

Evaluating System-Level Impacts of Innovative Truck Routing Strategies

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A Research Report from the Pacific Southwest Region University Transportation Center

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The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

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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Abstract

Heavy-duty diesel trucks (HDDTs) are significant contributors of fine particulate matter (PM_{2.5}) and nitrogen oxides (NO_x) emissions. As a result, communities with a large amount of truck traffic often experience elevated levels of diesel-related air pollution. One strategy for mitigating the air pollution impacts of truck traffic, called low exposure routing (LER), is to route HDDTs in a way that reduces the exposure of community members to air pollutant emissions from these trucks. In this research, we develop a novel framework that utilizes an activity-based transportation simulation model for the city of Riverside, California, to quantify the impacts of LER under different technology adoption rates. The results show that if the LER strategy is to become a standard routing strategy for all the HDDTs (i.e., 100% adoption rate), the amount of PM_{2.5} and NO_x emissions from the trucks that would be inhaled by the residents could be reduced by 11% and 17%, respectively. In addition, these public health benefits could be gained without imposing significant costs to the truck operators and the climate as the increases in the overall travel time and fuel consumption (and equivalently, carbon dioxide emission) for the trucks are only 1%.

Evaluating System-Level Impacts of Innovative Truck Routing Strategies

Executive Summary

Heavy duty-diesel trucks (HDDTs), the majority of which are used for freight movement, are significant contributors of fine particulate matter (PM_{2.5}) and nitrogen oxides (NO_x) emissions. As a result, communities close to freight hubs such as ports, railyards, and distribution centers often experience elevated levels of these pollutants. Studies have shown strong evidence that diesel emissions are associated with various health problems, including respiratory diseases and premature death. In the last few decades, efforts to reduce HDDT emissions and their health impacts have been focused on imposing increasingly stringent emissions standards. This has led to significant advancements in emission control technologies and alternative fuel vehicle technologies. While these technologies are effective at reducing emissions from HDDTs, the turnover of the existing HDDT population to these advanced technologies will require a large amount of investment and a long time. In the near term, other efforts to reduce emissions of the existing HDDTs and mitigate their impacts on communities are needed.

Recently, there have been efforts to develop strategies to reduce the air pollution impacts of truck traffic, especially in disadvantaged communities. One such strategy, called low exposure routing (LER), is to route HDDTs in a way that reduces the exposure of community members to air pollutant emissions from these trucks. It considers 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 LER strategy has already been evaluated at the vehicle level in our previous work. In this research, we develop a novel framework to quantify the impacts of LER under different levels of technology adoption rate, using the city of Riverside, California, as a case study. Specifically, the objectives of this project are to: 1) estimate potential public health benefits of the LER strategy, in terms of reduction in community-wide exposure to HDDT emissions, when multiple trucks take low exposure routes, 2) assess the impacts of such a large-scale adoption of the LER strategy on other performance metrics such as travel time and energy consumption.

To achieve the project objectives, we use truck origin-destination (O-D) trip data from a Southern California's regional transportation demand model, in conjunction with data about truck-related facilities and time-of-day profile of truck volume, to generate itineraries of trucks that traverse the city of Riverside. These truck trip itineraries are incorporated into an activity-based transportation simulation model for the city that was developed in prior research. The updated model, which simulates trips of passenger cars and freight trucks through reinforcement learning and dynamic daily activity planning techniques to achieve maximum utility by balancing preferences among travel duration, expenses, and convenience, is then used to evaluate the impacts of LER under different technology adoption rates. For the HDDTs adopting the LER

strategy, the estimated air pollution exposure, represented by the amount of pollutant emissions from the HDDTs inhaled by the local residents, is used as the cost in a least cost path algorithm to find a travel route that would minimize the total air pollution exposure value for the trips, subject to a limit in travel time increase as compared to the fastest route.

To evaluate the potential benefits and impacts of this air pollution mitigation strategy, simulation-based experiments were carried out for HDDT trips in and around the city of Riverside. The city has a road network with two major freeways that carry a large amount of truck traffic cutting through. It also has several densely-populated communities with a large fraction of children and seniors who are more sensitive to air pollution. The evaluation was conducted for the typical traffic and weather conditions during the hour of 10-11 AM on weekday. There were 992 HDDT trips across 498 unique O-D pairs in and around the city. The results show that for 27% of the unique O-D pairs, the fastest route for the trip is already the low exposure route. However, for 54% of the unique O-D pairs, a low exposure route that will take no more than 10% longer travel time than the fastest route can be found. If a HDDT takes the low exposure route between these O-D pairs, the amount of PM_{2.5} and NO_x emissions from the truck that would be inhaled by the residents would be reduced by 37% and 20% on average, respectively, as compared to taking the fastest route. On the other hand, the travel time and fuel consumption of the truck would increase by 3% and 3% on average, respectively.

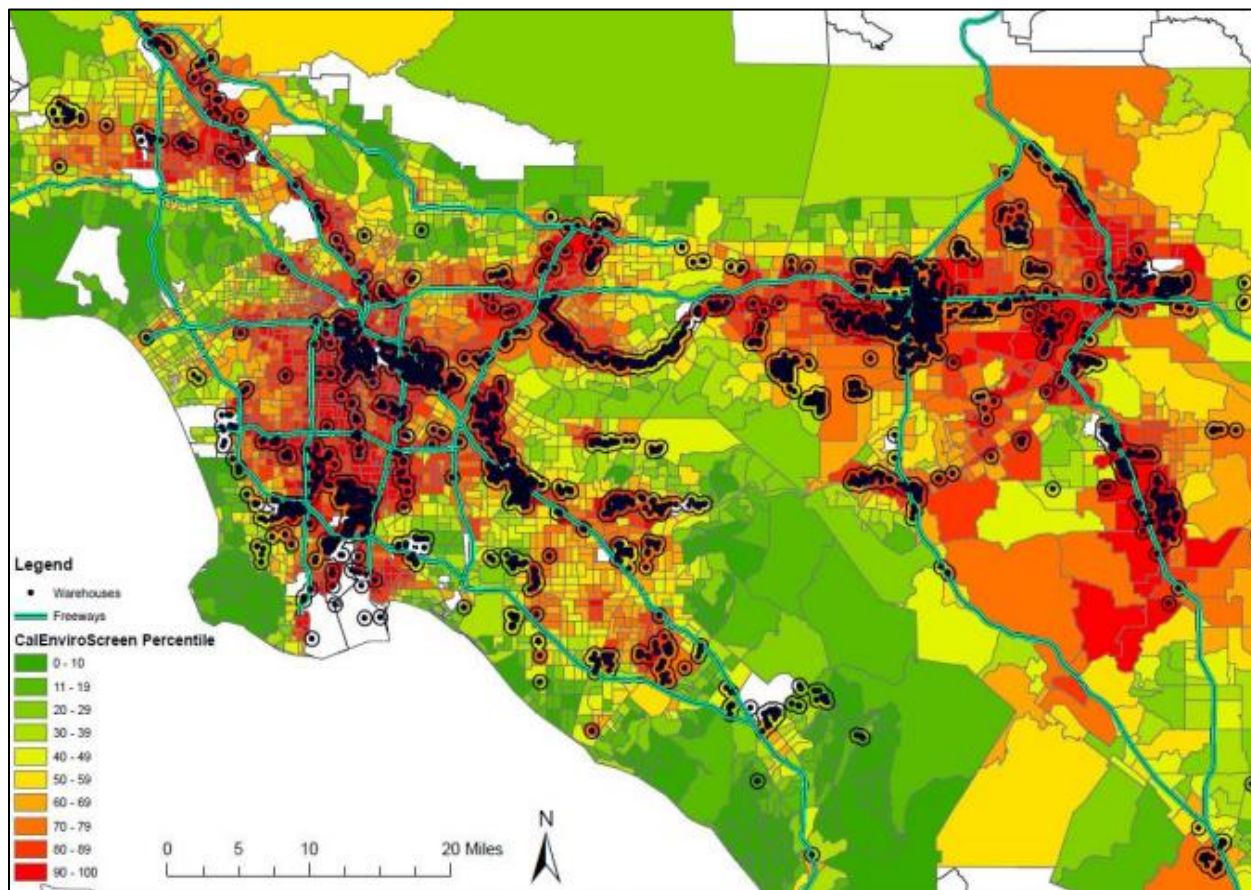
When evaluating the benefits and impacts of a large-scale adoption of the LER strategy among the 992 HDDTs traversing the city, it was found that both the reductions in air pollution inhalation by the residents and the increases in travel time and fuel consumption for the HDDTs are almost linearly proportional to the technology adoption rate. If the LER strategy with a limit of travel time increase of no more than 10% is to become a standard routing strategy for all the HDDTs (i.e., 100% adoption rate), the amount of PM_{2.5} and NO_x emissions from the trucks that would be inhaled by the residents could be reduced by 11% and 17%, respectively. In addition, these public health benefits could be gained without imposing significant costs to the truck operators and the climate as the increases in the overall travel time and fuel consumption (and equivalently, carbon dioxide emission) for the trucks are only 1%.

The evaluation results above indicate a high potential for the LER strategy to mitigate the air pollution impacts of HDDTs in cities and communities. This can be especially important for disadvantaged communities that are disproportionately affected by truck traffic. The strategy can serve as a near-term mitigation measure while the current HDDT fleet is turning over to cleaner or zero-emission vehicle technologies. From the implementation perspective, the technology readiness of the LER strategy is high as it can build on the existing software and hardware of fleet management and vehicle navigation systems. However, for the LER strategy to be impactful at the city or community scale, a technology adoption rate of more than 20% would be needed. Some incentives, policies, or even regulations may be required to help reach that level of technology adoption.

1. Introduction

Heavy duty-diesel trucks (HDDTs), the majority of which are used for freight movement, are significant contributors of fine particulate matter (PM2.5) and nitrogen oxides (NOx) emissions. As a result, communities close to freight hubs such as ports, railyards, and distribution centers often experience elevated levels of diesel-related pollutants [1]. For instance, Figure 1 shows that communities in the South Coast Air Basin, California, that are in close proximity to warehouse facilities are generally in the higher percentiles for their CalEnviroScreen scores [2], indicating that these communities experience more environmental and health burdens. In the last few decades, a large number of health studies have shown strong evidence that diesel emissions are associated with various health problems, including respiratory diseases and premature death [3].

