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Electrification, Connectivity, & Active Demand Management: Addressing the traffic, health, and environmental justice impacts of drayage trucks in Southern California

DISSERTATION

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for the degree of

DOCTOR OF PHILOSOPHY

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by

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DEDICATION

To

Denise

In recognition of her patience and support

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ABSTRACT OF THE DISSERTATION

Electrification, Connectivity, & Active Demand Management:
Addressing the traffic, health, and environmental justice impacts of drayage trucks in Southern California

by

Monica Ramirez Ibarra

Doctor of Philosophy in Civil and Environmental Engineering

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Professor Jean Daniel Saphores, Chair

Trucking electrification combined with connected and automated technologies promises to cut the cost of freight transportation, reduce its environmental footprint, and make roads safer. If electric trucks are powerful enough to cease behaving as moving bottlenecks, they could also increase road capacity and reduce the demand for new infrastructure, a consequence that has so far been overlooked by the literature. In this dissertation, I study the traffic and infrastructure demand impacts of electrifying and connecting (via cooperative adaptive cruise control, CACC) heavy-duty drayage trucks (HDDTs) that serve the San Pedro Bay Ports (SPBP; the ports of Los Angeles and Long Beach, which is the largest port complex in the U.S), quantify the resulting health, environmental, and Environmental Justice impacts, and explore how to maximize the benefits of connected vehicles with active demand management.

In Chapter 2, I explore the potential traffic and infrastructure implications of replacing conventional HDDTs that serve the SPBP with electric and/or connected HDDTs. I rely on microscopic simulation on a freeway and arterial network centered on I-710, the

country's most important economic artery. My results show that 1,000-hp electric/hydrogen trucks can be a substitute for additional road capacity. Accounting for the traffic impacts of new vehicle technologies is critical in infrastructure planning, and my results suggest shifting funding from building new capacity to financing zero-emission (ZE) 1,000 hp HDDTs until the market for these vehicles has matured.

In Chapter 3, I quantify the health and GHG reduction benefits of replacing the HDDTs serving the SPBP with ZE-HDDTs. I simulate ZE-HDDTs on a regional freeway network to analyze their $PM_{2.5}$ and CO_2 emissions in 2012 and 2035 using MOVES3 emission factors. I then estimate their contribution to $PM_{2.5}$ concentrations with InMAP and health impacts with BenMAP. I find that despite technology improvements and air quality regulations, SPBP HDDTs would still cause 106 premature deaths (valued at $1.3 billion in $2022) and 2,142 asthma attacks (over two thirds of which would accrue to disadvantaged communities) in 2035 due to population and drayage traffic growth, not to mention at least $220 million in climate costs. With ZE-HDDTs becoming attractive in the next few years from a total cost of ownership point-of-view, the main cost of achieving ZE road drayage is a scrappage program for non-ZE-HDDTs. My results justify implementing this program by 2035.

In Chapter 4, I study the performance impacts of lane management strategies implemented on I-710 to support the deployment of CACC-enabled vehicles and their potential to absorb the 2035 projected growth in cargo demand at the SPBP. I find that a designated lane for CACC-enabled vehicles can decrease congestion by creating more platooning opportunities, thus maximizing CACC benefits.

CHAPTER 1 INTRODUCTION

Electric and connected vehicles are expected to decrease the environmental footprint of transportation, improve road safety, and alleviate congestion by smoothing traffic flows (Hobert, Festag, Llatser, Altomare, & Visintainer, 2015; Ilgin Guler, Menendez, & Meier, 2014; Milakis, van Arem, & van Wee, 2017; Talebpour, Mahmassani, & Elfar, 2017). By changing the economics of transportation, they will also likely transform the built environment. In the freight sector, in addition to improved safety and environmental performance, zero-emission automated trucks are expected to decrease the cost of hauling freight and allow for more intensive use of freight logistics assets. However, one important implication of electrifying trucks appears to have been overlooked so far: if they were powerful enough (such as the forthcoming Tesla semi or the Nikola TWO), heavy-duty trucks would cease to be moving bottlenecks (Newell, 1998), which could substantially increase road capacity in areas with high heavy-duty truck traffic (e.g., around major ports or logistics complexes), thus reducing the need to expand the local road infrastructure. My dissertation also considers connected automated trucks because connected and automated technologies are known to have an impact on road capacity, and they are likely to be deployed in the next few years to boost truck safety.

The advent of vehicle connectivity in transportation systems promises to improve road safety, mitigate congestion, and create opportunities to manage traffic more efficiently as communication technology enables real-time freeway traffic management. One of the possible applications of traffic management is managed lanes. Variable lane eligibility based on known demand (i.e., vehicle position and classification recorded from the connected environment) can potentially support the deployment of Connected and Autonomous Vehicles (CAVs), even at low market penetration. More specifically, lane management could support the deployment of vehicles equipped with Cooperative Adaptive Cruise Control (CACC) (SAE Level 1) to enhance safety, add capacity, and improve performance by coordinating their deployment on dedicated lanes during selected periods. While the deployment of connected and autonomous vehicles is typically impeded by infrastructure and technology requirements, level 1 CAVs could be deployed with no change to the existing infrastructure.

While much of the transportation literature has analyzed the benefits of electrification, connectivity, and managed lanes for light-duty vehicles, I focus here on heavy-duty drayage trucks (i.e., heavy-duty trucks hauling containers and bulk to and from ports and intermodal railyards; CARB, 2022) because their typical driving cycles make them prime candidates for electrification (compared to long-haul trucking, they drive relatively few miles every day and they return to their base at night.) Like other heavy-duty trucks, drayage trucks contribute disproportionately to $PM_{2.5}$ (particulate matter with a maximum diameter of 2.5 micrometers), which is the common air pollutant of most health concern (CARB, 2022c; Pan, Roy, Choi, Sun, & Gao, 2019), nitrogen oxides (NO_x), a key component of smog and a precursor to secondary PM, and greenhouse gas (GHG) emissions. Indeed, heavy-duty trucks account for four-fifth of road transportation PM in California despite making up only 7% of registered vehicles (Tabuchi, 2020). They also contribute a third of total NO_x emissions (CARB, 2022b) and a fifth of GHG emissions from transportation, the main source of GHG in California (CARB, 2021a).

Unlike long-haul heavy-duty trucks, drayage trucks mostly operate in populated areas. This is the case for the heavy-duty drayage trucks (HDDTs) serving the San Pedro Bay Ports (SPBP; i.e., the ports of Los Angeles and Long Beach), the largest port complex in the U.S. and ninth in the world in 2021 (Bansard International, 2022). As reported in the environmental justice (EJ) literature (e.g., see Barnes and Chatterton, 2016; Clark et al., 2017; Grobar, 2008; Houston et al., 2004; Kingham et al., 2007), disadvantaged communities (i.e., census tracts in the top quartile for their combined pollution burden, as defined in CalEnviroScreen 4.0) are particularly exposed to air pollution from heavy-duty trucks.

Caltrans, Gateway Cities, community organizations, and environmental justice activists have clashed for years over how to manage increasing freight traffic on I-710 and the resulting air pollution, congestion, and accidents. However, to the best of my knowledge, little research has been done on the system-wide impacts of deploying electric vehicles of improved performance, CACC-enabled vehicles, and lane management strategies to support its deployment. In this context, my dissertation will examine the following questions:

1) What are the potential traffic and road infrastructure implications from replacing conventional drayage trucks with electric and/or connected heavy-duty trucks around the largest port complex in the U.S.?
2) What are the health and GHG reduction benefits from replacing the HDDTs serving the SPBP with ZE HDDTs while accounting for air quality regulations reflected in U.S. EPA's MOVES3?

3) Could lane management strategies, implemented to support the deployment of CACC-enabled vehicles, absorb the 2035 projected growth in cargo demand on I-710 and other freeways connecting the San Pedro Bay Ports to the Inland Empire?

To answer these questions, my dissertation makes the following contributions. First, in Chapter 2, I show that replacing diesel drayage trucks with powerful (i.e., 1,000 hp) electric drayage trucks would alleviate the need to add a lane to I-710 while absorbing the projected increase in drayage traffic between now and 2035, thus illustrating that adopting some new truck technologies is a substitute for road infrastructure expansion. To the best of my knowledge, this is the first regional analysis to study the impact of emerging truck technologies on infrastructure and system performance.

In Chapter 3, I expand the health and environmental justice (EJ) literatures by quantifying the health, environmental, and EJ impacts freeway drayage trucks in 2012 and 2035, and I show that these impacts would justify replacing conventional drayage trucks with ZE drayage trucks by 2035. To the best of my knowledge, no published academic study has estimated the health, environmental, and environmental justice benefits of replacing conventional HDDTs with ZE HDDTs in the nation's most important freight complex. Moreover, the freeway simulation model I developed for Chapter 3 is one of the largest ever built to analyze the benefits of a clean transportation program.

In Chapter 4 I simulate the system-wide impacts of deploying CACC-enabled vehicles jointly with active lane management. I show that while speed improvements are bounded by the share of HDDTs on the road, combining lane management strategies to support the deployment of CACC-enabled vehicles could absorb the impact of the 2035 cargo growth on selected segments when a mix of HDDTs and passenger vehicles are CACC-enabled and eligible to use the designated lane. My results also show that the best performance can be achieved when ~30% of passenger vehicles are CACC-enabled and eligible to use the designated lane, as average speed decreases with larger shares of CACC-enabled passenger vehicles.

Although I focus on Southern California, my results have national importance as other Metropolitan Planning Organizations have incorporated vehicle connectivity and electrification to their long-range transportation plans (Boston Region MPO, 2017; MTC, 2022; SANDAG, 2019), and because 14 other states have adopted California's GHG emission and ZE vehicle regulations under Section 177 of the Clean Air Act.

Lastly, in Chapter 5 I summarize my findings, discuss some limitations, and suggest possible future work extensions.

CHAPTER 2 POWERFUL ELECTRIC TRUCKS AS A SUBSTITUTE FOR MORE ROAD CAPACITY

2.1 Introduction

Much has been written about the potential benefits of electric and connected automated vehicles, which are expected to decrease the environmental footprint of transportation, make roads safer, and smooth traffic flows (Hobert et al., 2015; Ilgin Guler et al., 2014; Milakis et al., 2017; Talebpour et al., 2017). By changing the economics of transportation, they will also likely transform the built environment. In the freight sector, in addition to improved safety and environmental performance, zero-emission automated trucks are expected to decrease the cost of hauling freight and allow for a more intensive use of logistic assets. However, one important implication of electrifying trucks appears to have been overlooked so far: if they were powerful enough (such as the forthcoming Tesla semi or the Nikola TWO), heavy-duty trucks would cease to be moving bottlenecks (Newell, 1998), which could substantially increase road capacity in areas with high heavy-duty truck traffic levels (e.g., around major ports or logistics complexes), thus reducing the need to expand the local road infrastructure.

In this context, this chapter aims to quantify some potential traffic and road infrastructure implications from replacing conventional drayage[1] trucks with electric and/or connected heavy-duty trucks around the largest port complex in the U.S., and to explore the implications for road infrastructure financing in the U.S. My analyses also

[1] Drayage was originally used to describe the movement of goods in side-less carts, or drays, pulled by horses. It now designates the transport of containerized cargo between ports or rail ramps and shipping docks.

consider connected automated trucks because connected and automated technologies are known to have an impact on road capacity, and they are likely to be deployed in the next few years to boost truck safety.

To enhance the realism of my study, I relied on vehicular microsimulation to analyze scenarios that include a baseline (2012), three infrastructure configurations, and different truck technologies for the year 2035, a target date that regional and state agencies have used for planning, forecasting, and regulatory purposes. Although microscopic simulation has been employed numerous times before to analyze electric or automated vehicles, to my knowledge, this is the first regional analysis of how electric and connected trucks could affect regional traffic and the demand for road infrastructure.

In this chapter, my study area is centered on the I-710 corridor, which connects the San Pedro Bay Ports (SPBP, i.e., the Ports of Los Angeles and Long Beach in Southern California) with railyards and other major freeways south of downtown Los Angeles (LA; see Figure 2.1). Also known as the Long Beach Freeway, I-710 has been called the country's most important economic artery (Estrada, 2014) because of its critical role in moving goods to and from the SPBP complex. As it carries the bulk of the trucks that serve the SPBP, I-710 has one of the highest truck AADT in California (California Department of Transportation, 2020). My study area also includes I-110 and several arterials because the former is an alternative to I-710, and the latter carry many trucks between the Ports, warehouses, and railyards.

My study area is particularly well-suited to study the impact of changes in heavy-duty truck technologies for a couple of reasons. First, in a September 2020 Executive Order, the Governor of California reaffirmed the goal that all drayage trucks in the state be zero-emission by 2035. That deadline was initially set in the Clean Air Action Plan (CAAP) update, which was adopted in 2017 by the Ports of Los Angeles and Long Beach (hereafter the San Pedro Bay Ports, or SPBP), partly under pressure from environmental justice organizations and community activists concerned about the air pollution from port operations. A second reason is a pre-COVID-19 forecast (MERCATOR & Oxford Economics, 2016), which called for a 145% increase in drayage truck traffic by 2035. If realized, it would put considerable strain on the transportation infrastructure serving the SPBP, especially I-710.

