vehicles with the goal of minimizing energy and emissions on a large regional basis. To date, eco-routing and other Eco-ITS applications only consider minimizing mass emissions, instead of considering the *exposure* of unhealthy pollutants to humans. In many communities, on-road traffic emissions are of great concern due to heavy on-road traffic and densely populated communities that are adjacent to roadways. For example, in Los Angeles, California, more than 30% of the population is living within 50-100 meters of major roads [4]. Most pollutants disperse away from the roadways, but pollutant concentrations near the roadways are often 2-4 times higher than 100 meters away [5].

Built on a previous conference paper [6], this study aims at enhancing the proposed vehicle routing method that reduces pollutant exposure by localized population along the roadways. Essentially, the pollutant exposure to residents near roadways is estimated and used as a weight for vehicle routing to reduce overall exposure, while also considering economical travel duration. For the overall method, a similar modeling suite has been applied to assess pollutant exposure based on specific vehicle activities. This study, however, considers a range of details regarding spatial and temporal factors. The concept is particularly valuable for routing or regulating high-emitting vehicles near sensitive communities such as schools or disadvantaged neighborhoods.

II. Modeling Methodology

The methodology follows the modeling chain shown in Fig. 1, which is borrowed from our previous work [6]. The feedback loop on the top indicates that the modeled results of pollutant exposure can, in turn, be used to influence the traffic activities and hence mitigate pollutant exposure. Each model and data source that connects the four components in this research is described in the following subsections.

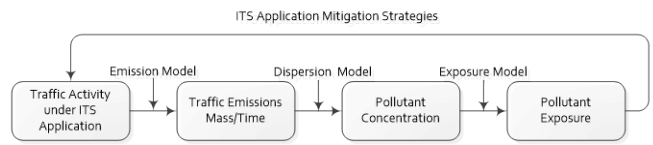

Fig. 1. Flow diagram of overall traffic pollutant exposure modeling method (from [6])

A. 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) [7]) 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 [8]. Posted speed limit values are assigned as average traffic speed in this study.

B. 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 [9], and MOVES (MOtor Vehicle Emission Simulator) by the U.S. Environmental Protection Agency (EPA), which is used for regulation in the other 49 states [10].

For this particular implementation, EMFAC2011 is applied for mesoscale emission factor calculation because it has well-

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established fleet composition database for California counties and air basins. Emission factors for specific vehicle categories are extracted from EMFAC2011 online database [11]. 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. In the case study, we will introduce diesel trucks as the primary sources in details (III A.).

C. 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. Recently, the U.S. 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 especially to simulate dispersion of line source emissions [12]. R-LINE requires the same surface micrometeorology inputs as AERMOD and performs accurate estimation [13]. 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:

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

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 [14]. For more details about the configuration, please refer to the R-LINE user guide [13].

D. Exposure Assessment

In this research, pollutant exposure is referred to the amount of pollutant inhaled by a group of subjects. Bennett *et al.* clarified several frequently-used terms applied in exposure study, such as intake and intake fraction [15]. To assess the pollutant intake, *inhaled mass (IM)* is used as a metric and is calculated as:

$$IM = C \cdot Pop \cdot t \cdot BR \quad (2)$$

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 [16]. Therefore, in this research we apply the proposed routing algorithm to high-emitting vehicles (e.g., diesel trucks) in order to minimize the target population's exposure to certain pollutants for the purpose of protecting their health.

E. 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., [17]). Several methods for solving multi-objective VPR were summarized by Demir *et al.* [18].

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:

$$IM_k = IM_{orig}/IM_{max}$$

$$t_k = t_{orig}/t_{max}$$

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:

$$total\ cost = \sum_{i \in L} cost_i \quad (4)$$

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 the previous sudy [6]. Based on the sensitivity analysis, we select specific weight factors to balance the tradeoff between travel duration and pollutant exposure. Section III 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.