Figure 1. Map of warehouse facilities (shown as black circles) in South Coast Air Basin and CalEnviroScreen percentile of each census tract [4]



To reduce HDDT emissions and protect public health, regulatory agencies have made continuous efforts in tightening the emission standards for these trucks. This has led to significant advancements in emission control technologies such as diesel particulate filter and selective catalytic reduction [5-7], as well as alternative fuel vehicle technologies such as compressed

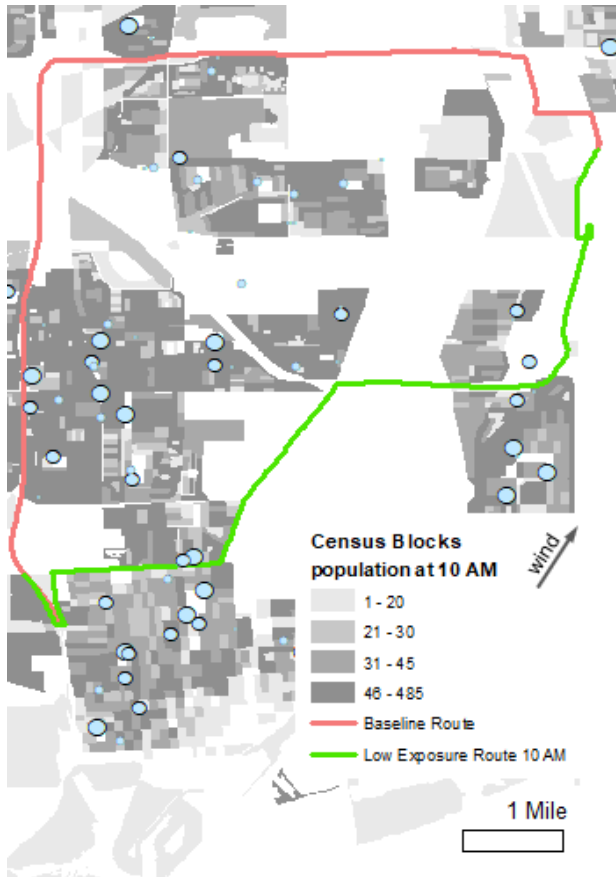
natural gas and electric trucks [8]. While these technologies are effective at reducing emissions from HDDTs, the turnover of the existing HDDT population to these advanced technologies would require a long-term and sizable investment. In the near term, other efforts to reduce emissions of the existing HDDTs and mitigate their impacts on communities are needed.

1.1 Review of innovative vehicle routing strategies

Vehicle routing is one strategy that has commonly been used to manage truck traffic in communities. Different vehicle routing strategies between the same origin-destination pair can result in significant disparities, not only in travel distance and travel time, but also in the amount of fuel consumption and emissions [9-10]. Over the last decade, there has been much research on developing and evaluating an eco-routing strategy. Eco-routing usually aims to minimize fuel consumption or emissions of the equipped vehicle. In [11], the authors proposed an eco-routing navigation system that utilizes real-time and historical data from different data sources, including loop detectors and probe vehicles. In [12], the authors developed an eco-routing application for HDDTs and evaluated the least fuel consumption route against the fastest route for more than 500,000 simulated trips in the Greater Los Angeles Metropolitan Area. It was found that the least fuel consumption route would require 4% to 33% less fuel, but would increase travel time by 6% to 53%. It was suggested that eco-routing could be beneficial to truck drivers and fleet operators where they can choose to use the fuel-optimized route for those trips where the fuel savings justify the extra travel time.

Recently, there has been increasing interest in a new vehicle routing strategy called low exposure routing that would either provide route guidance to vulnerable road users to reach the destination in the healthiest way, or suggest vehicles to select a travel route that minimizes air pollutant exposure to the localized population. In [13], the authors applied Clean Air Routing (CAR) on selected roads in Taiwan and used Neural Network Autoregression (NNAR) and an Autoregressive Integrated Moving Average (ARIMA) model to implement a spatio-temporal interpolation method to estimate PM_{2.5} concentration around the travel route. In [14-15], a low exposure routing method was developed to minimize the exposure of community members to air pollutant emission from HDDTs when they travel in the community, showing 30-80% reduction in the amount of PM_{2.5} from the truck that would be inhaled by the community members. As an example, Figure 2 illustrates the differences between the baseline route and the low exposure route of a truck trip in the city of Carson, California, as modeled in [15]. As compared to the baseline route, the low exposure route would take 4% longer travel time, but would reduce the amount of PM_{2.5} and NO_x from the truck that would be inhaled by the residents by 73% and 31%, respectively. Taking the low exposure route would also reduce carbon dioxide (CO₂) emissions of the truck by 9%. Based on these results, the truck driver should be encouraged to take the low exposure route for this trip.

Figure 2. Baseline route (BR) and low exposure route (LER) for an example truck trip [15]



	BR	LER	% Diff.
Trip Distance (miles)	11.9	9.3	-22%
Trip Time (minutes)	16.4	17.0	4%
Inhaled Mass of PM_{2.5} (µg)	0.3	0.1	-73%
Inhaled Mass of NO_x (µg)	29.9	20.6	-31%
Tailpipe emission of CO₂ (kg)	17.6	15.9	-9%

To the best of our knowledge, most research on innovative vehicle routing strategies has focused on determining the optimal routes for the individual vehicles. Little attention has been given to the impacts of a large-scale adoption of these innovative routing strategies. In fact, the impacts of a large-scale adoption of the low exposure routing strategy have never been evaluated.

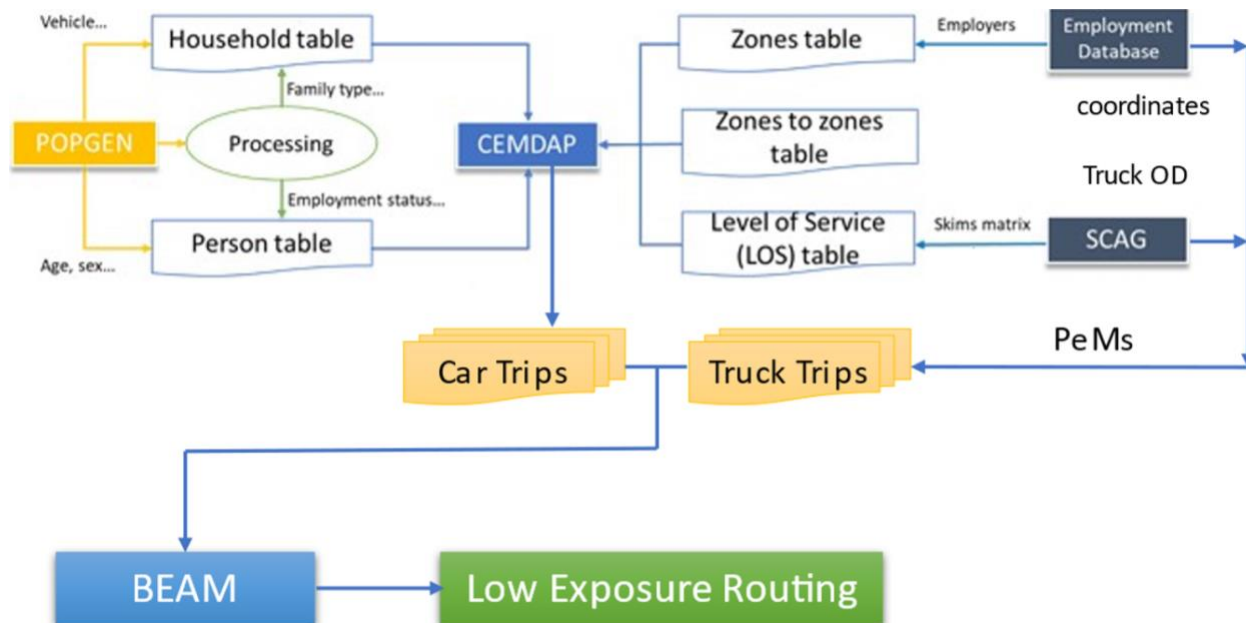
1.2 Objective and scope of the study

In this project, we aim to fill this research gap by first updating the activity-based transportation simulation model for the city of Riverside, California, that was previously developed by the project team [16] to include truck traffic, and then using the updated model to evaluate the system-level impacts of the low exposure routing (LER) technique for mitigating the impacts of truck emissions on communities in the city.

To achieve the project objective, we used truck origin-destination (O-D) trip data from the Southern California Association of Governments (SCAG)'s regional travel demand model [17], in conjunction with employment data from the Employment Development Department (EDD) [18] and hourly profiles of truck volume from the California Department of Transportation (Caltrans)'s Freeway Performance Measurement System (PeMS), to generate itineraries of trucks that traverse the city of Riverside. These truck trip itineraries were incorporated into the activity-based transportation simulation model for the city that was developed within the Behavior, Energy, Autonomy, and Mobility (BEAM) modeling tool [19]. The updated model, which simulates trips of passenger cars and freight trucks through reinforcement learning and dynamic daily activity planning techniques to achieve maximum utility by balancing preferences among travel duration, expenses, and convenience, was then used to evaluate the impacts of LER at the transportation system level. Specifically, we applied the LER strategy to route HDDT trips assuming different technology adoption rates. For the HDDTs adopting the LER strategy, the estimated air pollution exposure, represented by amount of pollutant emissions from the HDDTs inhaled by the local residents, was used as the cost in a least cost path algorithm to find a travel route that would minimize the total air pollution exposure value for the trip, subject to a limit in travel time increase as compared to the fastest route.

Figure 3 shows the workflow of the modeling and evaluation framework applied in this project.

Figure 3. Workflow of the modeling and evaluation framework



The remainder of the report is organized as follows. We first describe the modeling and simulation of truck traffic in the BEAM model for Riverside in Section 2. We then describe the methodology for determining low exposure route for HDDTs in Section 3. After that, in Section 4 we present the evaluation of the system-level impacts of the LER strategy. Finally, we discuss conclusions from the research in Section 5.