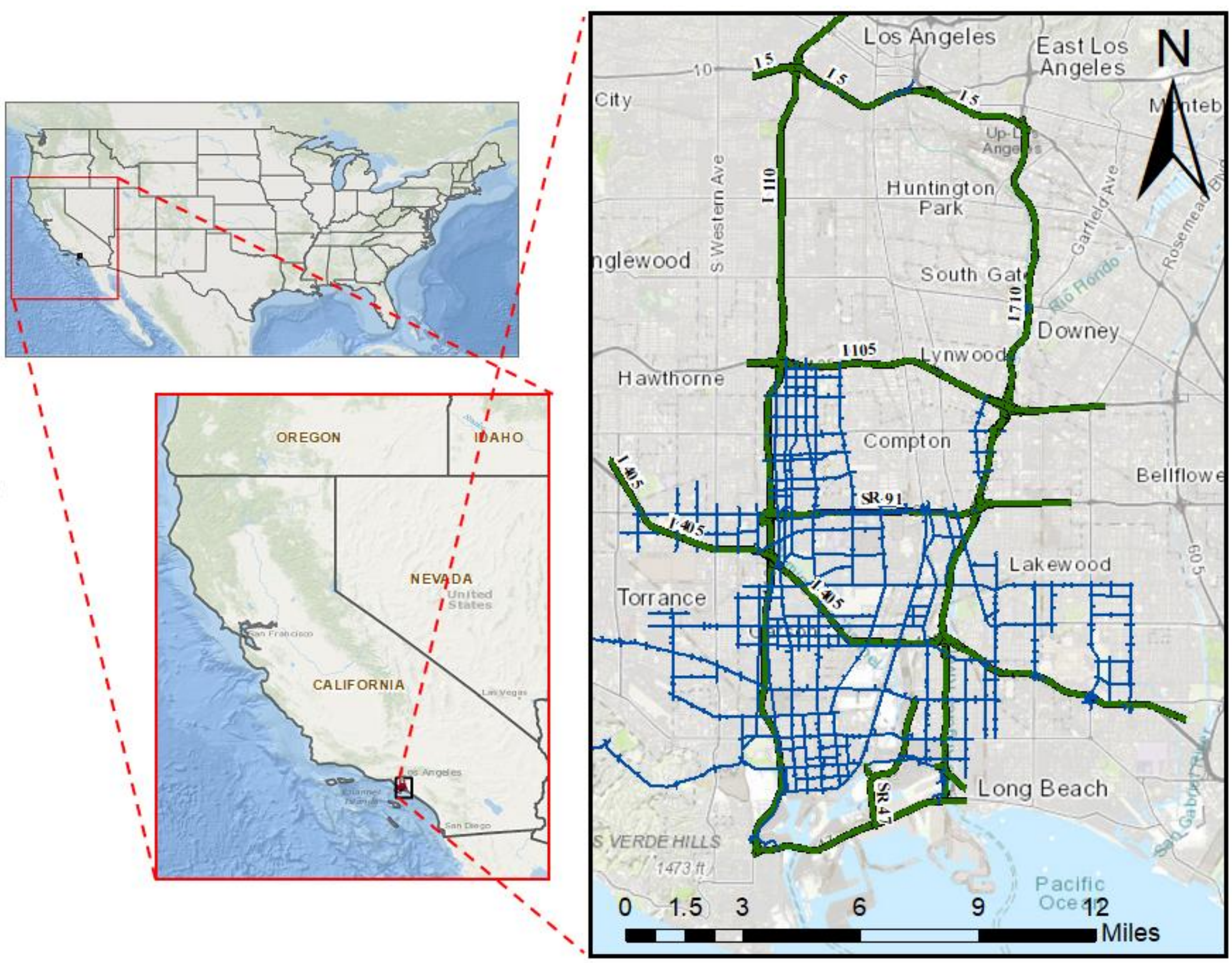


Figure 2.1 Study Area

At a time when policymakers are considering large investment programs to upgrade neglected infrastructure and create jobs as the COVID-19 pandemic finally wanes, both in the U.S. and abroad, my findings call for a change in the traditional infrastructure funding role of the federal government to help transition to heavy-duty electric vehicles in freight corridors. More specifically, I call to repurpose some public funds earmarked for capacity expansion in busy freight corridors to incentivize the purchase of heavy-duty electric trucks that are powerful enough to yield substantial traffic benefits until the market for these vehicles is mature enough.

In the next section, I review selected papers and present background information. In Section 1.3, I introduce my data and my methodology. After discussing my results (Section 1.4), Sections 1.5 and 1.6 summarizes my findings, discusses some limitations, and suggest possible extensions.

2.2 Background

Giuliano et al. (2021) noted that there is increasing interest in replacing conventional heavy-duty trucks with cleaner or zero-emission trucks to reduce air pollution and greenhouse gas emissions from freight transportation. Here, I briefly review selected papers that simulated electric trucks and analyzed the potential impacts of automated/connected heavy-duty trucks.

2.2.1 Electric Trucks Modeling

Simulation has been used extensively to study various aspects of electric trucks. For example, it has been used to optimize the design and control of electric vehicles (Butler, Ehsani, & Kamath, 1999; Feng, Dong, Yang, & Cheng, 2016; Kıyaklı & Solmaz, 2019; C.-C. Lin, Peng, Grizzle, Liu, & Busdiecker, 2003). In addition, discrete event simulation has helped investigate the impact of electric vehicles on fleet management and urban distribution, mostly to optimize the number of trips or deliveries given battery range limitations (Keskin, Çatay, & Laporte, 2021; Lebeau, Macharis, Van Mierlo, & Maes, 2013). Recent studies relying on agent-based simulation have explored electric vehicle adoption for urban freight transport and deliveries (Alves, da Silva Lima, Custódio de Sena, Ferreira de Pinho, & Holguín-Veras, 2019; Ewert, Martins-Turner, Thaller, & Nagel, 2021; Palanca, Terrasa, Rodriguez, Carrascosa, & Julian, 2021). Many of these studies were concerned with understanding how battery-induced range limitation could affect urban freight demand and management, particularly last-mile deliveries.

Simulation has also been widely used to assess the impact of various control systems on vehicle interactions, traffic flow, and traffic management (Guériau et al., 2016; Talebpour & Mahmassani, 2016; Talebpour et al., 2017; van Arem, van Driel, & Visser, 2006).

Other papers have relied on optimization methods to minimize cost and/or air pollutant emissions for a set of fixed freight demands and studied the feasibility of said technologies on stylized road networks (Davis & Figliozzi, 2013; Giuliano et al., 2021; J. Lin, Zhou, & Wolfson, 2016; Schneider, Stenger, & Goeke, 2014).

2.2.2 Automated and Connected Trucks

In addition to heavy-duty electric trucks, I analyzed level-1 (on the scale of the Society of Automotive Engineers (SAE, 2021), where level 5 corresponds to full automation) heavy-duty port trucks connected via Cooperative Adaptive Cruise Control (CACC). For level-1 CACC trucks, longitudinal motion, braking, and acceleration are controlled by onboard systems, so consecutive vehicles maintain a constant time gap when their driving is synchronized with a leading truck, while a human driver handles all other driving tasks. CACC trucks are said to travel in strings to distinguish them from automated platoons, where trucks attempt instead to keep a fixed distance gap (Shladover, Nowakowski, Lu, & Ferlis, 2015).

Coupling and clustering of CACC-connected trucks could occur whenever the leading vehicle is equipped with the right level of automation and with CACC or other radio access technologies such as dedicated short-range communications (Mavromatis, Tassi, Rigazzi, J. Piechocki, & Nix, 2018). Alternatives to short-range radio signals include establishing communication between vehicles using other devices, the surrounding infrastructure, or the internet (Mavromatis et al., 2018). However, approaches that would require significant infrastructure investments are less likely to be adopted because of the size of the investments needed and current strains on public budgets.

Organizing trucks in platoons could yield multiple benefits. The first two are improving fuel efficiency and reducing air pollution (Boysen, Briskorn, & Schwerdfeger, 2018; Larson, Liang, & Johansson, 2015; Liang, Mårtensson, & Johansson, 2013). Energy savings could come from reducing aerodynamic drag and from propulsion changes (e.g., hybrid, electric, or hydrogen-electric engines), which would cut tailpipe CO_2 and criteria pollutant emissions. Another motivation is congestion relief, my focus here. Overall, the effectiveness of cooperative driving relies on the market penetration of CACC-capable vehicles, the formation of stable strings, and their interactions with human-driven vehicles.

Several studies have explored the feasibility of connected automated trucks through field studies and simulation, along with their safety and fuel efficiency (Lu & Shladover, 2014a; Ramezani, Shladover, Lu, & Chou, 2018a). They have considered gaps as small as 4 meters (0.2 s at 85 km/h or 53 mph). The work of Ramezani et al. (2018) is particularly interesting because they simulated one hour of a 15-mile northbound segment of I-710 to explore the capacity effects of truck platooning. They reported speed improvements of 19% for trucks and 6% for passenger vehicles.

To the best of my knowledge, no published study currently explores regional network system-wide performance improvements stemming from replacing conventional heavy-duty trucks with more powerful, responsive, and possibly CACC-connected vehicles, as also noted by Bhoopalam et al. (2018).

2.2.3 Challenges Facing Electric Connected and Automated Vehicles

The main challenges associated with the deployment of battery-electric trucks lie in the capacity of current batteries, the availability of charging infrastructure, higher upfront costs, and the expected impacts of these limitations on the economic activities associated with freight operations. However, in the longer term, the net ownership costs of electric trucks are expected to dip well below those of conventional diesel and hybrid trucks (Giuliano et al., 2021; Vijayagopal & Rousseau, 2021).

Poorsartep and Stephens (2015) argue that the most significant challenge towards safely achieving high levels of vehicle automation is technical in nature. However, my literature review suggests that societal and institutional obstacles are also substantial, especially as they relate to safety and liability (Colonna, 2013; Duffy & Hopkins, 2013; Hevelke & Nida-Rümelin, 2015; Marchant & Lindor, 2012; Taeihagh & Lim, 2019). Since the current liability system is not designed for automated vehicles, new laws and policies are needed to protect manufacturers and users (Geistfeld, 2017; Noussia, 2020; Seuwou, Banissi, & Ubakanma, 2020).

Public acceptance is also an issue, as many Americans feel uneasy about sharing the road with large, self-driving freight trucks (Smith and Anderson, 2017). Furthermore, the arrival of automated technologies is expected to cause some job losses (although there is a chronic shortage of long-haul drivers in the U.S.), vehicle ownership changes, and travel behavior modifications that may disproportionately affect less affluent households. As a result, their introduction is likely to be challenged (Cheon, 2003; Pettigrew, Fritschi, & Norman, 2018). However, most of these reservations are not of concern here because the CACC-connected heavy-duty trucks I analyzed are only automated up to level 1, so they require a human driver.

2.3 Data and Methodology

For this study, I relied on vehicular microsimulation to capture the complex interactions between the road infrastructure and heterogeneous vehicles. I selected TransModeler for two main reasons. First, it can perform dynamic traffic assignment (DTA) directly, allowing for a more realistic distribution of trips on the network. Second, TransModeler offers useful features for simulating connected and automated vehicles, including Cooperative Adaptive Cruise Control (CACC) and the constant time gap car-following model (J. Wang & Rajamani, 2004).

2.3.1 Study Area

My study area (see Figure 2.1) extends from the SPBP gates to the portion of I-5 sandwiched between I-110 and I-710, on the southern end of downtown LA. My simulation models, which build on a network initially developed by Bhagat (2014), include 314 miles (~465 km) of freeways and 281 miles (~452 km) of arterials. Different network configurations and traffic control vary by scenario. Further details are provided below. The freeway of most interest in my study area is I-710 because of the large percentage of trucks (especially heavy-duty port trucks, HDPTs) it carries. In 2012, the percentage of trucks on I-710 varied from 13.9% (out of 153,000 vehicle AADT) northbound at the junction with Route 1 by the SPBP complex, to 7.8% (out of 177,000 vehicles AADT) northbound at the junction with I-5, with slightly higher southbound values (14.3% and 8.4% respectively) (Caltrans 2012). By comparison, the percentage of northbound trucks on I-110, which is parallel to I-710, is 5.7% and 0.76% at the junction with Route 1 and I-5, respectively.

2.3.2 Scenarios

To explore how the replacement of conventional HDPTs by electric and possibly CACC-equipped HDPTs may impact traffic and network performance in a realistic setting, I created 13 scenarios with 2012 as my baseline and 2035 as my target because these two years were selected in key studies of I-710 (Caltrans & L.A. Metro, 2012; Choi, 2015, Port of Long Beach and Port of Los Angeles, 2017).

For my 2035 scenarios, I tried to account for changes in the number of containers going through the SPBP complex, the evolution of truck technology, adjustments to the regional road infrastructure, and the development of freight rail capacity. I relied on a recent report (MERCATOR & Oxford Economics, 2016), a 2019 technical paper (Leue, Luzzi, Patil, Cartwright, & Sequeira, 2019), and personal communications with SPBP transportation experts. Before proceeding, it is worth remembering that forecasts published over the past two decades have been wildly over-optimistic about SPBP container traffic growth (see Figure 1 in Leue et al., 2019), although I acknowledge the difficulty of forecasting container traffic, which depends on global economic growth, U.S. trade policy, the evolution of ship technology, local infrastructure improvements, and the actions of competing ports.

In 2012, the SPBP complex handled 14.1 million 20-Foot Equivalent Units (TEUs) (Caltrans & LA Metro, 2017), including imports, exports, and empty containers. According to the Southern California Association of Governments (SCAG, 2013; Table 4.6), 23.6% of these 14,1 million TEUs (~3.3 million TEUs) were moved directly from port terminals to trains (on-dock[2]) and did not require trucking. Of the remaining 76.4%, 28.6% were moved only by truck, and 47.9% were hauled to off-dock[3] rail yards in the region. The latter (47.9%) can further be split into Inland Point Intermodal – IPI (11.4%, ~1.6 million

[2] On-dock refers to container yards located withing the ports.
[3] Off-dock refers to rail yards located outside the ports; containers leave the ports by truck and are transloaded there to be moved by rail.

TEUs), imported transloads (13.6%, ~1.9 million TEUs), and domestic containers (22.9%, ~3.2 million TEUs) (SCAG, 2013).

MERCATOR and Oxford Economics (2016) forecasted that the SPBP would handle 34.5 million TEUs by 2035. To break this down by mode, I relied on SCAG (2013) (see table 4.6, page 4-19), which estimated that in 2035 the share of cargo moved directly from port terminals to trains (on-dock) would account for 29.7% (~10.2 million TEUs) of container cargo. The remaining 70.3% would be moved by truck to nearby off-dock rail yards (46.9%, ~16.2 million TEUs) or exclusively by truck (23.5%, ~8.1 million TEUs). The share of off-dock cargo in 2035 can be further broken down into IPI (10.3% or ~3.6 million TEUs), transloads (15.6% or ~5.4 million TEUs), and domestic container (20.9% or ~7.2 million TEUs). Table 2.1 summarizes container traffic by mode for 2012 and 2035.

To reflect these forecasts in my 2035 OD matrix, I changed the 2012 OD matrix for HDPT demand by applying two factors. First, for off-dock rail, I applied a 140% increase to all HDPT trips starting or ending at one of the five on-dock railyards that serve the SPBP – two operated by BNSF (BNSF Hobart/Commerce Yard and BNSF Wilmington), and three by Union Pacific Railroad (UP East Los Angeles Yard, UP City of Industry Yard, and UP Carson) (The Port of LA, 2021). For the remaining OD pairs, where containers are moved exclusively by truck, I applied a 101% growth factor. As a result, road trips of port containers jumped from 57 thousand in 2012 to 118 thousand in 2035.

In 2015, the SCAG region housed nearly 19 million people, which was forecast to grow to ~21 million residents by 2035 (Choi, 2015a). While this growth will likely exacerbate the region's infrastructure and mobility needs, it will mainly occur in the inland Counties of Riverside and San Bernardino. The region's population is also expected to age (the share of people 65 years and older will jump from 11% to 18%), increasing the need for more efficient travel modes, particularly for those who can no longer rely primarily on their private vehicles. If SCAG's regional transportation plan (which includes investments in transit, high-speed rail, active transportation, and transportation demand management) is successful, my study area should see little to no increase in light-duty VMT.