III. Experiments and Results

This section introduces a case study area for our low-exposure road navigation in calendar year 2010. 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 Fig. 2. This area is chosen because the road network represents a variety of road types, including freeways, arterials, and collector 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. Children 5 years old and below make up another 6.3% [19]. Additionally, many residential zones, primary schools, and senior centers in this area are located near the roadways.

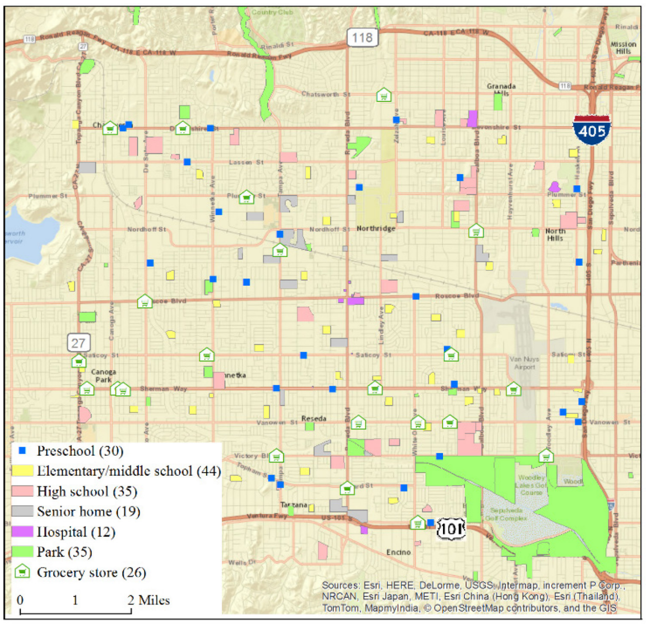


Fig. 2 Map of the facilities within the Reseda-Northridge area

As Fig. 2 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.

A. 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 [20]. In this experiment, fine particulate matter ($PM_{2.5}$) and is chosen as the pollutant 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 $PM_{2.5}$ 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.

B. Dispersion Modeling Implementation

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.

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'. Elevations are mapped from USGS DEM database [21]. 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 [13]. Emission factor is calculated in Section III.A
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 [14]. 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 [13].

C. Exposure Assessment and Network Characterization

Recalling Eqn. (2), inhaled mass is a function of pollutant concentration, exposure duration, breathing rate, 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 and the estimated number of population, and the spatial distribution of facilities are mapped in Fig. 2. The main reason for selecting these facilities is because of their population's susceptibility to various air pollutants [22, 23]. Other than the selected facilities, residential homes are also included because they should be protected from diesel exhaust as well. A breathing rate of 15 *L/min* is assigned to all the population [24].

Table 2 Sensitive facilities considered in the experiment

Facility type	Target population	Population data source	Number of facility	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

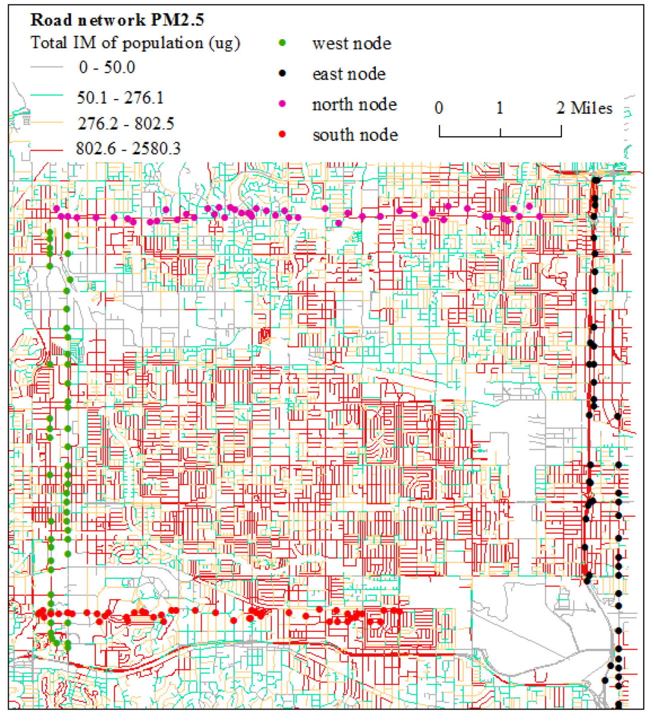
Note: Data sources are introduced in [25] and [26]