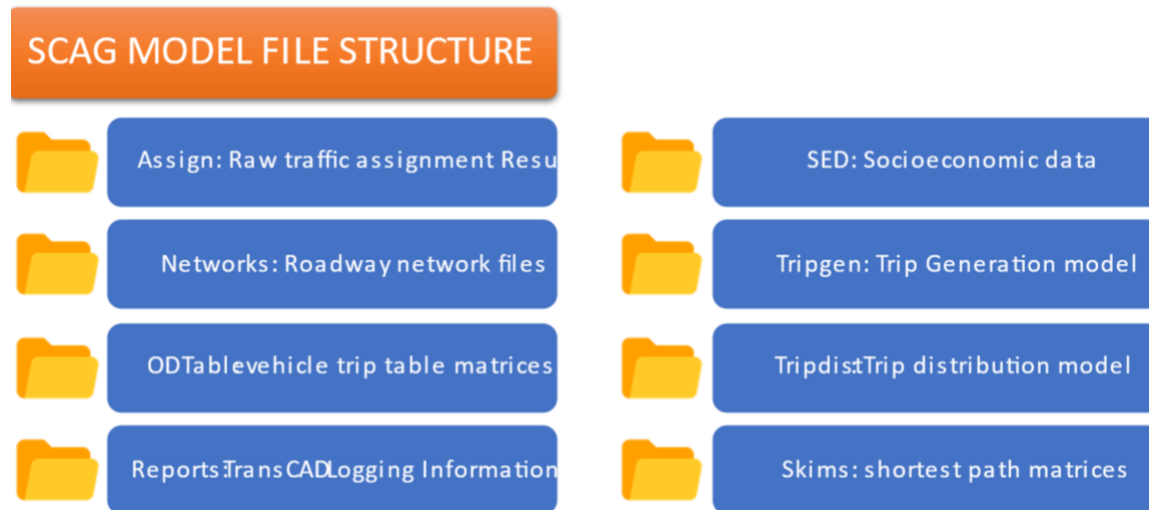
2. Traffic Modeling and Simulation in BEAM

2.1 Truck trip itinerary generation

To be able to simulate truck traffic in the BEAM model for the city of Riverside, we needed to input the trip itinerary of each truck in terms of start location, end location, and start time of each trip. This detailed itinerary data for all the trucks that traverse the city of Riverside was not readily available from any source, and thus, needed to be synthetically generated by combining truck-related data from multiple sources. We first extracted truck O-D trip data from the SCAG regional travel demand model. The model includes transportation network in six counties (Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura) and 191 cities in an area covering more than 38,000 square miles. Figure 4 shows the SCAG model file structure. SCAG develops long-range regional transportation plans including sustainable communities strategy and growth forecast components, regional transportation improvement programs, regional housing needs allocations, and a portion of the South Coast Air Basin’s air quality management plans. Zone-based O-D trip tables from the SCAG model were obtained for all three truck types in the model:

- 1) Light heavy-duty trucks (LHDTs) with gross vehicle weight rating (GVWR) 8,501-14,000 lbs
- 2) Medium heavy-duty trucks (MHDTs) with GVWR of 14,001-33,000 lbs
- 3) Heavy heavy-duty trucks (HHDTs) with GVWR of more than 33,000 lbs

Figure 4. SCAG model file structure



There are 11,267 Tier2 traffic analysis zones (TAZs) in the entire SCAG area (see Table 1), with 1,532 of them being in Riverside County in which the city of Riverside is located. To obtain truck O-D trip tables associated with the city of Riverside only, we used TransCAD modeling software to make the subarea selection and run the ‘Subarea Analysis’ tool. The Subarea Analysis tool output four groups of trips:

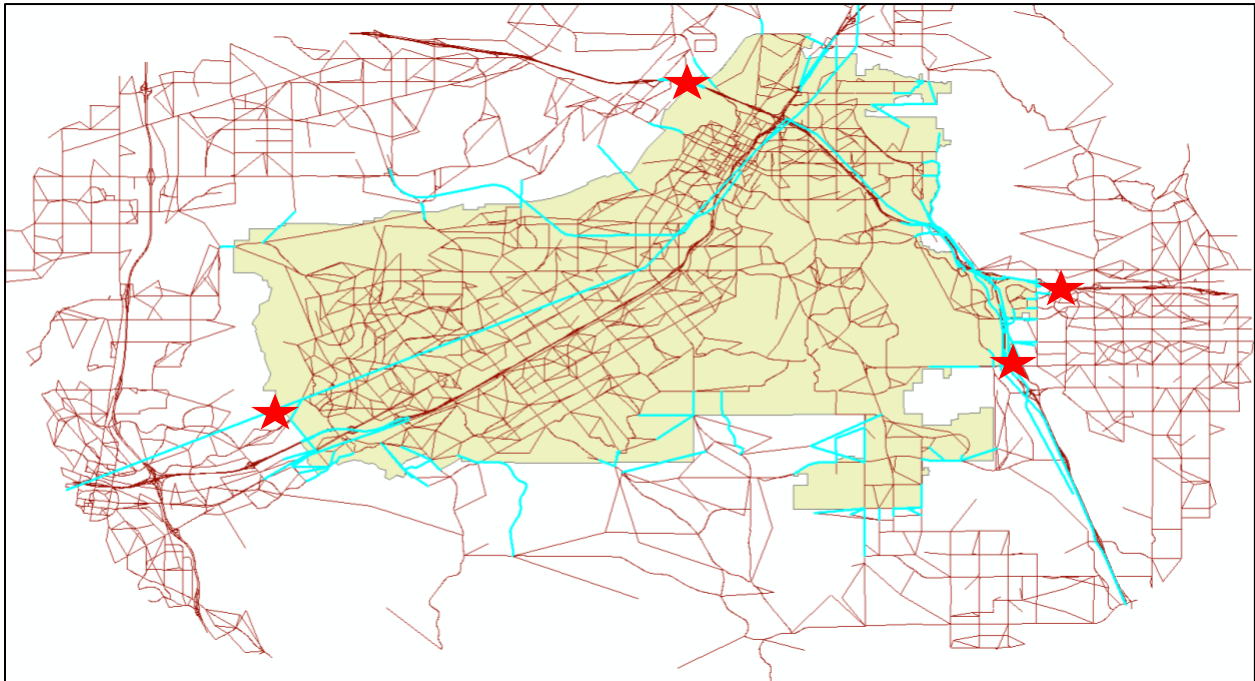
- 1) Trips that start and ends within the city of Riverside
- 2) Trips that start and ends outside the city
- 3) Trips that start in the city but end outside the city
- 4) Trips that start outside the city but end in the city

After that, trip origins and destinations outside the city were consolidated to a limited number of entry/exit points where roadways cross the city's boundary. Examples of the entry/exit points are shown as red stars in

Figure 5. This process reduced the size of truck O-D trip tables to 152 x 152, while preserving the number of truck trips entering, exiting, or passing through the city.

Table 1. Summary of geographic units in the SCAG region

Modeling Area	2010 Census Tract	2010 Census Block Group	RSA *	CSA**	Tier 1 TAZ (Internal)	Tier 2 TAZ (Internal)
Imperial County	31	96	1	15	110	239
Los Angeles County	2,346	6,425	21	155	2,243	5,697
Orange County	583	1,823	10	43	666	1,741
Riverside County	453	1,030	11	38	478	1,532
San Bernardino County	369	1,092	7	34	402	1,395
Ventura County	174	430	6	17	210	663
Total	3,956	10,896	56	302	4,109	11,267

Figure 5. Examples of entry/exit points at the boundary of the city of Riverside

In the O-D trip tables for the subarea, there were 12,318 LHDT trips, 10,142 MHDT trips, and 11,344 HHDT trips. For each truck type, there were five O-D tables, one for each of the five time-of-day periods:

- 1) Morning peak (6 AM to 9 AM)
- 2) Midday (9 AM to 3 PM)
- 3) Afternoon peak (3 PM to 7 PM)
- 4) Evening (7 PM to 9 PM)
- 5) Night (9 PM to 6 AM)

Truck trips in each time-of-day period are aggregate with no information on the start time of each trip. This is not sufficient for generating truck trip itineraries. One way to address this limitation is to assume that truck trips in a specific time-of-day period are uniformly distributed across the time period. However, this assumption is likely to be unrealistic. Therefore, we used hourly profiles of truck volume obtained from Caltrans' PeMS to further distribute truck trips temporally within each time-of-day period. PeMs collects real-time traffic data from over 39,000 individual detectors on freeway systems across California, which enables the monitoring of traffic volume by vehicle category.

Figure 6 depicts the network of detectors on the freeways in and around the city of Riverside. Figure 7 summarizes the workflow for generating hourly truck trip O-D tables applied in this project.

Figure 8 then shows the resulting hourly truck trip profiles for each type of trucks.