Table 2.1 Estimates of TEU volumes by mode for 2012 and 2035

	2012		2035		% change:
	million TEUs	**%**	**million TEUs**	**%**	**$(TEU_{2035} - TEU_{2012}) / TEU_{2012}$**
IPI (on-dock)[a]	3.3	23.6%	10.2	29.7%	207.8%
IPI (off-dock)[b]	1.6	11.4%	3.6	10.3%	120.6%
Transload[c]	1.9	13.6%	5.4	15.6%	182.0%
Domestic[d]	3.2	22.9%	7.2	20.9%	123.9%
Truck[e]	4.0	28.6%	8.1	23.5%	101.1%
Total off-dock (b+c+d)	*6.7*	*47.9%*	*16.2*	*46.9%*	*139.6%*
Total	*14.1*		*34.5*		*145%*

[a]: Inland Point Intermodal (IPI) on-dock refers to transloaded containers within the ports (loaded and empty, for imports and exports).
[b]: Inland Point Intermodal (IPI) off-dock refers to transloaded containers outside the ports (loaded and empty, for imports and exports).
[c]: "Transload" refers to containers that leave the ports by drayage truck and are transloaded to trains in off-ports railyards (loaded imports only).
[d]: Domestic containers, loaded and empty, originate from the US for imports and exports
[e]: "Truck" refers to containers that leave the ports for unloading and distribution by truck.
The off-dock market share forecast for 2035 is based on SCAG's good movements report (2013), for which IPI off-dock will account for 5% of container cargo demand or 22% of off-dock cargo demand (1.7 million TEUs), transloading for 33% of off-dock rail (2.6 million TEUs), and domestic for 45% of off-dock rail (3.5 million TEUs). Thus, the remaining cargo, which is expected to be moved by truck, is 49.3% of the cargo demand forecast for 2035.

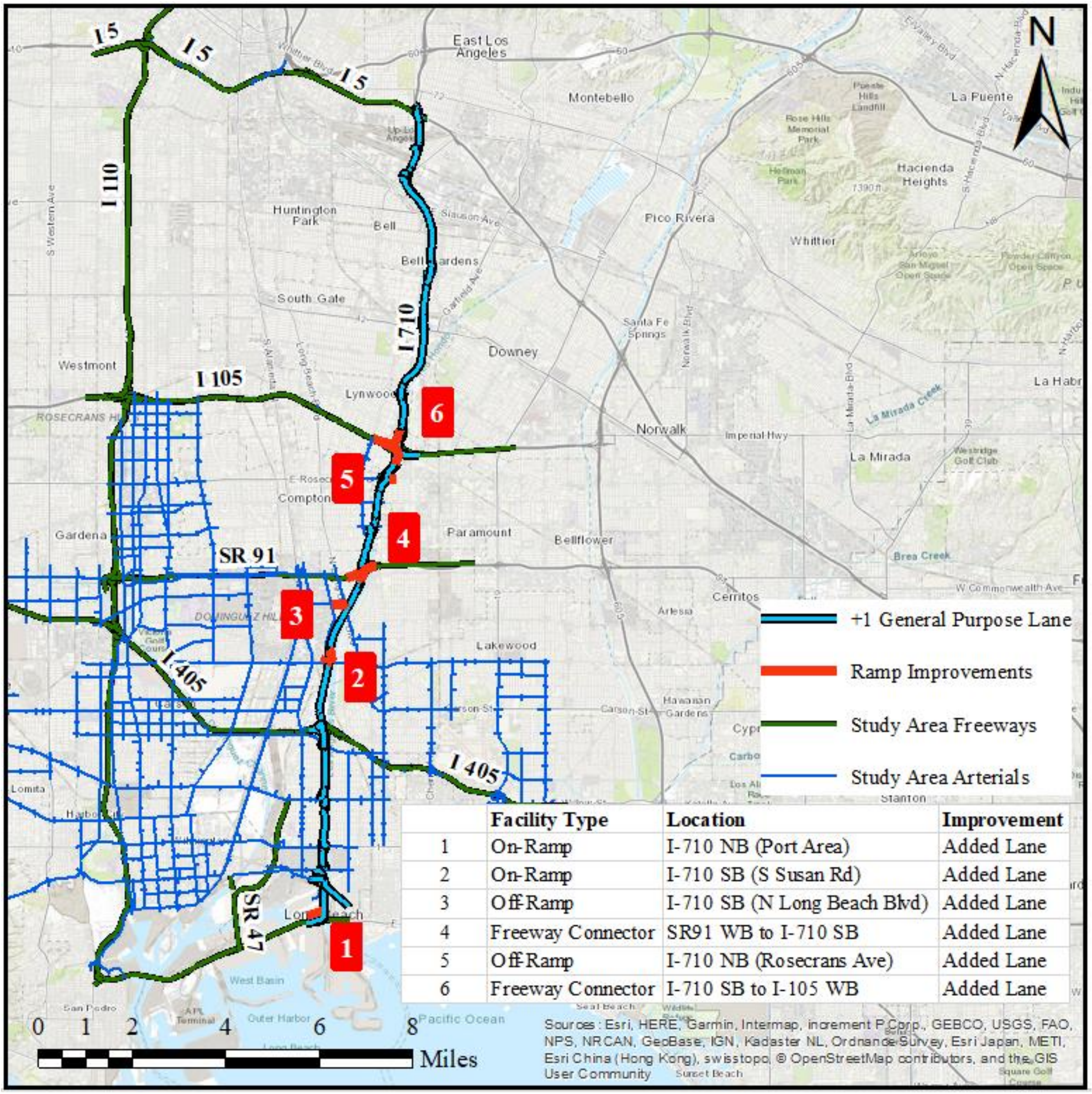
In this context, I considered twelve scenarios for 2035, in addition to a 2012 baseline scenario (Scenario 1). All 2035 scenarios assume an increase in HDPT traffic compared to 2012 with no growth in other categories of vehicles, but they differ based on road infrastructure and the characteristics of the HDPTs serving the SPBP complex.

In Scenarios 2A-2D, the road infrastructure in my study area is unchanged compared to 2012. In Scenario 2A, HDPTs are diesel trucks (dTs) that are similar to current HDPTs. In Scenario 2B, current HDPTs are replaced by diesel trucks connected via CACC (level 1 automation) (dCATs). In Scenario 2C, HDPTs are assumed instead to be battery-electric or hydrogen-electric trucks (eTs) with a much lower mass-to-power ratio (MPR) and are not connected. In Scenario 2D, HDPTs are eTs connected via CACC (eCATs). For more details about the MPR of eTs and eCATs, see sub-Section 1.3.3.

Scenarios 3A-3D feature ramp improvements along I-710, in addition to the demand increase in port trucks common to all 2035 scenarios. Despite the approval of funds for local improvement projects in my study area (Scauzillo, 2018), the lack of published geometric design prevents us from incorporating these into my network. Instead, after running some simulations, I identified six intersections/ramps that were most in need of improvement to serve the 2035 demand forecast (see Figure 2.2.)

Scenario 3A features conventional diesel HDPTs, 3B HDPTs are level-1 dCATs with an MPR similar to current HDPTs, while in 3C and 3D, HDPTs are 1,000 hp eTs and 1,000 hp eCATs, respectively.

Scenarios 4A-D include the ramp improvements from 3A-D, plus an additional general-purpose lane on each side of I-710 between East Ocean Blvd and I-5, as shown in Figure 2.2. Like Scenarios 2A-D and 3A-D, 4A features conventional diesel HDPTs, 4B has level-1 dCATs with an MPR similar to current HDPTs, and 4C and 4D feature 1,000 hp eTs and 1,000 hp eCATs, respectively. Table 2.2 summarizes the key characteristics of my scenarios.



	Facility Type	Location	Improvement
1	On-Ramp	I-710 NB (Port Area)	Added Lane
2	On-Ramp	I-710 SB (S Susan Rd)	Added Lane
3	Off Ramp	I-710 SB (N Long Beach Blvd)	Added Lane
4	Freeway Connector	SR91 WB to I-710 SB	Added Lane
5	Off Ramp	I-710 NB (Rosecrans Ave)	Added Lane
6	Freeway Connector	I-710 SB to I-105 WB	Added Lane

Figure 2.2 I-710 infrastructure improvements

Table 2.2 Summary of scenario characteristics

	Year	Scenario	HDPTs are dCATs?	HDPTs are eTs?	HDPTs are eCATs?
2012 road infrastructure	2012	1	--	--	--
	2035	2A	--	--	--
		2B	✓	--	--
		2C	--	✓	--
		2D	--	--	✓
Ramp improvements on I-710	2035	3A	--	--	--
		3B	✓	--	--
		3C	--	✓	--
		3D	--	--	✓
Ramp improvements + general-purpose lane on I-710	2035	4A	--	--	--
		4B	✓	--	--
		4C	--	✓	--
		4D	--	--	✓

All 2035 scenarios assume the following increase in HDPT traffic compared to 2012 with no growth in other vehicle categories: a 140% increase in all HDPT trips starting or ending at one of the five on-dock railyards that serve the SPBP and a 101% increase for the remaining OD pairs where containers are moved exclusively by truck.

2.3.3 Modeling 1,000 hp Electric Trucks (eTs)

It is well-known that conventional trucks form moving bottlenecks (Newell, 1998) because of their relatively sluggish acceleration compared to passenger cars. One approach to capture this aspect of a vehicle's performance is via its mass-to-power ratio (MPR). For the distribution of MPR, I relied on data from the National Cooperative Highway Research Program (Figure D-5 page D4 in NCHRP, 2003). Then, based on the mass distribution of heavy-duty trucks in my model, I assumed that the median value of the power of a heavy-duty diesel truck is ~400 hp.

This value could increase markedly for heavy-duty electric/hydrogen-electric trucks, however. For example, Nikola announced two hydrogen-electric Class 8 trucks (the TWO and the TRE), whose engines are expected to deliver 645 continuous hp (Nikola Motor, 2020). Another much-expected entrant is Tesla's Semi (Tesla, 2018), a 100% battery-electric truck that will be equipped with an independent electric motor for each of its four rear wheels. Each could produce up to 300 hp and 550 pound-feet of torque so that the Semi could have a minimum of 1,000 hp and 2,000 pound-feet of torque (O'Dell, 2019). A key difference between electric and diesel engines is that the former reach peak torque almost instantly, whereas diesel engines require a high MPR. As a result, Nikola's TWO and Tesla's Semi will accelerate several times faster than conventional diesel tractors. According to Tesla (O'Dell, 2019), a Semi pulling an empty trailer could go from 0 to 60 mph in 5 seconds (20 seconds when fully loaded). This would mostly remove the shock wave generated by slow-moving trucks in busy traffic. Unfortunately, TransModeler cannot currently capture differences in torque availability, which will mask in my results the important difference in acceleration potential between conventional and electric trucks with the same hp.

I, therefore, simulated electric trucks by altering the MPR distribution in my simulations, starting with the MPR distribution of HDPTs, which I modified to allow for 1,000 hp HDPTs. Since current battery-electric trucks such as BYD's Class 8 truck report power ratings equivalent to those of conventional diesel trucks, my simulations considered both 400 hp and 1,000 hp HDPTs. The MPR distribution alters accelerations as a vehicle's maximum acceleration is a function of its MPR and speed. That maximum acceleration rate serves as an upper bound for vehicles during a simulation.

The MPR distribution of eTs with a power of 1,000 hp was derived based on the distribution of HDTs on California freeways (NCHRP, 2003), and on the expected increase in power from ~400 for conventional diesel trucks to 1,000 for battery electric trucks. Tables 2.3 and 2.4 compare the mass and MPR distributions of HDT, both conventional and those with 1,000 hp.

Table 2.3 Mass distributions of HDTs

Class	Average (lbs)	Std dev (lbs)	Minimum (lbs)	Maximum (lbs)
dTs	36,396.6	30,049.7	26,000.0	80,000.0
eTs	36,396.6	30,049.7	26,000.0	80,000.0

Table 2.4 MPR distribution of HDTs

Class	25th (lbs/hp)	50th (lbs/hp)	75th (lbs/hp)	85th (lbs/hp)	90th (lbs/hp)
dTs	112.0	141.0	164.0	183.0	198.0
eTs	45.3	57.0	66.3	73.9	80.0

In my simulation models, the maximum acceleration rate of a vehicle is directly a function of its MPR, speed, and road surface grade. However, the latter term does not come into play as my model assumes a level terrain. TransModeler employs a maximum acceleration table (see Table 2.5) as the highest acceleration applied by a vehicle with values borrowed from the ITE Traffic Engineering Handbook (1999). The maximum acceleration thus follows the following relation:

$$A_{ij}^{Max+}[R_i, V_i] = A^{Max+}[R_i, V_i] + g^* G_j/100 \tag{E1.1}$$

where, $A_{ij}^{Max+}[R_i, V_i]$ is the maximum acceleration rate of vehicle i on segment j, and $[R_i, V_i]$ are the MPP and speed of vehicle i, respectively. $A^{Max+}[R_i, V_i]$ comes directly from the maximum acceleration table using a bilinear interpolation and represents the maximum acceleration at level terrain. g^* and G_j represent the effect of gravity on acceleration and the gradient of road segment j, respectively.

Table 2.5 Maximum acceleration rate at level terrain in ft/s^2

MPR (lbs/hp)	< 10 mph	10-20 mph	20-30 mph	30-40 mph	40-50 mph	> 50 mph
25	13.22	11.32	9.45	7.55	5.68	3.77
30	11.29	9.68	8.07	6.46	4.82	3.22
35	9.88	8.46	7.05	5.64	4.23	2.82
100	4.20	3.61	3.02	2.40	1.80	1.21
201	2.76	2.36	1.97	1.57	1.18	0.79
299	2.26	1.94	1.61	1.28	0.98	0.66
399	2.13	1.84	1.51	1.21	0.92	0.62

However, under normal driving conditions, there are differences in acceleration based on vehicle specifications and/or driver preference and comfort. Thus, the normal acceleration of a vehicle is expressed as a function of the maximum acceleration that the vehicle can achieve at any given time (E1.2).

$$A_{ij}^{+}[R_i, V_i] = \alpha_i + \beta_i A_{ij}^{Max+}[R_i, V_i] \quad \text{(E1.2)}$$

where α_i and β_i are parameters used to distinguish between aggressive and conservative drivers or the variation in acceleration ability. With lack of local data to calibrate these parameters, I used the default TransModeler distribution for my simulation runs with an Alpha value of zero and Beta values from a normal distribution (1.1 for 20% of vehicles, 1.0 for 60% of vehicles, and 0.95 for 20% of vehicles).

Then, a normal deceleration is applied under normal driving conditions (i.e., not during emergency braking), such as decelerating to the desired speed, approaching a red light, or trying to abide by the posted speed limit. TransModeler employs a normal deceleration rate table (see Table 2.6) to interpolate a vehicle's acceleration rate based on the vehicle's mass and travel speed. Thus, the normal deceleration of a vehicle is expressed as a function of the normal acceleration table (E1.3).

$$A_i^{Norm-}[M_i, V_i] = \alpha_i + \beta_i \, A^{Norm-}[M_i, V_i] \qquad \text{(E1.3)}$$

Where, $A_i^{Norm-}[M_i, V_i]$ is the normal deceleration rate for a vehicle of mass M_i traveling at speed V_i. For the parameter used to distinguish different vehicle and driver characteristics, I once again used the default TransModeler distribution with an alpha value of zero and Beta values from a normal distribution (1.1 for 20% of vehicles, 1.0 for 60% of vehicles, and 0.95 for 20% of vehicles).