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 depository and linked to GIS (geographic information system) shapefiles [19, 27]. Next, we use geoprocessing tools in ArcMap to join the nearby census blocks to facilities, and then summarize the number of population in an appropriate age range for each facility. Finally, the estimated population value at each facility is calibrated according to California schools' enrollment rates [25] 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.

IM values of the population in residential homes are calculated independently from those of sensitive facilities. In general, the *IM* values are positively correlated with the population density in the nearby residential areas.

Next, the facility *IM* and residential *IM* are aggregated, and the final $PM_{2.5}$ *IM* map of the roadway is shown in Fig. 3.



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

Fig. 3 Aggregated contribution to $PM_{2.5}$ inhaled mass (*μg/link*) from roadway links in the experiment network and locations of test nodes

Generally, the aggregated *IM* values of the roadway links are sensitive towards the critical variables shown in Eqn. (1), including traffic activity, dispersion condition, and the number of sensitive population in the proximity. In the experiment, *IM* calculation for the network should be repeated if any critical variables mentioned above changed.

Meanwhile, the aggregated *IM* values for the roadway network are calculated for $PM_{2.5}$. With the *IM* values synthesized for the entire roadway network, it is now 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 [28]. Then, a low exposure route is calculated using the weighting method described in Section II-E. The calculations are scripted in Matlab. The tested OD pairs are described in the following section.

D. Experiment Scenarios

To compare the low exposure route and the least duration route, we set up a few experiment scenarios. As explained in Section III-A, we choose $PM_{2.5}$ as the pollutant that we desire to reduce for the selected population groups. The weight factors (Eqn. (3)) for normalized travel duration and normalized $PM_{2.5}$ inhaled mass are 0.5 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 estimate the *IM* reduction of the low exposure route (LER), we set up another scenario where the same truck takes the LER instead.

To test a variety of trip scenarios, we choose 400 OD pairs for potential driving trips. Fig. 3 shows 50 test nodes in each side of the area. These test nodes are used to create 400 OD pairs. The setup covers a wide 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 the LER and LDR.

E. Experiment Results

In one example trip scenario, the calculated routes are shown in Fig. 4 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). The comparison results are summarized in Table 3. 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.

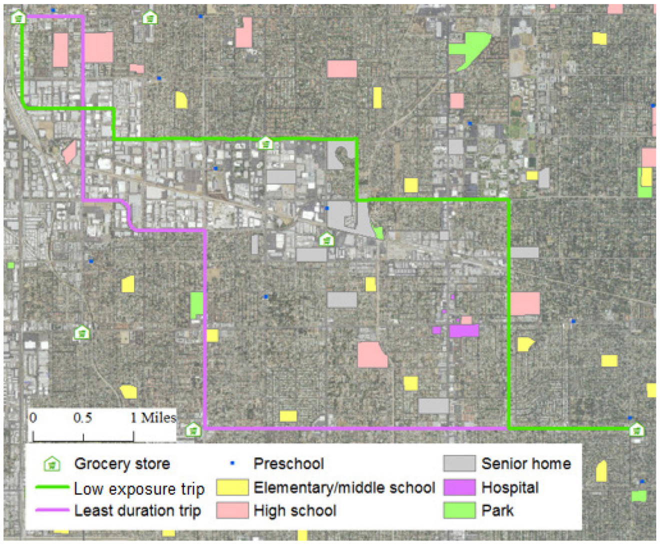


Fig. 4 LER and LDR of an example trip

Table 3 Comparison results between experiment scenarios

Scenario	Driving duration (min)	$PM_{2.5}$ *IM* (μg)
A(pink, MY 2005 LDR)	20.3	588.2
B (green, MY 2005 LER)	21.0	74.7
Change (%)	3.3	-87.3

Note: Change is relative to the baseline scenario A. The mass emission and IM are for the one truck in the experiment.