Figure 6. PeMs detectors in and around the city of Riverside

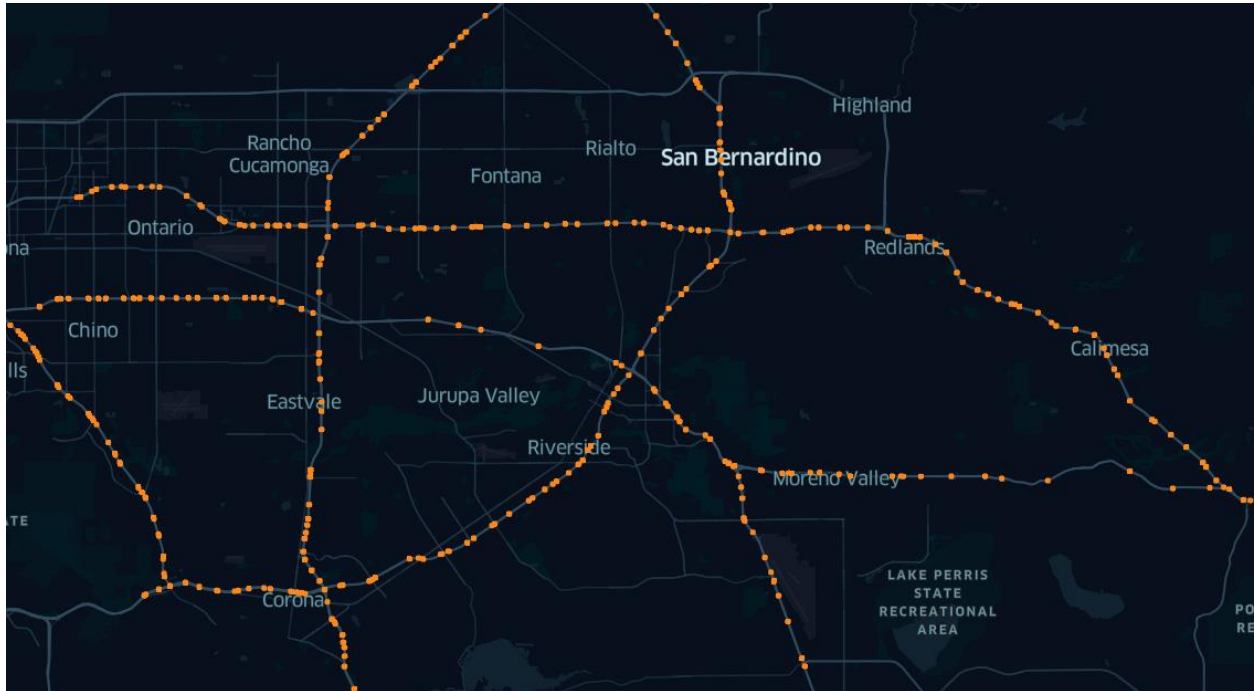


Figure 7. Workflow for generating hourly truck trip O-D tables

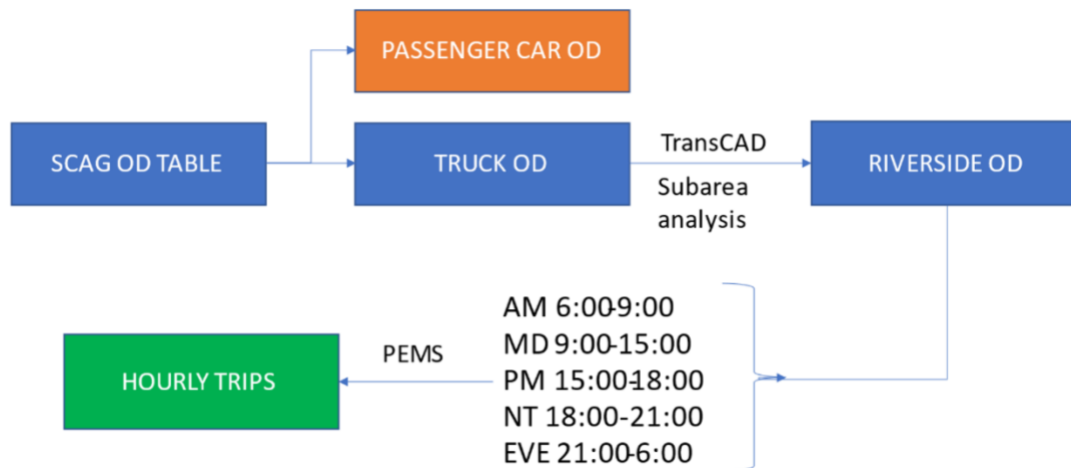
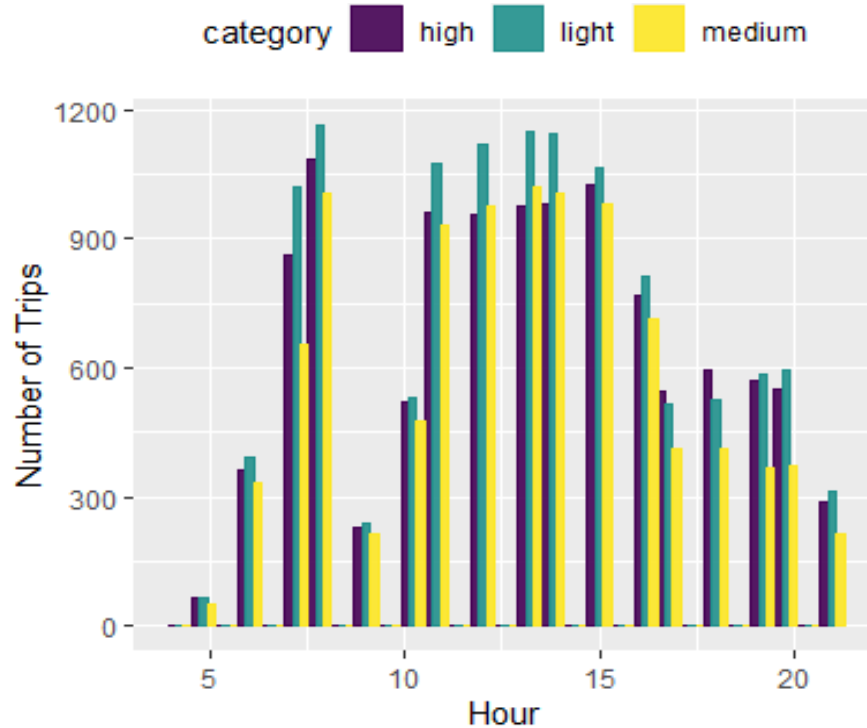


Figure 8. Number of LHDT, MHDT, HHDT trips by hour of day from 4 AM to 9 PM



After disaggregating truck trips temporally, we proceeded to disaggregate them spatially. The hourly truck trips from the previous step were stored in zone-based O-D trip tables of the size 152 x 152. We assumed that the majority of HDDTs are commercial vehicles. The Employment Development Department (EDD) maintains records of businesses in the city of Riverside. Certain types of businesses (warehouses, grocery stores, big box stores, etc.) can be reasonably assumed to generate or attract truck trips. Thus, for truck trips that start or end in a TAZ within the boundary of the city of Riverside, we assigned the coordinates of those types of businesses in the corresponding TAZ to the truck trips as their origins or destinations. For truck trips that just passes through the city, we assigned the closest boundary points as their origins or destinations.

Figure 9 shows the resulting truck trips between specific origin and destination locations.

Figure 9. [Top Left] Locations of truck trip origins; [Top Right] Locations of truck trip destinations; [Bottom] Truck trips between the origins and the destinations



Since the zone-based O-D trip tables provide information about the number of truck trips within each specific time-of-day period, it was not possible to tie multiple trips that may have made by the same truck together into a tour or a full itinerary for the day. That means a truck trip that ends at one location was assumed to be independent of all the truck trips that start at that same location. This assumption may be unrealistic, but it is unlikely to have a major impact on the route choice of the individual truck trips, which is the focus of this research.

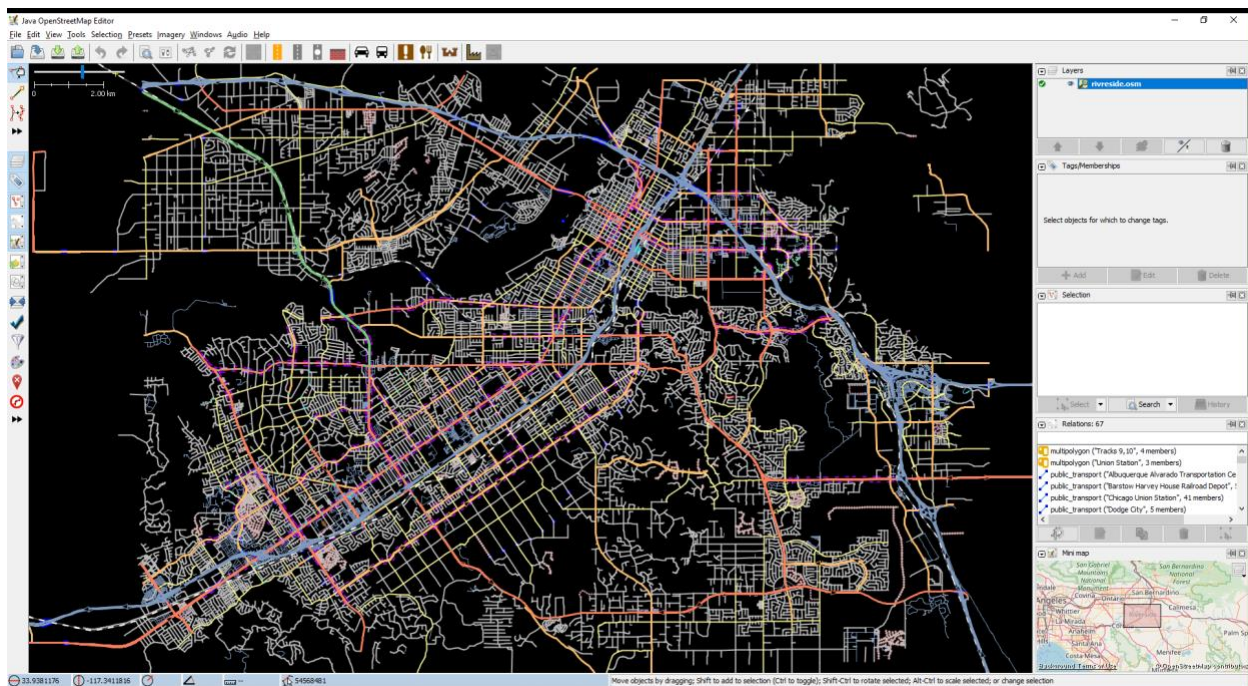
2.2 Riverside BEAM model with truck traffic

The BEAM modeling tool is developed by researchers at the Lawrence Berkeley National Laboratory to support evaluation of the energy and mobility impacts of modern transportation technologies, such as connected and automated vehicles and shared mobility services. Extended from MATSim (Multi-Agent Transportation Simulation), BEAM includes an efficient trip planning

and routing module to allow agents to tradeoff their preferences among travel duration, expenses, and convenience. Agents request routes from the routing engine, which provides alternative routes for them to choose from. BEAM places an emphasis on within-day planning, which means agents can dynamically respond to the state of the system and select what service or mode to use. BEAM is an open-source simulation platform and has the flexibility to accommodate the modeling of emerging mobility services. It is designed to be scalable and can utilize high performance computing services.

To develop the BEAM model for the city of Riverside, we first imported the roadway network file for the city from OpenStreetMap, a crowd-sourced map data platform. The raw network files in osm (OpenStreetMap) format was opened in Java OpenStreetMap Editor and transformed into pbf file (Figure 10). After placing this pbf file in the R5 folder under BEAM repository, the files network.dat and physsim.xml that stores all map-related data were automatically generated. The network.dat file contains some basic information about road links in the network. After examining link speed information, we found that the free-flow speed of local roads in some residential areas are much higher than the actual speed limit in the real world. Thus, the free-flow speed of these roads was updated to match their actual speed limit.

Figure 10. Roadway Network Map for City of Riverside from OpenStreetMap



In the next step, we prepared other input files needed for running the BEAM model. The BEAM model for Riverside that was developed in a previous research project already included traveler agents. Thus, in this project we focused on adding freight truck agents to the model. The

minimum input files needed for conducting a model run include data about households, persons, vehicle fleet, vehicle types, map, and model configuration. As discussed in Section 2.1, we had already generated synthetic itineraries of truck trips in the city. However, in order to conform with BEAM's model syntax and file structure, these truck trip itineraries needed to be associated with 'households' and 'persons'. Therefore, we assigned virtual households and virtual drivers to the truck trip itineraries. More detailed information about each input file is provided in Table 2. Many of these input files are not relevant to truck traffic, but they need to be specified and included in order to run the model.