Table 2.6 Maximum acceleration rate at level terrain in ft/s^2

Normal Deceleration Rates						
Mass (lbs)	**< 19 mph**	**19-31 mph**	**31-43 mph**	**43-56 mph**	**56-68 mph**	**> 68 mph**
3307	-4.6	-5.9	-7.2	-8.5	-9.5	-11.2
17637	-4.6	-5.9	-7.2	-8.5	-9.5	-11.2
Maximum Deceleration Rates						
3307	-21.3	-18.7	-14.8	-13.5	-12.8	-11.5
17637	-21.3	-18.7	-14.8	-13.5	-12.8	-11.5

2.3.4 Simulating Connected Automated Trucks (CATs)

To simulate connected automated trucks, I relied on CACC, which provides longitudinal control of vehicle motions (Figure 2.3), so the time gap between consecutive vehicles in a "string" remains approximately constant (Caliper, 2018; Shladover et al., 2015), in accordance with the Constant Time Gap (CTG) car-following model (J. Wang & Rajamani, 2004).

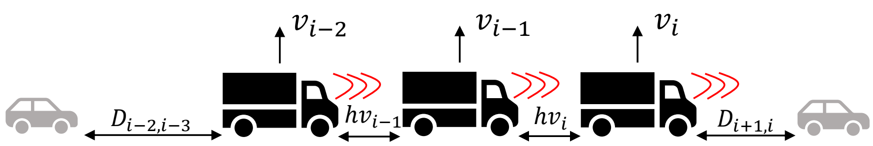


Figure 2.3 Longitudinal Control of CACC-equipped vehicles

In a string of CACC-connected vehicles, I assumed that the lead heavy-duty truck follows the General Motors Car-Following model (GM) (Subramanian, 1996). I restricted the use of the CTG model to HDPTs operating on freeways.

In this framework, the value of the desired constant time gap is essential. Based on my literature review, I assumed that the constant time gap ranges from 0.3 s to 0.9 s, with a preferred value of 0.6 s. While the lower bound of this interval is lower than the [0.5 s, 1.0 s] range considered by Darbha et al. (2017), it is within the headway range [4 m, 10 m] used for PATH's truck platoon field test (Lu & Shladover, 2014a), and at the low end of the [0.3 s, 1.0 s] interval in Janssen et al. (2015). I note that a 0.6 s time gap at 55 mph is approximately 50 ft (15 m), which falls in the 30 to 60 feet interval considered in Peloton Technology's Truck Platooning safety report (2018).

Based on SCAG demand data, I used five vehicle classes to represent all vehicles in the network, lane eligibility, and vehicle attributes for simulation: LDV, LDT, MDT, HDT, plus an additional class Autonomous Heavy-Duty Trucks (ATT). Further, HDT demand was divided into port (PHDT) for all trips starting or ending at the ports and non-port HDTs. This enables me to model different technology deployment scenarios for PHDT trips only.

TransModeler enables the simulation of CACC by the Constant Time Gap (CTG) car-following model (J. Wang & Rajamani, 2004), which seeks to maintain a constant time gap, h, with the leading vehicle. In that model:

$$A_i(t) = -\frac{1}{h}(V_i(t) - V_{i-1}(t) + \lambda\delta_i), \tag{E1.4}$$

where the spacing error is estimated by:

$$\delta_i(t) = D_{i,i-1}(t) + hV_i(t) + D_{i,i-1}{}^{desired}. \tag{E1.5}$$

In the equations above, $A_i(t)$ is the acceleration of vehicle i at time t; h is the desired following time gap (s); $V_i(t)$ is the speed of vehicle i at time t; δ_i is the spacing error for vehicle i requiring correction to achieve the desired headway; $D_{i,i-1}(t)$ is the distance between vehicle i and the front of vehicle i-1 at time t; $D_{i,i-1}^{\text{desired}}$ is the desired distance between vehicle i and the front of vehicle i-1 at 0 speed; and λ is the control gain.

Yet, the leading vehicle in a string, as well as most of the vehicles on the network, follow the Modified General Motors Car Following Model (Caliper, 2018; Subramanian, 1996), in which a driver's acceleration is broken down into three regimes (Emergency, Car Following, and Free Flow regimes).

The emergency regime only applies during the most extreme cases where the vehicle tries to avoid a collision because it has fallen below a predetermined headway threshold. Thus, emergency deceleration applies unless other factors require a more severe response (e.g., maximum deceleration). If the headway is above the predefined upper bound threshold, or if there is no lead vehicle, the free flow model applies in which the vehicle speed or position is not influenced by the vehicle in front, and the normal acceleration rate applies. Otherwise, if the headway falls between the lower and upper bound thresholds (i.e., the lead vehicle is not close enough to justify emergency braking but is not far enough for normal acceleration rates to apply), the car following regime applies. The lower and upper bound thresholds are about 0.3 seconds at the lower bound and about 1.5 seconds at the upper bound.

2.4 Results

2.4.1 Traffic Performance

To evaluate some of the traffic impacts of the vehicle and infrastructure changes in my scenarios, I collected network-wide summary statistics by vehicle class and by facility type, including vehicle counts, vehicle miles traveled (VMT), vehicle hours traveled (VHT), and average speed (mph; calculated from VMT/VHT). Before finalizing my results, I performed extensive visual checks of my simulations, which were repeated several times to detect and correct questionable traffic behavior.

In my presentation of results, I focus on the average speed of all vehicles by facility type, time period, and average speed of heavy-duty port trucks (HDPTs, or drayage trucks), given their economic importance to the economy of Southern California and the U.S.

2.4.1.1 *Average Network Traffic Speeds*

Table 2.7 presents summary statistics for my 2012 baseline (Scenario 1), which corresponds to 2012 traffic infrastructure, vehicles, and traffic demand. In the 2012 baseline scenario, 3.76 million vehicles travel 20.54 million miles in 0.54 million hours at an average speed of 37.8 mph during the 24 hours of my simulations.

Several points are worth noting. First, the average network speed of all vehicles (37.8 mph) is dominated by the speed of light-duty vehicles (LDVs) (37.3 mph), which make up over 90% of all network vehicles. Second, the average network speed of LDVs is strongly affected by their average speed on the 281 miles of arterials in my network (~half of total network miles). Third, the average speed of HDPTs (51.5 mph) is substantially higher than the average speed of all other vehicles because they drive mostly on freeways in my study area, including during times (midday and after the evening peak hour) when freeway traffic is lighter. A calculation of 24-hour average speed by facility type (see sub-Section 1.4.1.2) shows that the average freeway speeds of different vehicle classes are similar.

Table 2.7. 2012 baseline (scenario 1) traffic performance results

Vehicle Class	Vehicle Count	VMT	VHT	Average Vehicle Speed (mph) [VMT/VHT]		
				Network	Freeways	Arterials
Light duty vehicles (LDV)	3,556,976	19,054,598	510,839	37.3	57.7	23.7
Light duty trucks (LDT)	50,899	323,331	7,030	46.0	57.9	25.8
Medium duty trucks (MDT)	42,107	231,742	5,549	41.8	57.9	24.0
Heavy duty trucks (HDT), excl. HDPT	51,350	321,052	7,674	41.8	56.6	23.1
Heavy-duty port trucks (HDPT)	56,886	612,490	11,902	51.5	57.8	27.2
All vehicles	3,758,218	20,543,212	542,994	37.8	57.7	23.8

Whereas in 2012 (Scenario 1, Table 2.7), trucks represented 2% of all vehicles and 28% of all trucks were heavy-duty port trucks (HDPT), in 2035, the percentage of trucks jumps to 3%, and 45% of all trucks are HDPTs. As a result, without infrastructure improvements (Scenario 2A), average network speeds drop from 37.8 to 33.3 mph, and the average speeds of HDPTs sink to 18.5 mph compared to 51.5 mph in 2012 (-64%) (see Figure 2.4). Ramp improvements (Scenario 3A) boost speeds to 36.3 mph overall and 29.6 mph for HDPTs, but these are still below 2012 speeds. Adding a general-purpose lane along I-710 without changing drayage trucks (Scenario 4A) would increase overall network speeds to 38.4 mph (slightly more than the 37.8 mph average for 2012), although HDPT average speed would only reach 45.1 mph, well below the 2012 value of 51.5 mph. Results shown in Figure 2.4 thus suggest that adding a lane to I-710 is necessary but not sufficient to ensure that road containers will continue to move on average at their 2012 speeds.

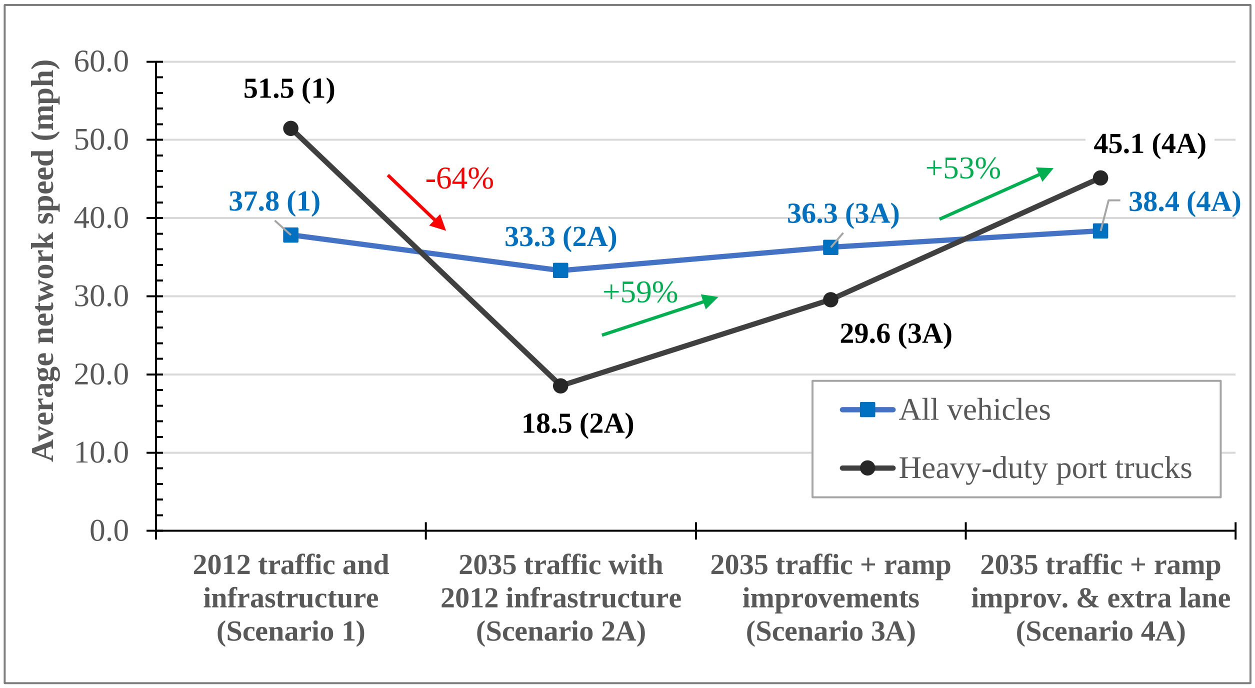


Figure 2.4 Average network speeds (mph) for different traffic and infrastructure conditions

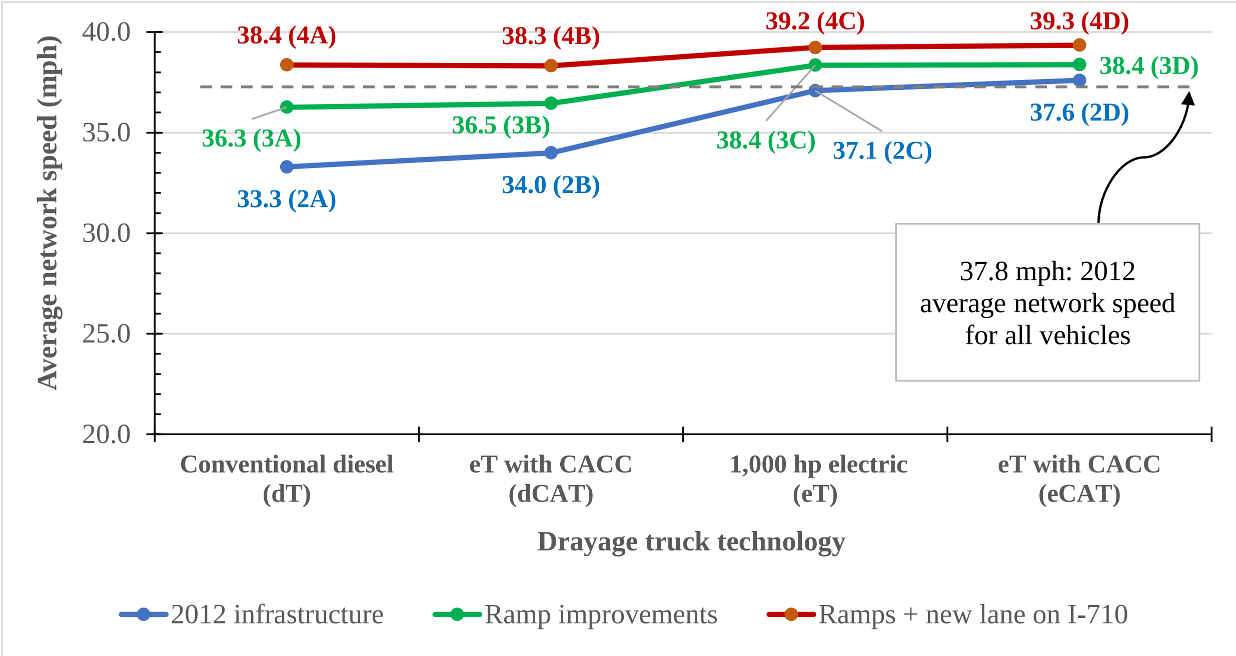
Note: the scenario that generated a speed is indicated in parentheses after that speed.

However, results from my other scenarios (see Panels A and B in Figure 2.5) suggest that adding a lane to I-710 to absorb the projected increase in drayage truck traffic by 2035 may not be necessary if conventional HDPTs are replaced with 1,000 hp electric trucks, which have a much lower mass to power ratios than current HDPTs.