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

To better understand the effects of LER, the *IM* and duration results for all the 400 LER trips are compared with their LDR counterparts. Fig. 5 shows that for 30% of the routes, the LER and LDR are identical, resulting zero *IM* reduction. Other than that, $PM_{2.5}$ *IM* can be significantly reduced by the low exposure routing method. For example, about 40% of the trips lead to more than 30% inhalation reduction.

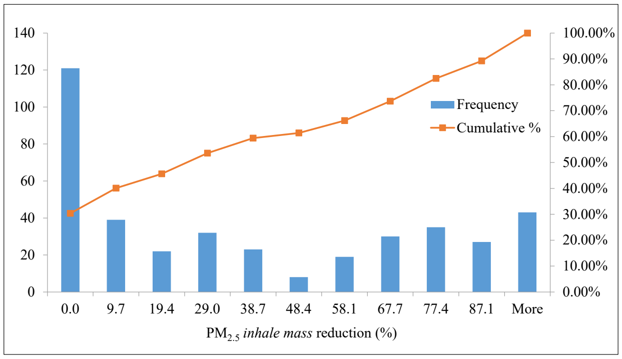


Fig. 5 $PM_{2.5}$ *IM* reduction for 400 OD pairs

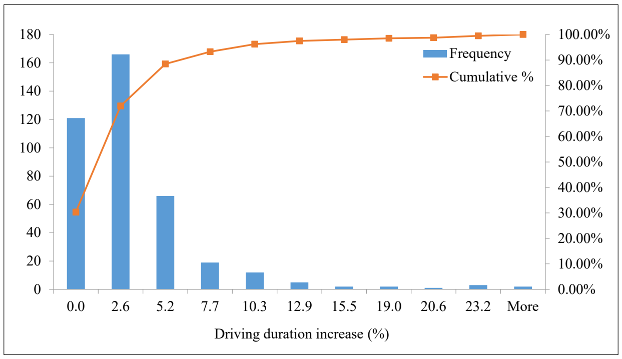


Fig. 6 Driving duration increase for 400 OD pairs

Fig. 6 shows that 96% of the LER driving trips' duration increases 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. 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.

IV. Conclusions and Future Work

In this paper, we introduce a novel vehicle routing method that aims to minimize overall population's *inhaled mass* of traffic-related air pollutants for driving trips within a reasonable range of trip duration. This method is accomplished using a modeling suite that relates traffic activity, to emissions production, to dispersion modeling, and finally to human inhalation. It is 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%.

Therefore, using local population activity and atmospheric dispersion parameters, it is possible for high-emitting vehicles (e.g., heavy-duty diesel trucks) to find routes that could cause lower health impacts on sensitive population groups such as children, seniors, and patients. The concept is particularly valuable for routing or regulating high-emitting vehicles near sensitive communities such as schools or disadvantaged neighborhoods. As a matter of fact, a few on-going geofencing and dynamic emission control projects are applying such a strategy to reduce emission in disadvantaged communities [*29*].

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

(1) In the case study, population activities are static estimates in year 2010. 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, and more population groups, such as workers, commuters' exposure can be accounted for.

(2) 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.

(3) Fuel consumption, carbon dioxide emissions, and economic impacts should also be evaluated.

(4) More efficient algorithms for routing such as the A* algorithm can be applied to make the low pollutant exposure navigation more practical. More options of solving optimal paths could be further explored.

V. Acknowledgment

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