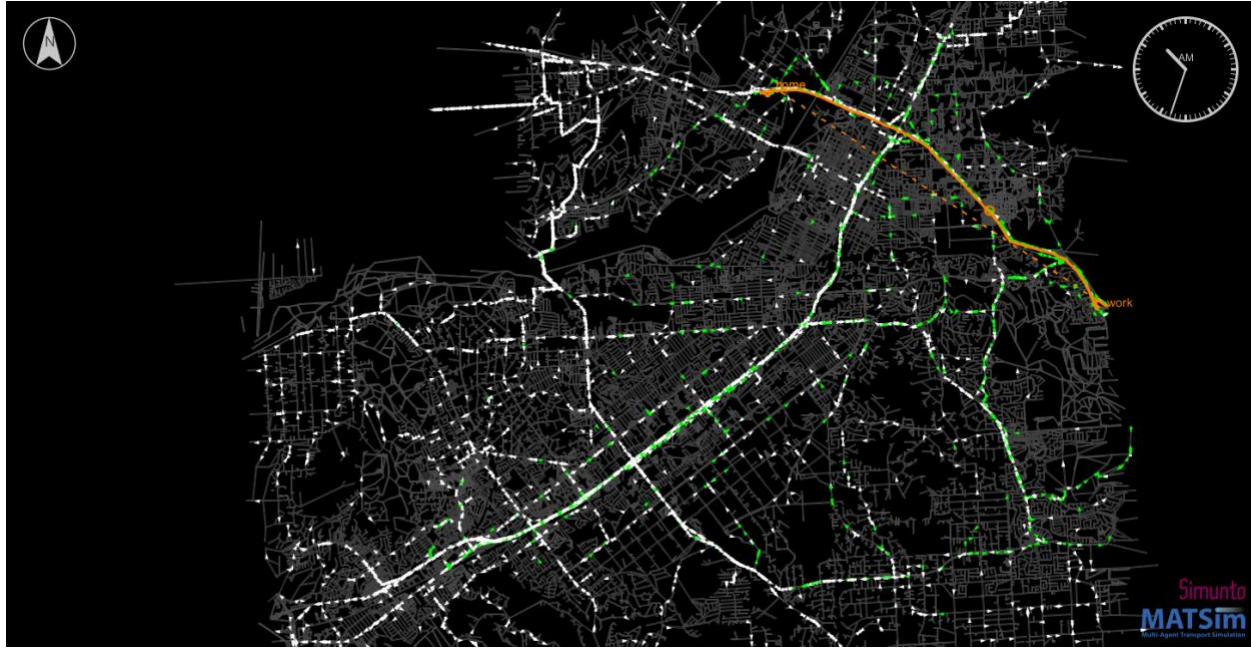
Table 2. Inputs files for simulating truck traffic in Riverside BEAM model

File Name	Specifications for Truck Trip Itineraries
Households.csv	<ol style="list-style-type: none"> 1) Unique household ID 2) Number of vehicles is one in each household 3) Number of persons is one in each household 4) Different household income for LHDTs, MHDTs, HHDTs
Persons.csv	<ol style="list-style-type: none"> 1) Unique person ID 2) Age is 35 3) Gender is male 4) Corresponding household ID
Plans.csv	This file contains the previously generated truck trip itineraries.
Vehicletypes.csv	<ol style="list-style-type: none"> 1) Add LHDTs, MHDTs, and HHDTs as new vehicle types 2) Length of LHDTs is 10 m; length of MHDTs is 15 m; length of HHDTs is 20 m 3) Diesel engine 4) Different sampling income group for LHDTs, MHDTs, and HHDTs
Buildings.csv Units.csv Parcels.csv	Associated with households.csv
Taz_parking.csv Taz_center.csv	Assign parking location uniformly in the city

Once all the input files were properly specified and loaded, BEAM executed the model run and generated output files that included detailed activity and event logs for each traveler and each truck, along with travel time, average speed, link speed, and mode choice statistics (for traveler agents). Using a software tool called VIA, outputs from the model run can be simulated and visualized. Figure 11 shows a snapshot of VIA displaying the roadway network and simulating vehicles traveling in the network. Freight trucks were in green color while passenger cars were in

white color. VIA is also capable of displaying the O-D locations and travel route of each agent, such as those marked by the orange circles and orange curve in the snapshot.

Figure 11. Simulation and visualization of BEAM model run outputs in VIA



We tested the Riverside BEAM model in two scenarios to verify its reasonableness. In the car-only scenario, only passenger car trips were loaded into the model to simulate the traffic condition without truck traffic. In the car & truck scenario, the truck trips were added to the network to incorporate the impact of freight transportation. In total, there were 46,368 trips in the car-only scenario in the morning, while the number of trips in the car & truck scenario was 57,262. Due to the added truck traffic, the network-wide average speed was expected to decrease. Figure 12 shows the comparison of the network-wide average speeds between the two scenarios at different hours of day. The average speeds in the car & truck scenario were generally lower, especially between 8 AM and 12 PM.

Figure 13 shows the maps of link speeds on the roadway network during 10 AM. The map for the car-only scenario is on the left while the map for the car & truck scenario is on the right. In the maps, the roadway links are colored based on their ratio of link speed to free-flow speed. Light blue represents the link speed being 90%-100% of the free-flow speed; green 80%-90%; brown 50%-80%; red 30%-50%; and black 0%-30%. As expected, there are more congested links in the car & truck scenario. Most of the congested roadways (e.g., SR-91 and I-215) have similar trends to the congestion patterns observed on Google Maps during the same time of day.

Figure 12. Network-wide average speed comparison

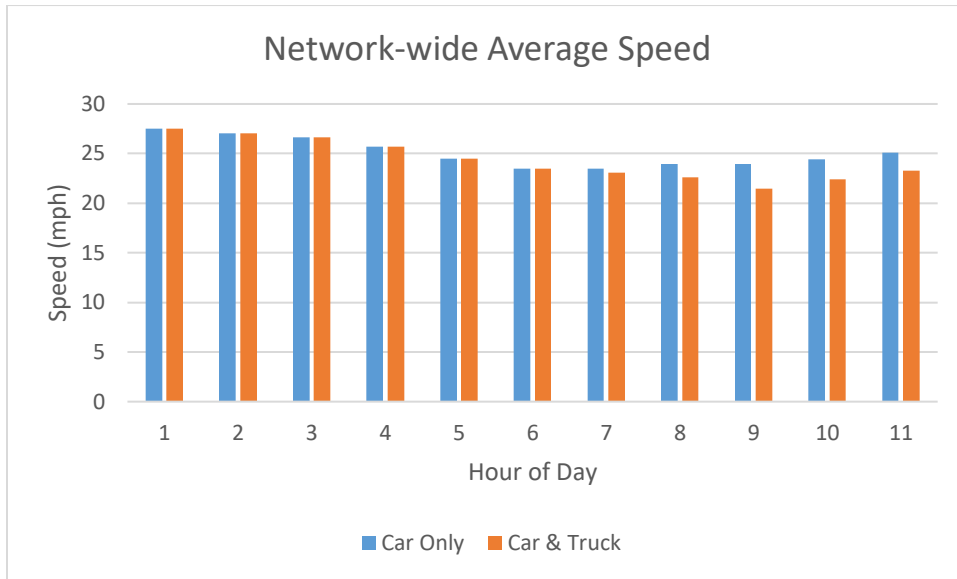


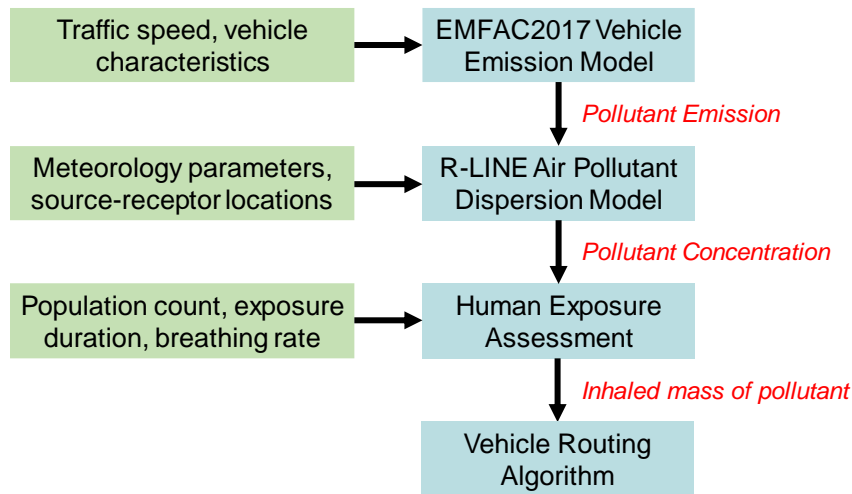
Figure 13. Link speeds during 10 AM in the car-only scenario [left] and the car & truck scenario [right]



3. Low Exposure Routing for Heavy Duty Diesel Trucks

Figure 14 presents the methodological framework of exposure-based routing. It involves a modeling chain that starts from vehicle emission modeling to air dispersion modeling, human exposure assessment, and finally vehicle route calculation where the output from one step is used as an input for the next step. In addition, each step also requires other inputs. The inputs and assumptions associated with each modeling step are described in the subsections that follow.

Figure 14. Methodological framework of low exposure routing



3.1 Vehicle emission modeling

To determine vehicle emission factors (in the unit of *gram/mile*), data about link average speed and vehicle characteristics (e.g., vehicle type and model year) are needed as inputs. 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 [20], and MOVES (MOTOR Vehicle Emission Simulator) developed by the U.S. Environmental Protection Agency (EPA), which is used for regulatory purposes in the other 49 states [21].

In this project, the average speeds on roadway links in the city of Riverside were obtained from the BEAM model run outputs as described in Section 2.2 [22]. The modeling of vehicle emissions was performed for HDDTs of model year 2012. For each roadway link, running exhaust emission factors of PM_{2.5}, NO_x, and CO₂ for these trucks were obtained from the EMFAC2017 model based on the link average speed from BEAM. By assuming that all the HDDTs traversing the city are all diesel trucks, the emissions of their trips can be calculated using the emission factors obtained.

3.2 Dispersion modeling

A dispersion model is commonly used to estimate the concentration of air pollutants emitted from vehicular sources at specific receptor locations. In this project, R-LINE, a research grade dispersion model for near-roadway assessment was used [23]. Micrometeorology data inputs for R-LINE such as air temperature, wind speed, wind direction, surface friction velocity, and Monin-Obukhov length were obtained from the South Coast Air Quality Management District (SCAQMD)'s website [24]. The data for Monday May 9, 2016, were used. Source height was assumed to be 2.5 meters (~8.2 ft), which represents a typical height of exhaust stacks of HDDTs. Receptor height was assumed to be 1 meter (~3.3 ft), which represents an average height of 5 years old children. A sensitivity analysis revealed that the modeled concentration values were similar at the typical heights of older children and adults as well. For more details about other model configurations, please refer to the R-LINE user guide [25].