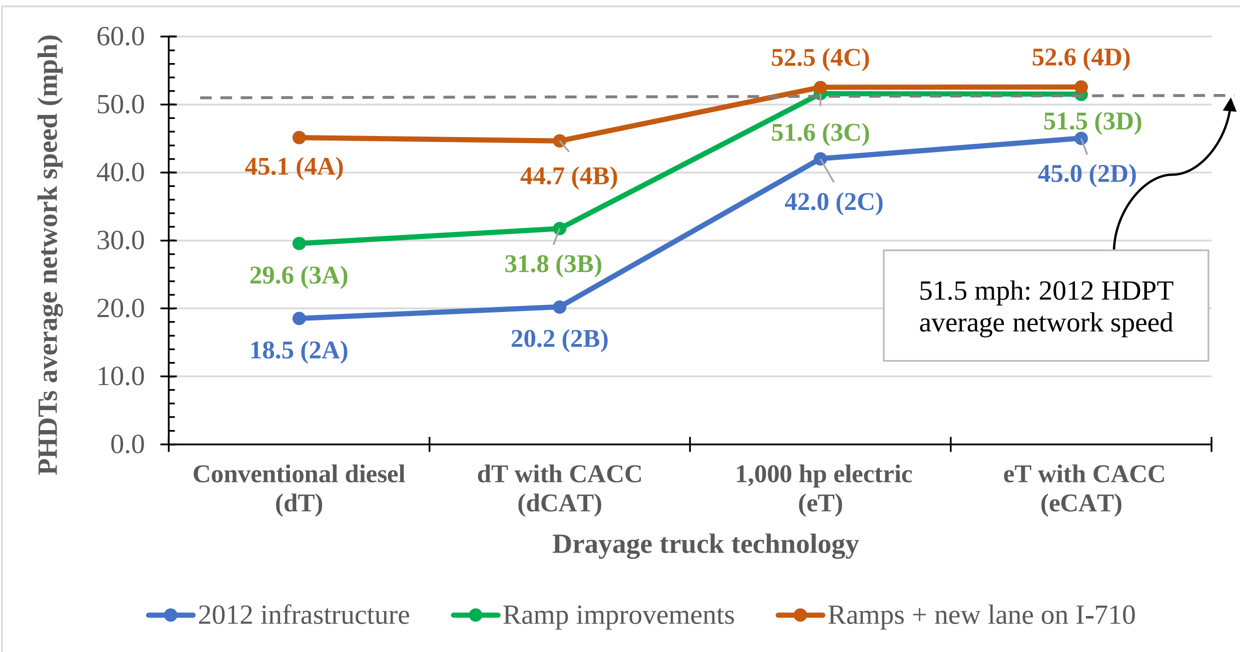
Figure 2.5 shows how average network speed changes overall (Panel A) and for heavy-duty port trucks (Panel B) when conventional diesel HDPTs (dTs) ("A" scenarios) are replaced with CACC-enabled drayage trucks (dCATs) with the same mass to power ratio as current HDPTs ("B" scenarios), 1,000 hp electric/hydrogen-electric trucks (eTs) ("C" scenarios), and with CACC-enabled 1,000 hp electric/hydrogen-electric trucks (eCATs) ("D" scenarios), for three different levels of road infrastructure represented by separate lines.

Starting with conventional diesel trucks (dTs) (left side of Figure 2.5 Panels A and B), I see that while ramp improvements and an additional general-purpose lane on I-710 would increase overall network speed for all vehicles above its 2012 value (38.4 mph vs. 37.8 mph, see Panel A), they would not be sufficient for drayage trucks, whose network speed would lag at 45.1 mph (versus 51,5 mph in 2012).

Replacing conventional heavy-duty port trucks with CACC-connected HDPTs would only have a small impact on average network speeds, both overall and for drayage trucks. That impact is positive when speeds are relatively low (2012 infrastructure or ramp improvements only) but negative with the addition of another lane on I-710 (the overall average speed drop to 38.3 mph from 38.4 mph, while the average speed of HDPTs dips to 44.7 mph from 45.1 mph). The likely reason for these speed drops is negative interactions between strings of CACC-connected HDPTs and light-duty vehicles, where the former



Panel A: All network vehicles



Panel B: Heavy-duty port trucks (HDPTs)

Figure 2.5 Average network speeds for different truck technologies and road infrastructures

Note: the scenario corresponding to a speed is indicated in parentheses after that speed.

impedes lane changes or access to freeway ramps.

However, replacing conventional HDPTs with 1,000 hp trucks (eTs; e.g., battery-electric trucks such as the Tesla Semi or hydrogen-electric such as the Nikola TWO) would substantially improve average speeds by decreasing the moving bottleneck effect created by slow-moving conventional heavy-duty trucks (Newell, 1998). Without road infrastructure improvements, replacing dTs with eTs would increase the overall average network speed to 37.1 mph (up from 33.3 mph). Also, implementing the ramp improvements shown in Figure 2.2 would increase average network speeds above their 2012 value, overall (38.4 mph versus 37.8 mph; see Panel A) and for drayage trucks (51.6 mph versus 51.5 mph; see Panel B). Adding a general-purpose lane to I-710 in addition to these ramp improvements would further improve network speeds, but gains would be relatively small (39.2-38.4=+0.8 mph overall, and 52.5-51.6=+0.9 mph for drayage trucks), which suggests that adding a general-purpose lane to I-710 is not necessary.

Finally, replacing conventional heavy-duty port trucks with CACC-connected HDPTs would yield only small benefits overall (right side of Panel A) and for heavy-duty port trucks (right side of Panel B), except when the road infrastructure is unchanged. In that case, I observe a 3-mph gain (Scenario 2D versus Scenario 2C). I note, however, that CACC-equipped trucks are likely to substantially decrease the number of incidents, which would contribute to improving average speeds, but this effect is not captured by my simulations, which assume an accident-free environment.

2.4.1.2 ***Average Speed by Facility Type and Time Period***

To further assess the effect of HDPT technology on overall traffic conditions, I also explored average speeds by facility type and time of day. Results are presented on Panels A-F of Figure 2.6.

Panels A and B display the impact on average speed on freeways (A) and arterials (B) of changing drayage truck technology for the 2012 road infrastructure. Starting with Panel A, I observe that increasing HDPT demand severely impairs freeway speeds (2035 dT), especially during the AM peak, mid-day, and PM peak. Connecting diesel HDPTs via CACC (2035 dCATs) slightly increases the average speed of all vehicles during mid-day and the PM peak, saving ~5,000 vehicle hours per day on freeways). The observed speed improvements for HDPTs on freeways are up to 14%, compared to a 2% speed improvement overall. By comparison, (Ramezani et al., 2018a) found that enabling CACC string on HDT improved the average speed of HDTs and passenger vehicles by 19% and 6%, respectively, for a one-hour simulation of a segment of I-710.

Replacing dTs with 1,000 hp electric trucks (eTs) improves freeway speeds by 2 to 3 mph during mid-day and PM peak periods (saving ~12,600 additional vehicle hours per day on freeways). Connecting these electric trucks with CACC only yields small speed gains during the AM peak and mid-day and a small speed loss during the PM peak.

For arterials (Panel B), I note that the 2035 increase in HDPTs demand affects arterial traffic only during midday (see the red line corresponding to 2035 dT). Replacing conventional HDPTs with 1,000 hp eTs erases the average speed impact of the 2035 increase in HDPT traffic on arterials during midday. However, connecting drayage trucks

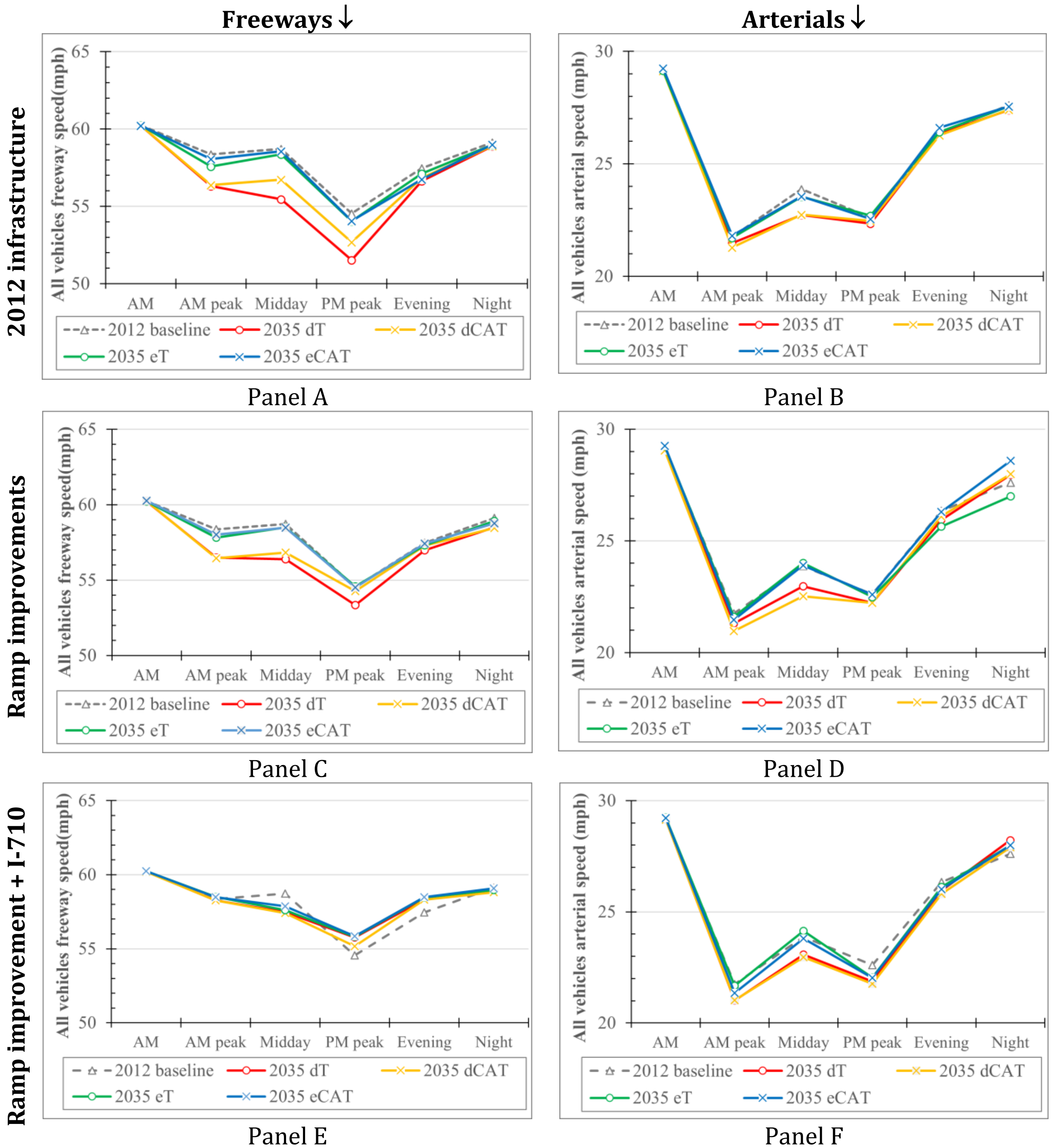


Figure 2.6 Average speed by time period

Notes. 1) 2012 baseline = Scenario 1, with conventional diesel HDPTs (heavy-duty port trucks).
2) dTs = diesel HDPTs; dCATs = diesel HDPTs with CACC; eTs = electric/hydrogen-electric (1,000 hp) HDPTs; eCATs = electric/hydrogen-electric (1,000 hp) HDPTs with CACC.
3) AM: from midnight to 6 am; AM Peak: morning peak, from 6 am to 9 am; Midday, from 9 am to 3 pm; PM Peak: afternoon peak, from 3 pm to 7 pm; Evening: from 7 pm to 9 pm; and NT: nighttime, from 9 pm to midnight.

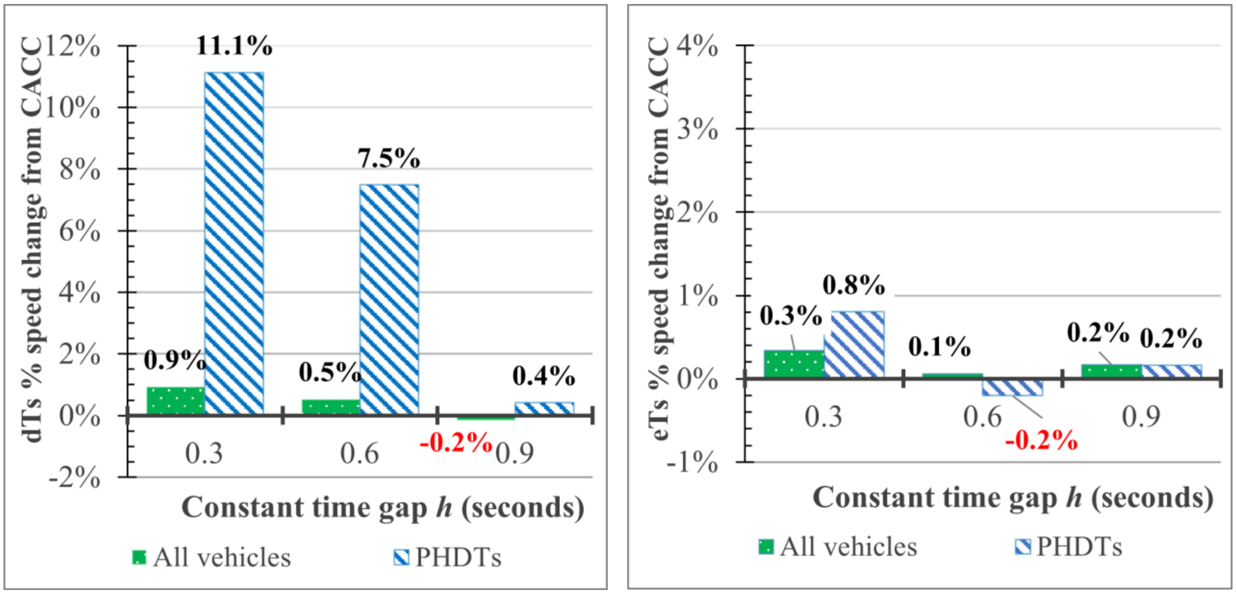
via CACC has no impact on average speeds (for either conventional or 1,000 hp trucks) because my simulation models assume that CACC is only active on freeways.

Panels C and D present similar information after ramp improvements. These improvements have the largest impact on midday and PM peak traffic. My simulations illustrate that several ramps on I-710 are inadequate for current (and even less so future) traffic conditions. Panel C shows that replacing conventional HDPTs with dCATs makes little difference on freeways, and that eTs improve average speeds the most, with ~8,200 vehicle hours saved per day on freeways compared to the 2035 baseline (Scenario 3A). However, eCATs have no noticeable additional impact over eTs. On arterials (Panel D), eTs and eCATs provide the largest improvement, but the difference in average speeds between different HDPT technologies is small.

Finally, Panels E and F summarize scenario results respectively for freeways and arterials after both ramp improvements and the addition of a general-purpose lane (in each direction) to I-710. There are almost no speed differences between my scenarios in both cases because road capacity is sufficient to accommodate demand, with close to free-flow speeds on freeways.

2.4.1.3 *Constant Time Headway Sensitivity Analysis*

As part of my sensitivity analysis, I explored how average network speed could change with the constant time gap parameter $h \in \{0.3, 0.6, 0.9 \text{ s}\}$ for Scenarios 3A-D (ramp improvements only). Results are shown in Figure 2.7.



Panel A: dCATs vs. dTs Panel B: eCATs vs. eTs

Figure 2.7 Constant time gap sensitivity analysis

Starting with Panel A, I see that the speed gain from replacing conventional HDPTs (dTs) with dCATs drops from 11.1% to 0.4% when the constant time gap parameter *h* increases from 0.3 s to 0.9 s. Moreover, the impact on overall speed, which is small (0.9%) for *h*=0.3 s, turns negative (-0.2%) for *h*=0.9 *s*, suggesting that, as expected, long platoons at larger time gaps create more slowdowns in the traffic stream.

By contrast, when 1,000 hp battery or hydrogen-electric trucks (eTs) are equipped with CACC (and become eCATs with my abbreviations), speed gains are much smaller (Panel B of Figure 2.7); possibly because eTs can accelerate/decelerate much faster than conventional heavy-duty trucks, so they do not benefit as much from the coordination of longitudinal motions provided by CACC. Speed differences for *h*=0.6 s are even negative, possibly because of interferences between strings of eCATs and the rest of the traffic. I note, however, that my simulations do not account for aerodynamic gains resulting from eCATs in a string traveling close to each other, so my results likely underestimate the benefits of CACC.

2.4.1.4 *CACC and Traffic Smoothing*

I also explored the impact of connected and electric/hydrogen-electric trucks on the fundamental diagram of traffic flow for I-710 sensors by recording five-minute observations with the flow, occupancy, speed, and headway. I used the simulated flow and derived density for plotting five-minute flow-density data for each sensor. Figure 2.8 shows these data for Scenarios 2A-C under a 0.6 s time gap, which differ only by the technology of HDPTs – the road infrastructure corresponds to baseline (2012) conditions – so any improvements can only be attributed to vehicle technology differences. A comparison between the baseline (Scenario 2A on Panel A), which features conventional diesel trucks (dTs), with Scenario 2B (Panel B), where dTs have been replaced with dCATs, and Scenario 2C (Panel C), where dTs have been replaced with eCATs shows that the deployment of dCATs and eTs reduces the scatter of the fundamental diagram. While speed gains associated with connectivity alone are somewhat small, scatter dissipation in the fundamental diagram shows that connectivity can smooth traffic, resulting in a safer driving environment. Similar results were observed for most other detectors along I-710.

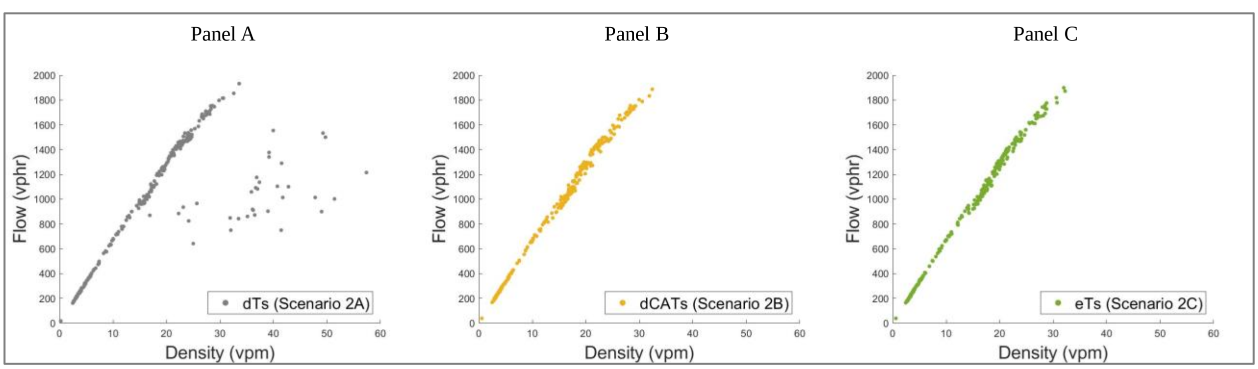


Figure 2.8 Comparison of flow-density relationships for scenarios 2A-B-C

2.5 Discussion

According to the I-710 corridor project RDEIR, the estimated cost of acquiring the right of way, relocating utilities, and building an additional general-purpose lane along I-710 is approximately $4.67 billion. In addition to federal and state funding and local Measure R and Measure M sales tax funds, the Los Angeles County Metropolitan Transportation Authority (Metro) also considered the applicability of a Public-Private Partnership (PPP) for the I-710 Corridor Project (Caltrans & L.A. Metro, 2017). However, the share of funding from each source is unclear.

To put infrastructure costs in perspective, the advertised base price for Tesla's Semi electric Class 8 semi-truck is $150,000 for the 300-mile range option and $200,000 for the 500-mile range option, which represents a premium of $33,000 to $83,000 over the $117,000 pre-COVID-19 average price for a Class 8 diesel semi-truck (Hirs, 2020). Currently, approximately 18,000 drayage trucks are registered in the SPBP drayage truck registry, a necessary condition to enter the SPBP complex, so the cost of replacing all currently registered drayage trucks with electric drayage trucks ranges from $2.7 billion to $3.6 billion, which is less than the expected cost of adding a lane to I-710. Moreover, in the longer term, the net ownership costs of electric trucks are expected to dip well below those of conventional diesel and hybrid trucks (Giuliano et al., 2021; Vijayagopal & Rousseau, 2021).

In California, in addition to the advanced clean trucks regulation, which sets a target for the sale of zero-emission trucks and mandates company and fleet reporting (CARB, 2020), the governor's September 2020 executive order N-79-20 sets a goal of 100 percent zero-emission drayage truck sales by 2035 (Sommer & Neuman, 2020). The ports of Los

Angeles and Long Beach adopted in the 2017 Advance Clean Trucks (ACT) Now Plan, a slightly more ambitious goal of banning diesel truck registration from the Ports Drayage Truck Registry as early as 2023 (California Natural Gas Vehicle Coalition, 2017). As part of this commitment, the SPBP harbor commissioners approved in March 2020 a $10 fee per TEU (twenty-foot equivalent units) loaded container to finance the replacement of diesel drayage trucks with zero-emission trucks (Barboza, 2020), which is considered too low to finance the purchase of a large enough number of zero-emission drayage trucks by 2035. Moreover, there is no provision for targeting subsidies at the most efficient clean trucks, and current economic analyses do not account for the potential impacts of different zero-emission HDPTs on demand for regional road infrastructure.

Other programs to foster the adoption of zero-emission heavy-duty vehicles in California include the Hybrid and Zero-Emission Truck and Bus Voucher Incentive Project (CARB, 2018), the Carl Moyer Memorial Air Quality Standards Attainment Program (CARB, 2017b, 2017a), the Volkswagen Mitigation Trust ("Volkswagen Environmental Mitigation Trust for California," n.d.), and California's Truck Loan Assistance Program ("Truck Loan Assistance Program," n.d.). However, these programs do not have enough money to fund by 2035 the $2.7 billion and $3.6 billion that would be needed to pay for the difference between conventional and electric drayage trucks serving the SPBP, let alone the few thousand drayage trucks serving the other California ports (mostly the Ports of Oakland, and San Francisco). Moreover, these programs do not specifically target electric trucks powerful enough to alleviate the moving bottleneck created by conventional heavy-duty trucks.

In addition to the structural weaknesses of current road infrastructure funding in the U.S., this calls for changes in the way road infrastructure is funded since replacing current HDPTs with powerful (possibly CACC-connected) electric heavy-duty trucks would alleviate the demand for additional capacity on I-710. Currently, California's highway funding comes from federal, state, local, and tribal governments and from private revenue sources. Regional and local sources account for roughly half of California's transportation funding, with federal and state funding accounting for approximately 25% each (Caltrans, 2020). One possibility would be for the federal government to authorize repurposing some of the funds earmarked for road infrastructure to help finance the transition to (preferably connected, for safety reasons) heavy-duty electric trucks in selected freight corridors at least until that the market for these trucks is mature enough that subsidies are no longer needed. This measure could be coupled with increased taxation on diesel fuel, possibly combined with a ban on heavy-duty diesel vehicles in specific freight corridors and a leasing program for smaller HDPT operators.

Overall, given the political challenges of increasing the gas tax that funds the Highway Trust Fund (HTF), the increasing fuel efficiency of motor vehicles, the emergence of electric vehicles, and the reduction in VMT from the Covid-19 pandemic (Caltrans, 2021), a new road infrastructure financing model is needed, but this is beyond the scope of this analysis. However, my analysis highlights the need to consider the potential impact on road infrastructure demand of new technologies for heavy-duty trucks (electric propulsion and connection between vehicles to enhance safety) and appropriately tailor public policy.

2.6 Conclusions

In Chapter 1, I improved and calibrated a large microsimulation model of selected freeways and arterial roads in the corridor that links the San Pedro Bay Ports and downtown Los Angeles (California) to explore the impact on traffic and road infrastructure demand of replacing conventional diesel heavy-duty port trucks (dTs), with CACC-connected dTs, eTs (1,000 hp heavy-duty electric/hydrogen-electric trucks), and CACC-connected eTs (eCATs) during an accident-free day (24 hours). In addition to a 2012 baseline, I analyzed twelve scenarios for year 2035, where SPBP cargo demand was assumed to have increased by 145% compared to 2012, while the demand for non-port-related vehicle classes was unchanged. Although I focus on a specific freight corridor, my methodology is widely applicable.

My results show that the effectiveness of different heavy-duty truck technologies depends on the state of congestion of the road infrastructure. Without road infrastructure improvements, the forecasted increase in HDPTs for 2035 adds substantially to the congestion on freeways and slows down traffic on arterials in my study area. Replacing conventional HDPTs with dCATs on freeways (CACC is active only on freeways in my simulations) would impact mid-day and PM peak traffic, but it would be insufficient to go back to 2012 network speeds. Replacing conventional diesel heavy-duty port trucks with 1,000 hp eTs, however, would increase speeds on both freeways and arterials enough to exceed 2012 speeds on freeways and arterials slightly. Connecting these eTs via CACC would only have small speed benefits, but it would likely substantially enhance traffic safety, a topic not explored here.

Improving selected freeway ramps would alleviate congestion on freeways (and most notably on I-710) in my study area for all heavy-duty port truck technologies considered. However, also adding a general-purpose lane on I-710 appears unnecessary because selected ramp improvements on I-710 alone, combined with the replacement of conventional HDPTs with powerful eTs, would improve average speeds on both freeways and arterials sufficiently to exceed 2012 values slightly. Finally, I note that by making HDPTs much nimbler, eTs would also improve arterial speeds during most of the day. Although the electric trucks I simulated are not yet available (the Tesla Semi is now expected for 2023), my results illustrate that heavy-duty truck technology improvements can be a substitute for additional road infrastructure, allowing to avoid expensive and politically controversial road infrastructure investments in the nation's busiest freight corridor. More generally, future road infrastructure plans should account for the performance changes from new vehicle technologies. Although this is challenging in an environment where vehicle technologies are quickly evolving, it is possible, as shown by the detailed simulations presented in this chapter, and necessary at a time when governments around the world are phasing out the sale of vehicles with internal combustion engines and adopting policies to foster the adoption of zero-emission vehicles. My results suggest that encouraging the "right" truck technology is critically important.

Like all simulation studies, my results are only as good as my underlying assumptions, the many sub-models in my simulation software, and the data they require (especially OD demand data for 2035). In addition, I would like to mention a few additional limitations. The first is the uncertainty about the technical characteristics of the technologies I considered. For CACC-connected trucks, I could not restrict the number of vehicles in a CACC string, which could have decreased potential conflicts between dCATs/eCATs and other vehicles. A second limitation is that my simulations do not reflect that electric trucks can almost instantly generate high torque, whereas diesel engines require high RPMs to reach similar torque values. My results, therefore, likely underestimate the performance improvements of electric HDPTs compared to similar conventional HDPTs. Third, my simulations are accident-free, even though days without accidents or mechanical breakdowns impacting traffic in my study area are rare. This is left for future work.

In addition to conducting field tests of zero-emission drayage trucks as they become available, future work could explore the traffic impacts of higher levels of automation both for drayage trucks and other types of vehicles as a function of their penetration level and investigate the impact of electric/hydrogen-electric and connected trucks on traffic safety. Analyzing the air quality, greenhouse gas emissions, and environmental justice implications of replacing conventional drayage trucks with zero-emission alternatives are also critically important as it is a key motivation for their introduction; this is explored at a regional scale in Chapter 3.

CHAPTER 3 ACHIEVING ZERO-EMISSION DRAYAGE BY 2035

3.1 Introduction

Like other heavy-duty trucks, drayage trucks (i.e., heavy-duty trucks hauling containers and bulk to and from ports and intermodal railyards; CARB, 2022) contribute disproportionately to $PM_{2.5}$ (particulate matter with a maximum diameter of 2.5 micrometers), which is the common air pollutant of most concern for health (CARB, 2022c; Pan et al., 2019), nitrogen oxides (NO_x), a key component of smog and a precursor to secondary PM, and greenhouse gas (GHG) emissions. Indeed, heavy-duty trucks account for four-fifth of road transportation PM in California despite making up only 7% of registered vehicles (Tabuchi, 2020). They also contribute a third of total NO_x emissions (CARB, 2022b) and a fifth of GHG emissions from transportation, the main source of GHG in California (CARB, 2021a).

Unlike long-haul heavy-duty trucks, however, drayage trucks mostly operate in populated areas. This is the case for the heavy-duty drayage trucks (HDDTs) serving the San Pedro Bay Ports (SPBP; i.e., the ports of Los Angeles and Long Beach), the largest port complex in the U.S. and ninth in the world in 2021 (Bansard International, 2022). As reported in the environmental justice (EJ) literature (e.g., see Barnes and Chatterton, 2016; Clark et al., 2017; Grobar, 2008; Houston et al., 2004; Kingham et al., 2007), disadvantaged communities (i.e., census tracts in the top quartile for their combined pollution burden, as defined in CalEnviroScreen 4.0) are particularly exposed to air pollution from heavy-duty trucks.

To reduce air pollution and help meet California's GHG reduction goals set by Assembly Bill 32 (2006), subsequent executive orders, and Senate Bill 32 (2016), the SPBP adopted in 2006 the Clean Air Action Plan (CAAP). As part of the CAAP, the Clean Trucks Program (CTP) phased out pre-2007 HDDTs serving the ports by 2012, ahead of the deadline set by the State Drayage Truck Rule at the time (SPBP, 2017). The 2017 CTP update further required that any new trucks in the Port Drayage Truck Registry (a necessary condition to enter the SPBP) be model year 2014 or newer starting October 1, 2018, although already registered HDDTs compliant with the Drayage Truck Regulation and the Truck and Bus Regulation are grandfathered.