3.3 Exposure assessment

In this research, pollutant exposure is referred to the amount of pollutant inhaled by a group of subjects. To assess the pollutant exposure, *inhaled mass (IM)* is used as the metric and is calculated as in Equation (1) [26].

$$IM = C \cdot Pop \cdot t \cdot BR \quad (1)$$

where C is the pollutant concentration ($\mu\text{g}/\text{m}^3$) in a given microenvironment; Pop is the number of subjects in the microenvironment; t is the duration of each trip (*hour*); and BR denotes the breathing rate ($\text{m}^3/\text{hour}/\text{capita}$) of the subjects exposed to the pollutant.

The population at sensitive locations, such as schools, homes, and workplaces were estimated based on a number of sources [27-29]. Breathing rates of different age groups were based on U.S. EPA Exposure Factors Handbook [30]. In addition, the California Office of Environmental Health Hazard Assessment's Technical Support Document of Exposure Assessment and Stochastic Analysis included detailed breathing rate scenarios [31]. It is desirable to reduce population exposure to traffic-related air pollutants because tailpipe emissions, such as PM_{2.5} and NO_x, are associated with health risks in young children, older adults, patients, and even healthy adults [32]. In this study, a population-wide average breathing rate of 17 m³/day was assumed.

3.4 Vehicle route calculation

Vehicle route calculation was done by solving the shortest path problem (SPP). SPP is traditionally aimed at finding a travel route between a pair of origin-destination points that has the shortest distance or shortest travel time. However, the routing objective in this project is to minimize inhaled mass of pollutant while limiting the increase in travel distance to be within a reasonable range for the trip. This is a multi-objective SPP studied by many researchers (e.g., [33]). Several

methods for solving multi-objective SPP were summarized in [34]. In this study, a weighting method was used to transform the multi-objective SPP into a single-objective SPP as in:

$$\mathit{weighed_cost}_k = \sum_{f=1}^F (w_f \times \mathit{cost}_{f,k}) \quad (2)$$

where $\mathit{weighed_cost}_k$ is the combined cost for link k ; w_f is the weighting factor for $\mathit{cost}_{f,k}$ (a single cost f for link k), which can be distance, time, monetary cost, inhaled mass of pollutant, etc. There are a total of F single costs and weighting factors, and $\sum_{f=1}^F w_f = 1$. Assume t_k is the travel time of the truck on link k as derived from link length and link average speed, and IM_k is the total mass of pollutant inhaled by localized population as the truck traverses link k . Since the two costs have different units and numerical ranges, a normalization is applied as:

$$IM_k = IM_{orig}/IM_{max} \quad (3)$$

$$t_k = t_{orig}/t_{max} \quad (4)$$

where IM_{orig} and t_{orig} are the original inhaled mass and link travel time; IM_{max} and t_{max} are the maximum inhaled mass and link travel time in the entire network.

The routing algorithm finds a route with the least total cost for a given O-D pair where:

$$\mathit{total\ cost} = \sum_{i \in L} \mathit{cost}_i \quad (5)$$

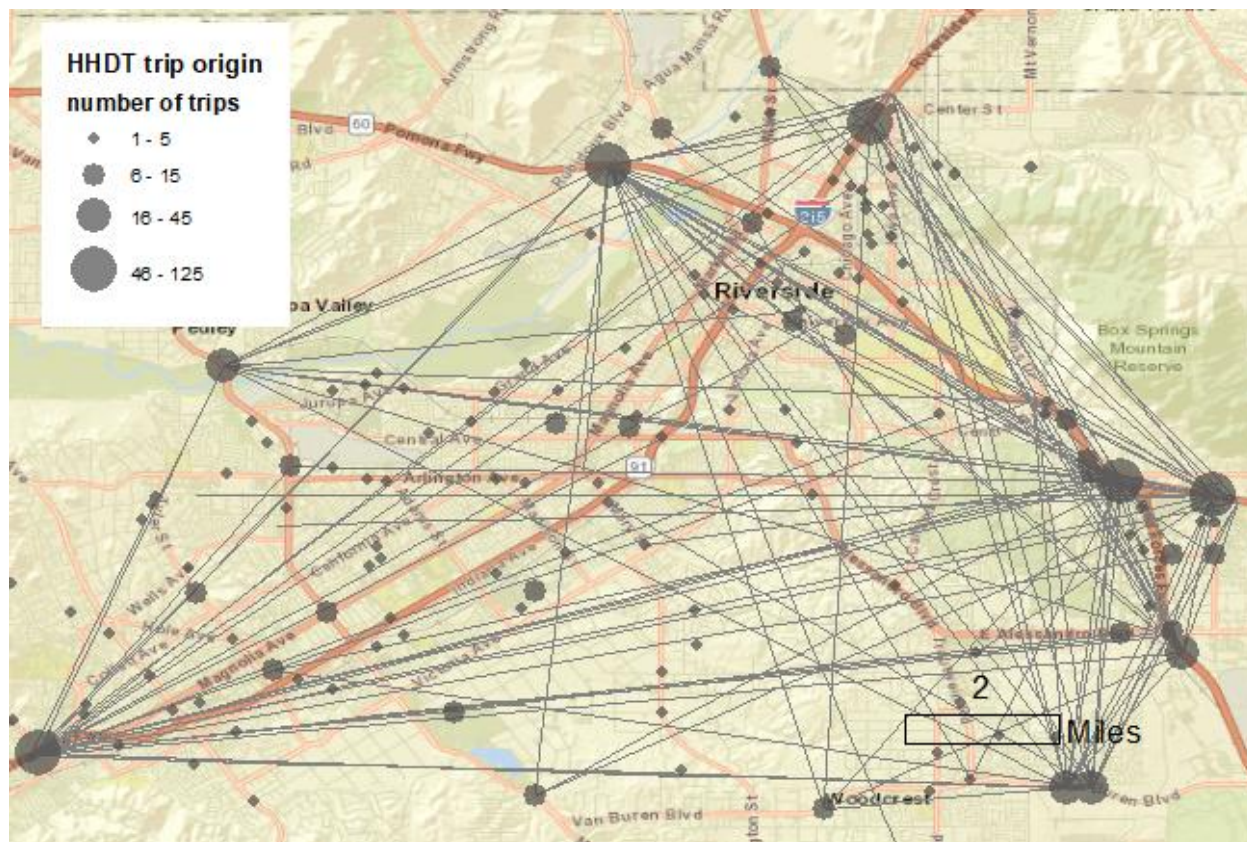
and L is the set of links in the least-cost path computed by the routing algorithm.

The total cost is sensitive to w_f . When w_f for travel time is 1, the routing algorithm simply finds the fastest route. When w_f for inhaled mass of pollutant is 1, the algorithm simply finds the least pollutant exposure route. Based on a sensitivity analysis of w_f , the values of w_f for PM2.5 IM , NOx IM , and travel time were set to 0.25, 0.25, and 0.5, respectively. The route calculated using these weighting factors is thus referred to as a low pollutant exposure route or low exposure route (as opposed to the least exposure route).

4. Case Study Evaluation

The city of Riverside is located about 60 miles east of Los Angeles with population of 334,000 in 2021. Riverside City is the county seat of Riverside County and a rapidly developing suburban with several urban cores. As mentioned in Section 3.3, we estimated the population at schools, homes, and workplaces in the city from a variety of sources. Then, the pollutant exposure values were modeled for the traffic and meteorological conditions during 10-11 AM on a typical work day. Based on the truck trip itineraries generated as explained in Section 2.1, there are 992 HHDT trips during 10-11 AM. Figure 15 displays the locations of trip origins as grey solid circles. The size of the circles corresponds with the number of trips that start at those locations. The bigger circles are the major entry points to the city and large stores/warehouses. The grey lines in the figure represent the trip O-D pairs across the city. For There are many trips that go from one side of the city to the other side on the freeways that cut through the city including SR-60, SR-91, and I-215.

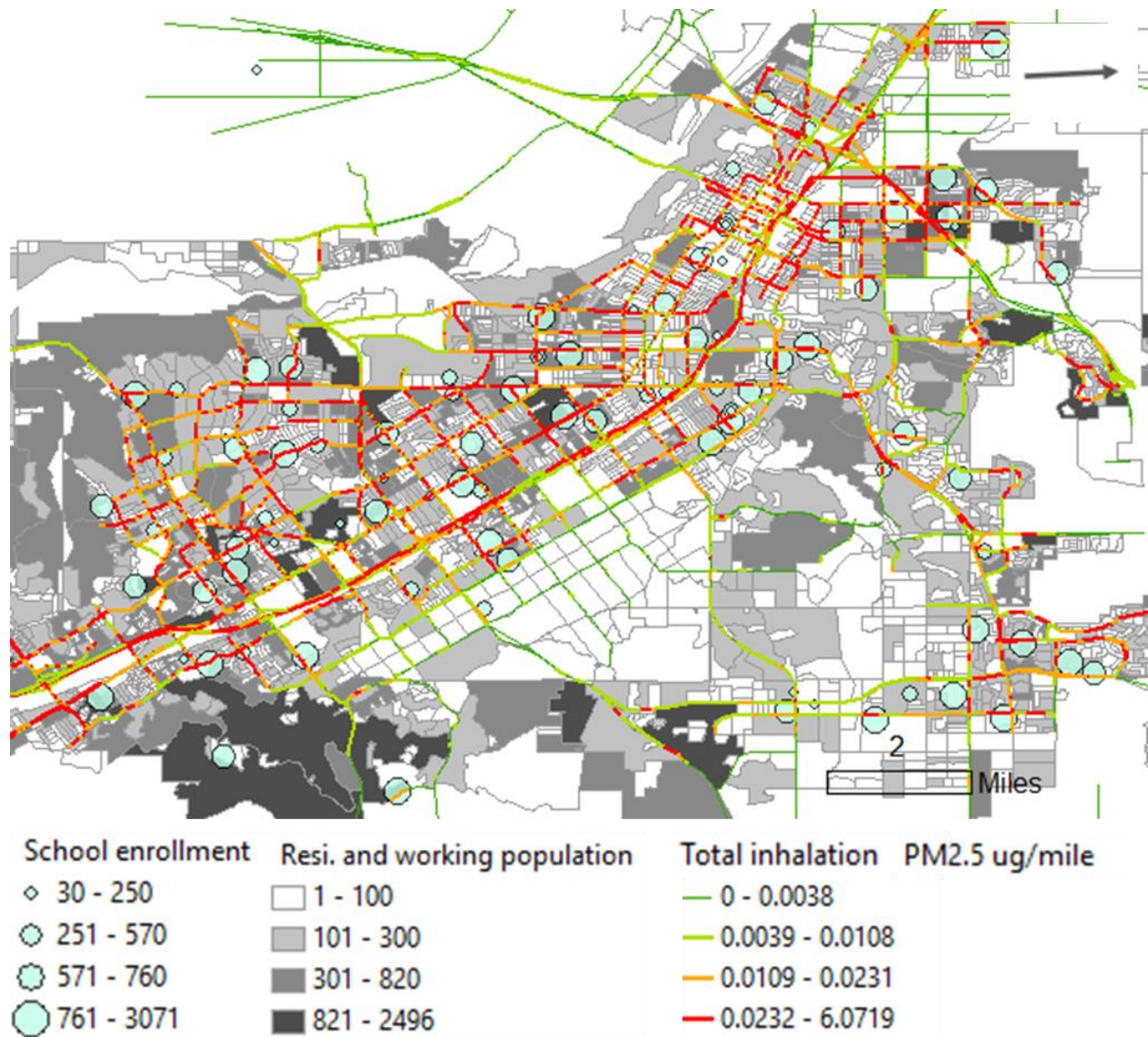
Figure 15. HHDT trip origins and number of outbound trips