Despite improvements, air pollution from HDDTs remains a very sensitive issue, as acknowledged by the June 2017 public declaration from the Mayors of Los Angeles and Long Beach seeking "zero-emissions for on-road drayage trucks serving the ports by 2035" (Barboza, 2017). However, industry lobbyists added in the 2017 Senate Bill 1 (SB 1) a provision that "prohibits new regulatory requirements to replace, retire, repower, or retrofit heavy-duty trucks before they have reached the earlier of either 800,000 vehicle miles traveled or 18 years from the engine model year" (SPBP, 2017). California Executive Order N-79-20, issued in September 2020, therefore adopted a more modest goal of ending sales of HDDTs with internal combustion engines by 2035.

In this context, Chapter 3 analyzes the health and GHG reduction benefits from replacing the HDDTs serving the SPBP with ZE HDDTs while accounting for air quality regulations reflected in U.S. EPA's MOVES3. To the best of my knowledge, no published academic study has estimated the health, environmental, and environmental justice benefits of replacing conventional HDDTs with ZE HDDTs in the nation's most important freight corridor despite its economic importance. Moreover, my freeway simulation model is one of the largest ever built to analyze the benefits of a clean transportation program. Although I focus on Southern California, my results have national importance because 14 other states have adopted California's GHG emission and ZE vehicle regulations under Section 177 of the Clean Air Act.

My analysis of environmental and health benefits focuses on two years, 2012 and 2035, the former as the deadline for phasing out pre-2007 HDDTs in the CAAP, and the latter as the deadline in Executive Order N-79-20 and in the June 2017 public declaration from the Mayors of Los Angeles and Long Beach. My work relies on projections about the fleet of HDDTs in EMFAC2021 v1.0.2, and emission factors from U.S. EPA's MOVES3, which reflect technological improvement and known regulations. Moreover, my 2035 traffic demand includes a 145% increase in cargo demand at the ports over 2012 that reflect projected freight growth.

My study area (Figure 3.1) is located within the Southern California Association of Governments (SCAG) region. It stretches between the San Pedro Bay Ports and the Inland Empire, home to large warehouse complexes. The SCAG region is well-suited to study the environmental justice implications of electrifying drayage trucks because minority groups (predominantly Hispanics and Asian/Pacific Islanders) account for two-thirds of the population, according to the 2020 U.S. census. As shown in Figure 3.1, many census tracts near my selection of freeways are designated as disadvantaged in CalEnviroScreen 4.0. Their proximity to freeways exposes them to diesel pollution, a percentage of which comes from SPBP HDDTs.

My methodology includes three main steps. In Step I (traffic simulation), I performed 24-hour microscopic traffic simulations of an accident-free day to model vehicle trajectories on freeways in my study area. In Step II (health and environmental impact assessment), I first estimated emissions associated with each vehicle trajectory using the methodology proposed by Claggett, (2009). I then used InMAP (Intervention Model for Air Pollution) to calculate the $PM_{2.5}$ concentrations due to HDDTs in 2012 and 2035, and BenMAP to estimate selected health Outcomes. In Step III (environmental justice implications), I quantified the expected benefits for communities designated as disadvantaged by CalEnviroScreen 4.0.

In the next section, I present background information and review selected papers to set the stage for my analyses. In Section 2.3, I describe my data and my methodology. Section 2.4 summarizes my results before discussing some of their implications in Sections 2.5. In Section 2.6, I conclude, mention some limitations of my work, and suggest ideas for future work.

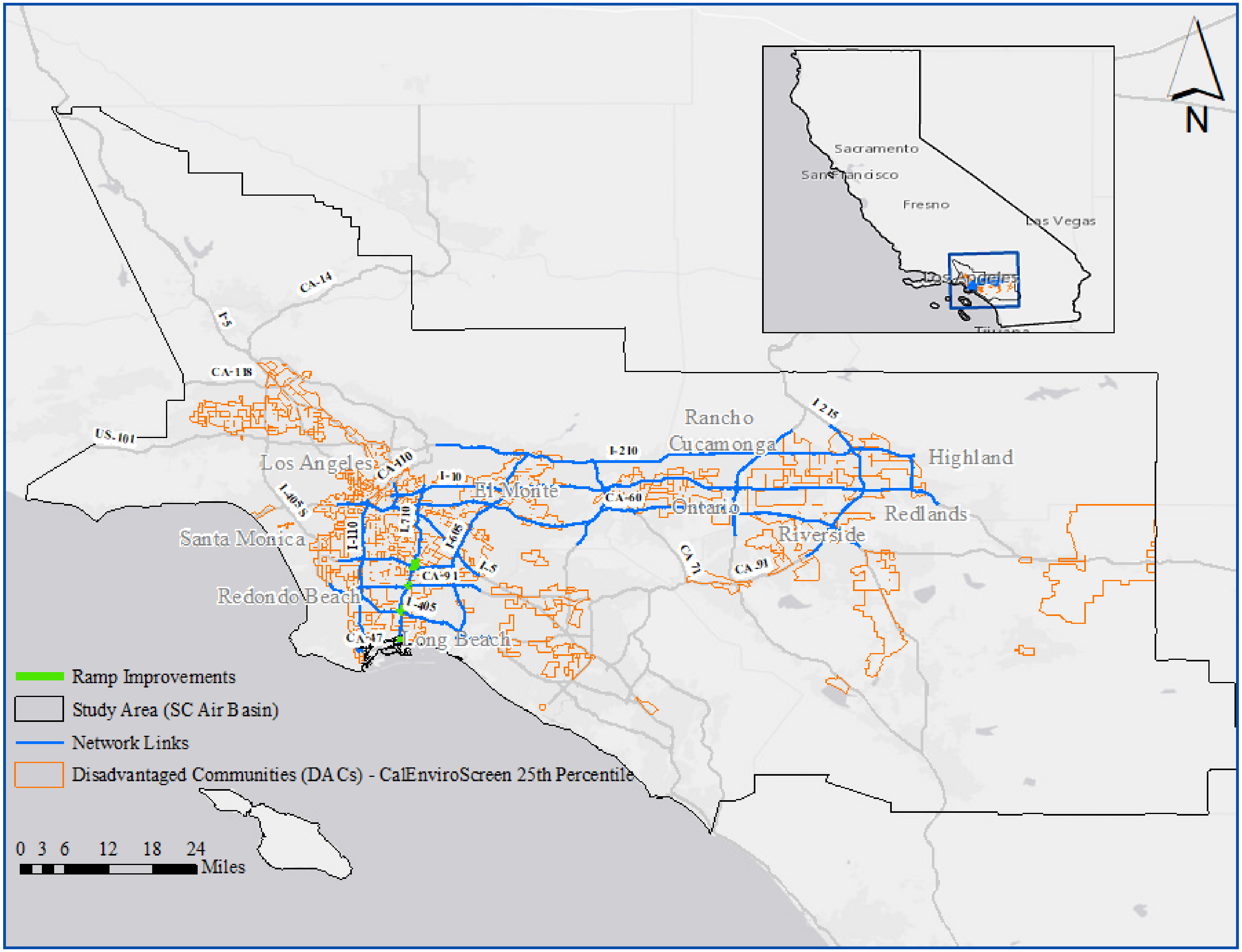


Figure 3.1 Study Area and 2035 ramp improvements

3.2 Background

3.2.1 Zero Emission Heavy-Duty Trucks

As of mid-2022, manufacturers in the U.S. or the E.U. are offering several dozen models of ZE HDDTs (Sharpe & Basma, 2022), including BYD, Daimler, Nikola, Toyota / Kenworth, and Volvo (Brown et al., 2021). Other automakers, such as Cummins and Tesla, have announced their own all-electric models (Carter, 2017; Chauhan, 2021). These Class 8 trucks currently qualify for California incentives of up to $120,000 (BYD, 2022).

Much of the ZE trucks literature explores the feasibility of ZE truck deployment to achieve environmental goals. This literature can be organized into three groups: 1) policy studies (e.g., see Breed et al., 2021; Burke and Miller, 2020; Buysse and Sharpe, 2020); 2) assessments of infrastructure needs (e.g., see Hall and Lutsey, 2019; Lajevardi et al., 2022; Minjares et al., 2021); and 3) technology feasibility studies (examples include Basma and Rodríguez, 2021; Cunanan et al., 2021; Giuliano et al., 2021; Tanvir et al., 2021). The most relevant studies for my work explore the ability of the electric grid to support the charging infrastructure, the adequacy of battery technology to handle current fleet operations, and the overall impact of the deployment of zero or near-zero-emission heavy-duty trucks on well-to-wheels emissions (Giuliano et al., 2021; Gunawan & Monaghan, 2022; Liu, Elgowainy, Vijayagopal, & Wang, 2021; Moultak, Lutsey, & Hall, 2017; Tanvir et al., 2021). In the discussion section below, I also rely on studies of the activity patterns of conventional drayage trucks, conducted either to better understand their use (Scora et al., 2019; You & Ritchie, 2018), optimize truck routing and scheduling (Erera & Smilowitz, 2008), reduce air pollution (Schulte, González, & Voß, 2015), design cleaner drayage trucks

(Amar, Desai, Kailas, & Gallo, 2017), or assess emission reductions from electrification (Ambrose & Jaller, 2016).

3.2.2 Environmental Justice

Communities of color in the United States have been disproportionately affected by environmental harms derived from industry, development, and, more generally, economic activity, including transportation, as documented by decades of EJ research (Borunda, 2021).

Most of the environmental justice (EJ) literature focuses on issues of race, class, policies, and on creating a consensus of theories and terms (Brulle & Pellow, 2006; Cutter, 1995; Mohai, Pellow, & Roberts, 2009), and by transportation engineering standards, it is mostly qualitative.

The strand dealing with the impacts of heavy-duty trucks is currently relatively small and includes both quantitative and qualitative studies. The latter frequently deal with freight transport governance issues over time and analyze plans and policies through an EJ lens (Cui, Dodson, & Hall, 2015; Garcia et al., 2013; Ryan, 2017; Sampson, Schulz, Parker, & Israel, 2014).

Quantitative studies typically employ a macroscopic approach using aggregate emission inventories or traffic counts to quantify the air pollution generated by heavy-duty trucks in adjacent communities (Houston et al., 2014, 2008; Patterson and Harley, 2021). These papers typically rely on traffic counts or historical pollution and air quality data to disentangle the role of freeways and other sources in explaining the disproportionate environmental burden carried by disadvantaged communities (Clark et al., 2017; Houston et al., 2014).

More disaggregated modeling approaches, such as microscopic simulation, have started to become more prevalent in transportation equity analyses (Bills, Sall, & Walker, 2012; Bills & Walker, 2017; Karner & London, 2014; Nahmias-Biran & Shiftan, 2020), as they are better suited for analyzing infrastructure changes and technology deployment. However, this type of analysis is often used to study mobility and accessibility outcomes using activity-based models to assess the impact of regional transportation improvements. I am unaware of disaggregate EJ studies that analyze the air quality impacts of infrastructure improvements or technology deployment.

3.3 Data and Methodology

Figure 3.2 gives an overview of Chapter 2 methodology. It has three parts. I simulate traffic in my study area for each scenario in Part I. In Part II, I estimate vehicular emissions for each scenario, calculate changes in concentrations of various air pollutants with respect to my 2035 baseline, estimate the health impacts resulting from changes in $PM_{2.5}$ concentration, and calculate changes in GHG emissions. In Part III, I analyze the EJ implications of my results.

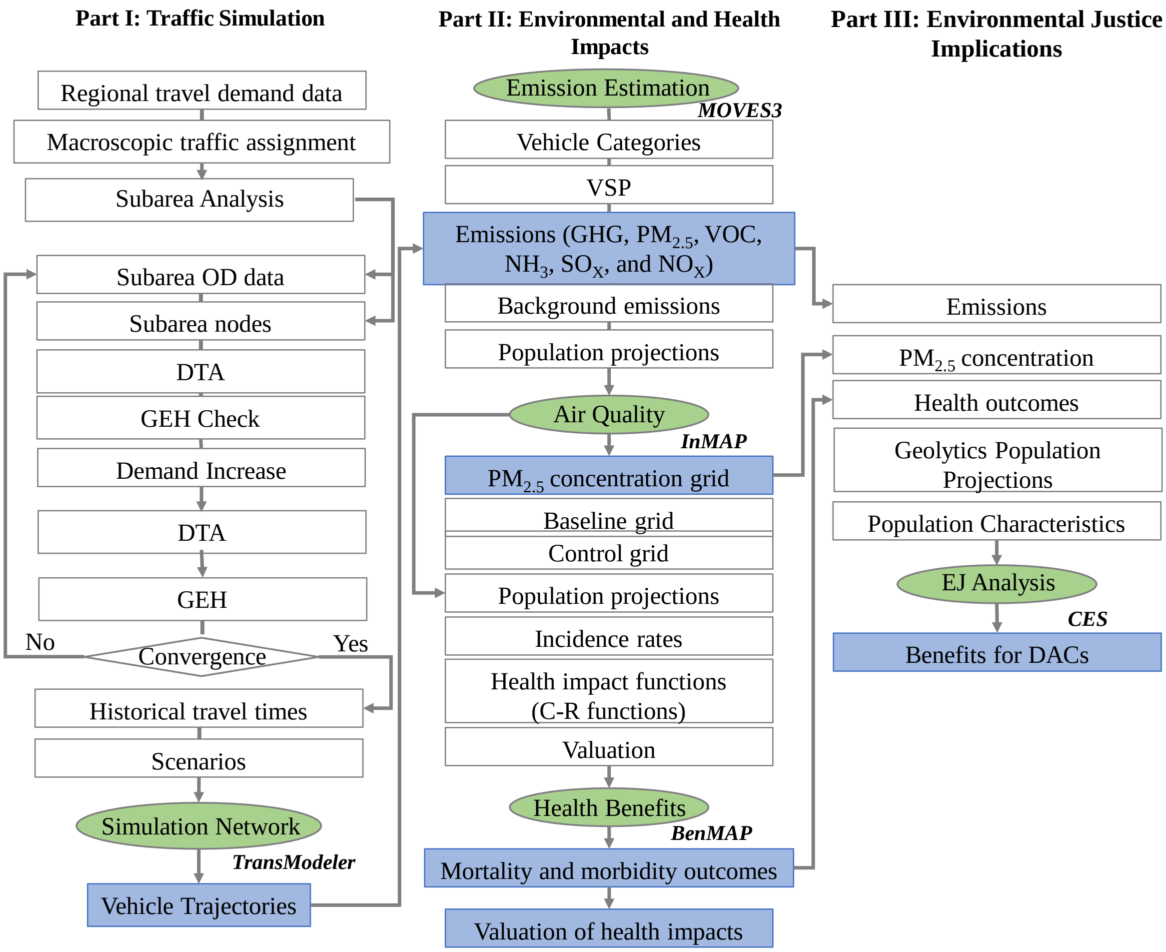


Figure 3.2 Methodology overview

3.3.1 Traffic Simulation

I first simulated traffic for 24 hours of a "typical" day in my study area to obtain estimates of vehicular emissions for my scenarios (see below). My study area (see Figure 3.1) includes parts of 13 freeways in the Southern California Association of Governments (SCAG) region. These 13 freeways were selected because they have the highest volume of container truck traffic based on sensor data from the Truck Activity Monitoring System (Tok et al., 2017) or because they provide alternative routes in case of congestion.