The map in Figure 16 shows aggregated PM2.5 *IM* values at both sensitive facilities and census blocks based on the traffic and meteorological conditions at 10 AM on May 9, 2016. For instance, a PM2.5 *IM* value of 3 µg/mile means that there would be 3 µg of PM2.5 inhaled by the nearby

population after the truck has traversed this one-mile roadway link in the given scenario. As air pollutants from one roadway link can reach multiple facilities and census blocks, the *IM* values are generally higher for roadway links with large sensitive facilities and densely populated census blocks within proximity. Figure 16 also shows the wind direction in the upper right corner. It can be observed that roadway links upwind of large sensitive facilities and densely populated census blocks generally have higher *IM* values than those downwind.

Figure 16. Estimated amount of PM_{2.5} inhaled by the population ($\mu\text{g}/\text{link}$) if a HDDT traverses the roadway links



For each of the 992 HHDТ trips, there are 498 trips with unique O-D pairs. We first evaluated the likelihood of finding a low exposure route for the trips between these unique O-D pairs, and its

attractiveness if one is found. For each unique O-D pair, both the baseline route and the low exposure route were determined and their route attributes compared, as presented in

Table 2. In determining the baseline route, it was assumed that the truck driver would normally take the fastest route.

In

Table 2, the HHDT trips were grouped based on how much longer the trip time of the low exposure route was as compared to that of the baseline route. The values of route attributes shown in the table are the average value for the trips in each group. It was found that:

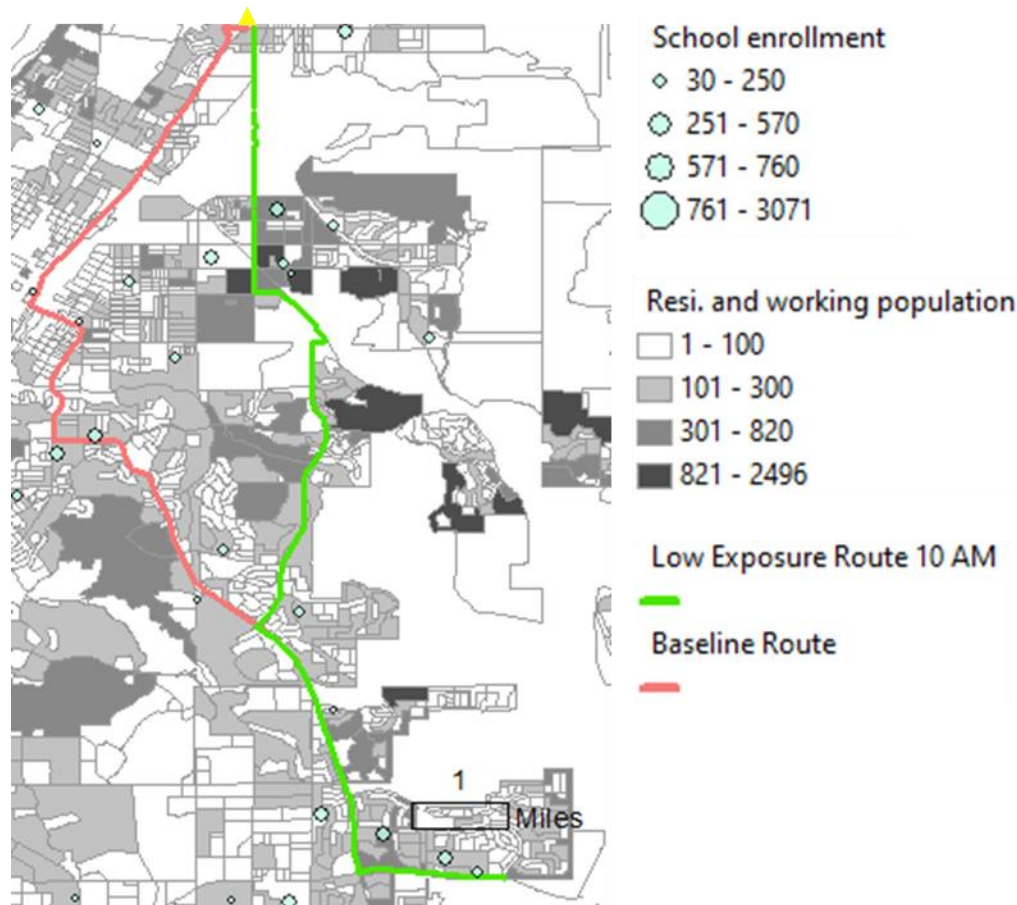
- Among the 498 trips, the baseline route and the low exposure route were the same for 136 trips (27%).
- An *attractive* low exposure route with up to 10% longer trip time was found in 268 out of 498 trips (54%). On average, the low exposure route for these trips would have 3% longer trip time as compared to the baseline route, but it would reduce the amount of PM2.5 and NOx emissions from the truck that would be inhaled by the local population by 37% and 20%, respectively. It would also reduce tailpipe CO2 emission from the truck by 3% on average.
- An *acceptable* low exposure route with 10%-20% longer trip time was found in 68 out of 498 trips (14%). On average, the low exposure route would have 15% longer trip time and generate 25% more tailpipe CO2 emission as compared to the baseline route, but it would reduce inhaled mass of PM2.5 and NOx emissions by 61% and 25%, respectively.

Table 2. Comparison of route attributes for truck trips between unique O-D pairs

May 9, 2016, 10 A.M.		Group 1: LER is the same as BR	Group 2: LER is 0%-10% longer	Group 3: LER is 10%-20% longer	Group 4: LER is >20% longer	All Trips
Number of trips		136	268	68	26	498
Percent of trips		27%	54%	14%	5%	100%
Baseline Route (BR)	Trip distance (miles)	4.3	9.1	10.9	12.6	8.2
	Trip time (minutes)	8.5	17.3	18.4	20.3	15.2
	Trip speed (mph)	30.6	31.6	35.5	37.3	32.5
	Inhaled mass of PM2.5 (µg)	0.10	0.31	0.48	0.58	0.29
	Inhaled mass of NOx (µg)	23.9	84.4	99.0	101.0	70.7
	Tailpipe emission of CO2 (kg)	15.5	31.4	32.7	35.5	27.5
Low Exposure Route (LER)	Trip distance (miles)	4.3	8.8	10.1	11.7	7.9
	Trip time (minutes)	8.5	17.8	21.2	25.0	16.1
	Trip speed (mph)	30.6	29.5	28.7	28.0	29.4
	Inhaled mass of PM2.5 (µg)	0.10	0.19	0.19	0.17	0.17
	Inhaled mass of NOx (µg)	23.9	67.2	74.4	75.5	56.8
	Tailpipe emission of CO2 (kg)	15.5	32.5	40.7	49.0	29.8
Percent Difference (LER vs. BR)	Trip distance	0%	-4%	-7%	-8%	-4%
	Trip time	0%	3%	15%	23%	6%
	Trip speed	0%	-7%	-19%	-25%	-10%
	Inhaled mass of PM2.5	0%	-37%	-61%	-70%	-42%
	Inhaled mass of NOx	0%	-20%	-25%	-25%	-20%
	Tailpipe emission of CO2	0%	3%	25%	38%	9%

Figure 17 shows an example trip where the low exposure route is different from the baseline route. It goes from a location in the northeast corner of the city (marked by the yellow triangle in the figure) to a destination in the southeast corner of the city. If taking the baseline route (red line), the truck will first get on the freeway before taking surface streets that go through a number of moderately populated census blocks. Along the way, the truck will drive past four schools. On the other hand, if taking the low exposure route (green line), the truck will primarily take surface streets without much population nearby, although it will drive past a few census blocks with high population. As compared with the baseline route, the low exposure route would take 3% longer travel time, but would reduce PM2.5 inhalation, NOx inhalation, and CO2 emissions by 66%, 56%, and 2%, respectively.

Figure 17. Baseline route and low exposure route for an example trip (yellow triangle is trip start location)



	BR	LER	%Diff.
Trip distance (miles)	12.6	11.0	-12%
Trip Time (minutes)	24.9	25.6	3%
PM2.5 inhalation (μg)	0.51	0.17	-66%
NOx inhalation (μg)	226.5	100.2	-56%
CO2 tailpipe emission (kg)	48.0	47.1	-2%

The above analysis was performed for trips with unique O-D pairs. In the next analysis, we accounted for all the 992 HHDT trips during 10-11 AM, and varied the technology adoption rate. A total of 9 scenarios were simulated:

1. Baseline
2. 10% limit for travel time increase; 10% technology adoption rate
3. 10% limit for travel time increase; 20% technology adoption rate
4. 10% limit for travel time increase; 50% technology adoption rate
5. 10% limit for travel time increase; 100% technology adoption rate
6. 20% limit for travel time increase; 10% technology adoption rate
7. 20% limit for travel time increase; 20% technology adoption rate
8. 20% limit for travel time increase; 50% technology adoption rate

9. 20% limit for travel time increase; 100% technology adoption rate

Scenario 1 (baseline) is where all 992 HHDTs use the fastest route for their trips. Scenario 2 means that randomly sampled 10% of the HHDTs are equipped with the LER technology, but they will take the low exposure route only if it will take no more than 10% longer travel time when compared with the fastest route. The remaining scenarios test a combination of four technology adoption rates (10%, 20%, 50%, 100%) and two thresholds for travel time increase (10%, 20%). The results are summarized in Table 3.

Table 3. Impacts of large-scale adoption of LER

May 9, 2016, 10 A.M.		Travel distance (mile)	Travel time (hour)	PM2.5 inhalation (µg)	NOx inhalation (µg)	PM2.5 emission (kg)	NOx emission (kg)	CO2 emission (kg)
	Baseline	8,509	250.7	305	63,395	0.052	21.1	27,006
Time Increase Threshold (TIT) 10%	PR 10%	8,497	251.0	300	62,877	0.051	21.1	27,026
	PR 20%	8,472	251.6	293	61,813	0.051	21.0	27,086
	PR 50%	8,432	252.5	279	59,552	0.051	20.9	27,168
	PR 100%	8,358	254.4	254	56,166	0.050	20.6	27,345
TIT 20%	PR 10%	8,488	251.8	296	62,887	0.051	20.9	27,167
	PR 20%	8,449	253.2	284	61,578	0.050	20.6	27,401
	PR 50%	8,363	256.6	255	58,773	0.049	19.9	27,927
	PR 100%	8,220	262.8	204	53,780	0.046	18.6	28,883
Percent change vs. baseline (TIT 10%)	PR 10%	0%	0%	-1%	-1%	0%	0%	0%
	PR 20%	0%	0%	-4%	-2%	-1%	-1%	0%
	PR 50%	-1%	1%	-8%	-6%	-2%	-1%	1%
	PR 100%	-2%	1%	-17%	-11%	-3%	-2%	1%
Percent change vs. baseline (TIT 20%)	PR 10%	0%	0%	-3%	-1%	-1%	-1%	1%
	PR 20%	-1%	1%	-7%	-3%	-2%	-2%	1%
	PR 50%	-2%	2%	-16%	-7%	-5%	-6%	3%
	PR 100%	-3%	5%	-33%	-15%	-10%	-12%	7%

According to Table 3, the impacts of LER are relatively small for the scenario where the technology adoption rate is at 10% and the threshold for travel time increase is 10%. The city-wide reductions in PM2.5 inhalation and NOx inhalation are merely 1%. This is because, first of all, in this scenario only 10% of the trucks are equipped with the technology (i.e., 99 trucks out of 992). Also, according to

Table 2 there is a 54% chance that these 99 trucks would have a low exposure route option with travel time increase of no more than 10%. That means as few as 53 trucks out of the 992 trucks could take the low exposure route for their trips, and the rest would take the baseline route. This number of trucks taking the low exposure route is not sizable enough to make a substantial impact. However, as the technology adoption rate increases, the city-wide reductions in PM2.5 inhalation and NOx inhalation also increase proportionally. At 100% adoption rate, the total amount of PM2.5 emission from the 992 trucks inhaled by city residents would reduce from 305 μg to 254 μg , a 17% decrease. And the total amount of NOx emission from the trucks inhaled by city residents would reduce from 63,395 μg to 56,166 μg , an 11% decrease. When considering the impacts of 100% adoption of the LER technology on other metrics such as travel distance, travel time, and CO2 emission, it was found that these impacts would all be minimal. Specifically, the total travel time and CO2 emission would both increase by 1%, while the total travel distance would decrease by 2%.

When examining the results for the scenarios with the threshold for travel time increase of 20%, it was found that the impacts of LER are larger than the scenarios with the travel time increase threshold of 10% across all the metrics. This is expected because by doubling the amount of travel time increase that truck drivers are willing to accept, the chance of finding a low exposure route for their trips will increase. According to

Table 2, there is a 68% chance that a truck would find a low exposure route with travel time increase of no more than 20%, which is 14 percentage points higher than if the threshold for travel time increase is 10%. For example, for the scenario where the technology adoption rate is at 10% and the threshold for travel time increase is 20%, at least 67 trucks out of 992 would have a low exposure route option for their trips. Nevertheless, this number of trucks taking the low exposure route is still too small to make a significant impact in terms of reducing the city-wide exposure to emissions from these trucks. On the other hand, the impacts would be substantial if all the trucks are equipped with the LER technology. At 100% adoption rate, the total amount of PM2.5 emission from the 992 trucks inhaled by city residents would reduce from 305 μg to 204 μg , a 33% decrease. And the total amount of NOx emission from the trucks inhaled by city residents would reduce from 63,395 μg to 53,780 μg , a 15% decrease. At the same time, the impacts of 100% adoption of the LER technology on travel distance, travel time, and CO2 emission would be more pronounced. The total travel time and CO2 emission would increase by 5% and 7%, respectively, while the total travel distance would decrease by 3%. In this scenario, it is also notable that the NOx emission from the trucks would decrease by 12%. Not only NOx contributes to local air pollution that harms public health through near-road exposure but it is also a precursor to regional air pollution such as tropospheric ozone. Thus, this result implies that the LER technology could provide secondary benefits in terms of improving the regional air quality as well.

5. Conclusions

In this project, we develop a novel framework to quantify the impacts of a large-scale adoption of the LER technology by HDDTs. Using truck O-D tables obtained from the SCAG' regional transportation model along with other truck-related data, we synthesize truck trip itineraries that travel in and around the city of Riverside, California, for incorporating into the BEAM activity-based transportation simulation model for the city. The updated BEAM model is then used to evaluate the impacts of LER under different technology adoption rates. For the HDDTs adopting the LER technology, the estimated air pollution exposure, represented by the amount of pollutant emissions from the HDDTs inhaled by the local residents, is used as the cost in a least cost path algorithm to find a travel route that would minimize the total air pollution exposure value for the trips, subject to a limit in travel time increase as compared to the fastest route. The evaluation involves comparing the various trip metrics (distance, travel time, tailpipe emissions, and pollutant inhalation) between the low exposure route and the baseline (fastest) route.

In the first stage, the evaluation is focused on determining whether a low exposure route could be found for truck trips in and around the city. This depends on several characteristics of the trip including O-D locations, number of route alternatives between the O-D pair, spatial distribution of population and sensitive facilities along those route alternatives, traffic and weather conditions at the time, among others. Many of these characteristics are different for each of the 498 unique O-D pairs in the case study. The results show that for 27% of the unique O-D pairs, the fastest route is already the low exposure route. If a truck is making a trip between any of these O-D pairs, taking the fastest route is simply the best option as it will also minimize the community exposure to emissions from the truck. At the same time, that also means a low exposure route can be found for the rest of the unique O-D pairs. However, not all of them would be practical. For some of them (5% of all unique O-D pairs), a low exposure route makes a long detour that increases the travel time by more than 20%, which is likely to be more than what truck drivers or fleet operators are willing to accept. On the other hand, for 54% of the unique O-D pairs, a low exposure route that will take no more than 10% longer travel time than the fastest route can be found. For many of them, the travel time increase is very small and the average is only 3%. This level of travel time increase is much more acceptable. If a truck takes the low exposure route between these O-D pairs, the amount of PM_{2.5} and NO_x emissions from the truck that would be inhaled by the residents would be reduced by 37% and 20% on average, respectively, as compared to taking the fastest route.

The second stage of the evaluation is focused on estimating the cumulative impacts of a large-scale adoption of the LER strategy. For the 992 truck trips traversing the city, it was found that both the reductions in air pollution inhalation by the residents and the increases in travel time and fuel consumption for the trucks are almost linearly proportional to the LER technology adoption rate. If the LER with a limit of travel time increase of no more than 10% is to become a standard routing strategy for all the trucks (i.e., 100% adoption rate), the amount of PM_{2.5} and NO_x emissions from the trucks that would be inhaled by the residents could be reduced by 11%

and 17%, respectively. In addition, these public health benefits could be gained without imposing significant costs to the truck operators and the climate as the increases in the overall travel time and fuel consumption (and equivalently, carbon dioxide emission) for the trucks are only 1%. And if the truck operators are willing to accept a higher threshold of travel time increase, the public health benefits would be even greater. In the case of 20% travel time increase threshold, the reductions in PM2.5 and NOx inhalation by the residents would be 33% and 15%, respectively.

The evaluation results above indicate a high potential for the LER strategy to mitigate the air pollution impacts of HDDTs in cities and communities. This can be especially important for disadvantaged communities that are disproportionately affected by truck traffic. The strategy can serve as a near-term mitigation measure while the current HDDT fleet is turning over to cleaner or zero-emission vehicle technologies. From the implementation perspective, the technology readiness of the LER strategy is high as it can build on the existing software and hardware of fleet management and vehicle navigation systems. However, for the LER strategy to be impactful at the city or community scale, a technology adoption rate of more than 20% would be needed. Some incentives, policies, or even regulations may be required to help reach that level of technology adoption.

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Data Management Plan

Products of Research

Data collected or produced in this research include digital map, estimated vehicle emissions on roadways, meteorological parameters, locations of sensitive receptors, census demographics, and truck trip itineraries derived from travel demand model for the study area.

Data Format and Content

- *hhdt_od_10.csv* – Zone-based Origin-Destination table (OD TABLE) from SCAG is necessary for generating three different truck trips: Heavy-Duty Diesel Truck Trips, Medium-Duty Diesel Truck Trips, and Light-Duty Diesel Truck Trips.
- *pems_output_i10e.xlsx* – PeMs collects real-time traffic data from over 39,000 individual detectors along with the freeway system crossing major cities, monitoring traffic volume by categories, such as number of trucks on the road. Thus, we can estimate deterministic time of travel by reading PeMs data. Since PeMs data is one-hour interval format, we randomly distribute these trips into corresponding hour.
- *truck_related_employment.csv* – The Employment Development Department (EDD) record business companies in Riverside City, which we can use them for potential truck trip position generation. Thus, for the truck trips inside Riverside City, we assign coordinates of companies in the corresponding zone to the truck trips as their origin and destination positions. For those truck trips just crossing city, we assign the closest boundaries points coordinates to them.
- *riverside_new.xml* – The network files for Riverside City is derived from OpenStreetMap.com, which is osm (OpenStreetMap) format file. The raw network file is opened in Java OpenStreetMap Editor and transformed into pbf file. After we place this pbf file in the R5 folder under BEAM repository, the initial simulation automatically generates network.dat and physsim.xml where all map-related data is stored.
- *households.csv*, *person.csv*, *plans.csv* – The minimum requirements needed for conducting a BEAM run are households, persons, vehicle fleet, vehicle types, map data, and configuration. We assign virtual household and virtual driver for these truck trips.
- *linkAttributes_RIV.csv* – To determine vehicle emission factors (in the unit of gram/mile), link-based traffic activities (e.g., average traffic speed) is needed as an input. We get the linkspeed from BEAM Model Results and use them here.
- *facilityAttributes.csv*, *blockAttributes.csv* – Attributes of facilities considered as sensitive receptors and of residential blocks.

Data Access and Sharing

All data can be accessed through DRYAD (<https://doi.org/10.6086/D1NH4N>).

Reuse and Redistribution

All data can be reused but not redistributed.