Using microscopic simulation allowed me to simulate individual vehicle trajectories. To the best of my knowledge, my network is one of the largest microsimulation networks in the literature. Its geographic coverage allows us to study the regional effects of the deployment of ZE HDDTs. To perform traffic simulations, I selected TransModeler, a powerful and versatile simulation software, because it can directly perform Dynamic Traffic Assignment (DTA), which allows for the calibration of realistic traffic flows. Moreover, TransModeler mapping and visualization tools make it easier to simulate and debug large, complex networks.

Freeway geometry and the location of healthy loop detectors come from Caltrans' Performance Measurement System (PeMS) data. I obtained the location of ramp meters from Caltrans' 2017 Ramp Metering Development Plan, which includes a list of all operational ramp meters in California, by County, with freeway name, number of lanes, postmile, and status. Geometry validation was performed with Google imagery. Ramp meters were programmed with global parameters. Since data about the operation of these ramp meters is unavailable, I assumed that they release one vehicle per green over a 4-second cycle (Z. Wang & Liu, 2014).

My travel demand data were extracted from SCAG's regional trip-based model and calibrated using PeMS data to approximate the flows of a representative, accident-free weekday. The calibration process entailed performing a subarea analysis to extract origin-destination pairs within my study area, conducting Dynamic Traffic Assignment (Peeta & Ziliaskopoulos, 2001), and calibrating the models that represent the behavior of conventional and electric trucks.

3.3.1.1 *Network and Demand Data*

Initial 2012 origin-destination (OD) data for 24 hours was obtained from SCAG. I performed a sub-area analysis using TransCAD to extract OD data for the freeways in my study area.

After defining a subarea cordon for the study area (Figure 3.3), I extracted subarea demand from the 2012 SCAG planning model. The outputs of my subarea analysis are matrices of 1,193 origins and destinations. These 1,193 centroids were coded into TransModeler. After excluding unnecessary centroids, I ended up with 1,151 centroids. I applied the Multi-Modal Multi-Class Assignment bi-conjugate user equilibrium method for the subarea assignment. I relied on SCAG's 2012 Model Validation Report to select a convergence criterion, which suggests 200 iterations or a relative gap of 0.001. I then repeated this process for each of the following time periods: AM Peak (6:00 – 9:00 am), Midday Off-peak (9:00 am – 3:00 pm), PM Peak (3:00 – 7:00 pm), Evening Off-peak (7:00 – 9:00 pm), and Night Off-peak (9:00 pm – 6:00 am). Figure 3.4 shows the assignment output of the AM peak period. The process was later repeated for each of the following time periods.

The outputs of subarea analysis, time-period (AM, MD, PM, EVE, and NT) OD matrices were then broken down into 15-minute intervals by applying the distribution of individual freeway directions as an initial guess for OD estimation. The 15-minute demand was later calibrated and validated using Dynamic Traffic Assignment and PeMS data for a representative day. Demand calibration and validation are explained in section 3.1.2.

In 2015, the SCAG region housed nearly 19 million people, which was forecast to grow to ~21 million residents by 2035 (Choi, 2015a). While this growth will likely exacerbate the region's infrastructure and mobility needs, it will mainly occur in the inland Counties of Riverside and San Bernardino. The region's population is also expected to age (the share of people 65 years and older will jump from 11 to 18 percent), increasing the need for more efficient travel modes, particularly for those who can no longer rely primarily on their private vehicles.

If SCAG's regional transportation plan (which includes investments in transit, high-speed rail, active transportation, and transportation demand management) is successful, my study area should see little to no increase in light-duty VMT. However, cargo demand in the region is forecast to increase by ~145% by 2035. Thus, I adjusted HHDT demand based on the same assumptions described in Chapter 1, more details in Section 2.3.2

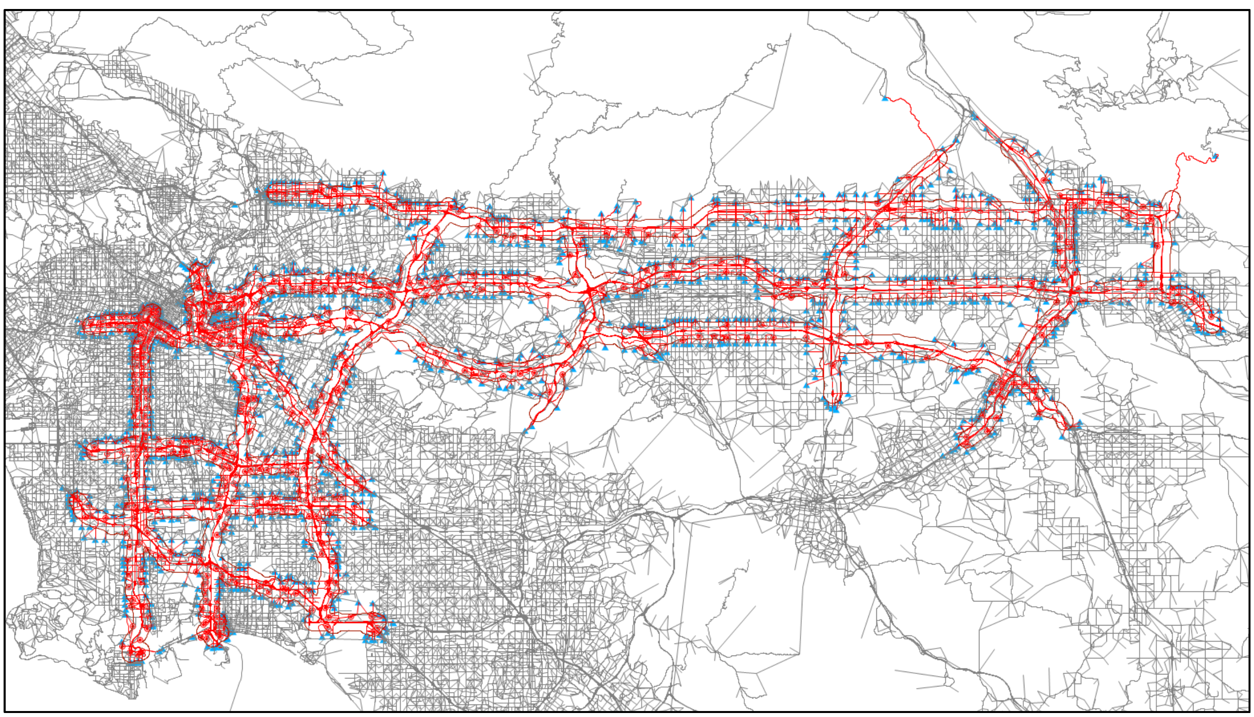


Figure 3.3 TransCAD subarea

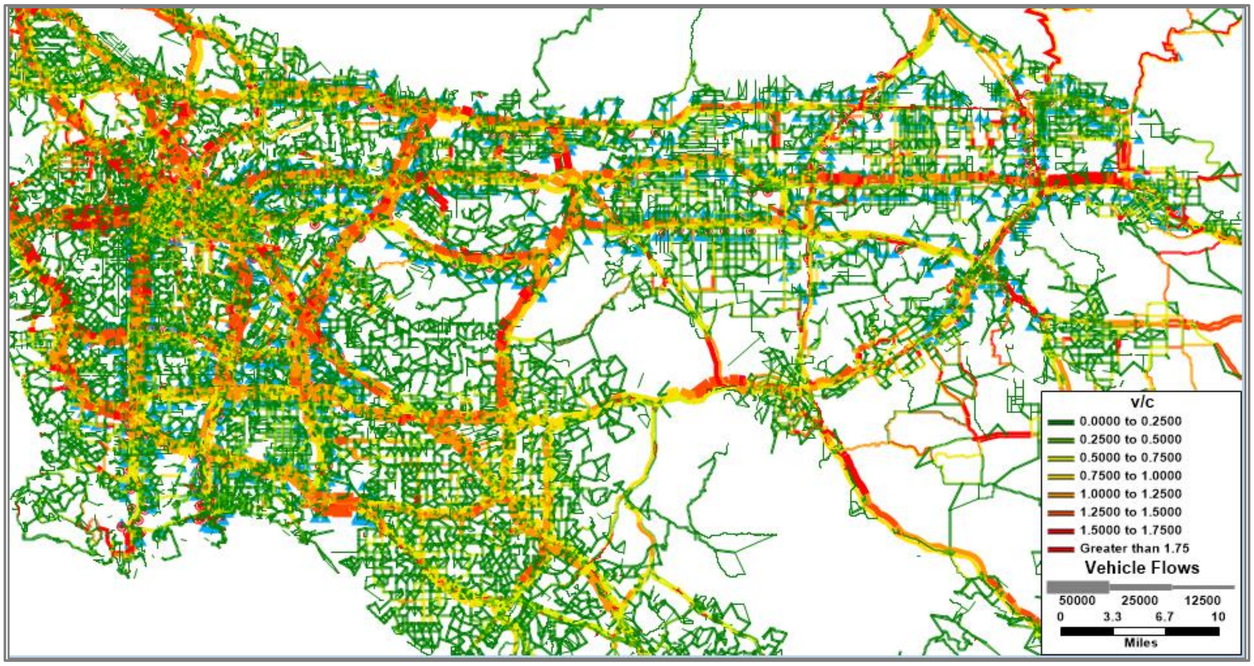


Figure 3.4 AM peak subarea analysis (MMMC assignment)

3.3.1.2 *Network, O-D Estimation, and Validation*

For calibration, I selected a representative accident-free day (July 19, 2012) selected based on data from the California Highway Patrol (CHP). PeMS performance measures such as speed and flow were extracted for the same day and then aggregated into 60-minute observations. For calibration and validation, I used the following 5-step process to compare 60-minute aggregate segment flows against Caltrans' Performance Measure System (PeMS) flows.

i. **Difference**: calculate observed minus simulation flows. Differences are used for calibrating all loading segments, i.e., segments connected to an inflow centroid.

ii. **Calibration**: calibrate the model based on the difference between observed and simulated flows for all loading segments with a PeMS ID within the segment (260 out of 1,189 PeMS Stations).

iii. **Capacity**: check 15-minute demand against the capacity of loading segments.

iv. **Convergence**: compare how close simulated flows are to observed flows (PeMS loop detector flows) using GEH statistics (E2.1).

v. **Performance**: As an additional measure, I compare 15-minute segment speeds from simulation to observations from PeMS healthy loop detectors.

$$GEH = \sqrt{\frac{2\times(Simulated-Observed)^2}{Simulated+Observed}} \qquad \text{(E2.1)}$$

3.3.1.2.1 Incremental Dynamic Traffic Assignment

After subarea analysis, the number of trips left within the study area was ~9 million for the 24 hours of simulation. To prevent the loading of 9 million vehicles on the shortest path and at free-flow speed that resulted in system crashes and excessive computational times, I used Incremental Dynamic Traffic Assignment (iDTA). This approach reduces the number of vehicles in the network at each time step. For this task, I used TransModeler 5.0, which executed simulation based DTA by running iterative simulations and applying the Method of Successive Averaging (MSA) to segment travel times and turning movement delay. Averaged travel times of the previous iteration are then used to find the Stochastic User Equilibrium (UE) solution by minimizing travel time. Figure 3.5 summarizes the steps TransModeler takes to complete DTA. The MSA formula can be written as:

$$x^{k+1} = x^k - \omega^k(f(x^k) - x^k),\ \ k = 1,2,3,4,\ldots \qquad (1)$$

where, x^k represents segment travel times or turning movement delay at iteration k (input), said travel times would generate an auxiliary solution (output), $f(x^k)$, as a function of x^k. The function, $f(\quad)$ represents the simulation model. Lastly, ω^k is the step size taken in the search direction $(f(x^k) - x^k)$. $\omega^k$is computed as:

$$\omega^k = \frac{1}{k+1} \tag{2}$$

DTA outputs (historical travel times and turning delays) serves as inputs for subsequent iDTA steps and simulation runs. Given the initial number of trips in my network (~9 million in 24 hours), I applied iD4TA using demand factors of 25%, 50%, 75%, and 100% of the demand.

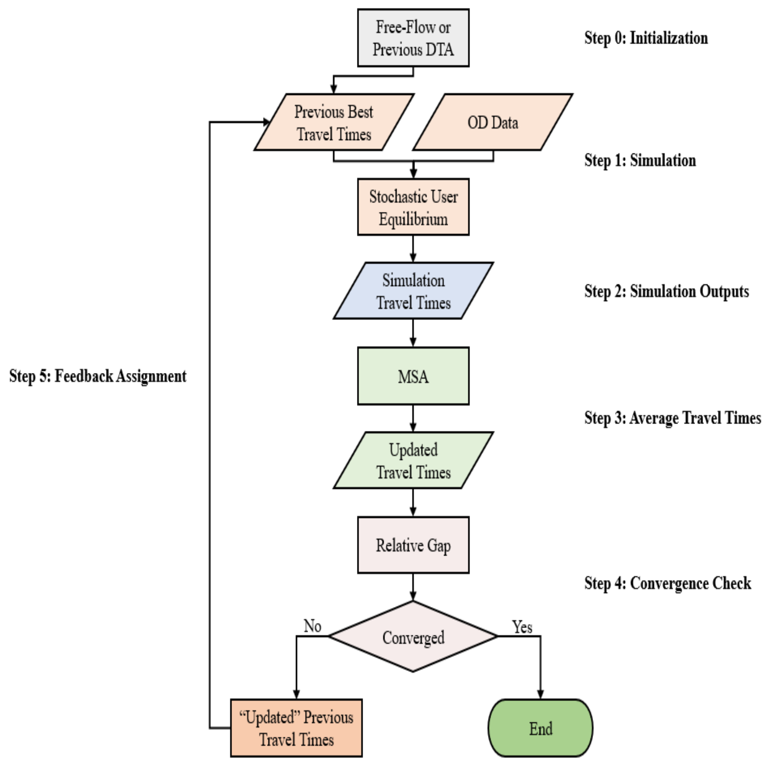


Figure 3.5 TransModeler DTA steps

3.3.1.3 *Analysis Framework*

To estimate the contribution of HDDTs to $PM_{2.5}$ concentrations in my study area in 2012 and 2035, I relied on vehicle distributions in EMFAC2021 and accounted for changes in demand and minor infrastructure improvements in 2035. I selected 2035 because it is a target date in Governor Newsom's Executive Order N-79-20 and several key studies in my study area (Caltrans and LA Metro, 2012; Choi, 2015; MERCATOR and Oxford Economics, 2016; SCAG, 2013; Southern California Association of Governments, 2012).

My 2035 freeway network differs from its 2012 version because I assumed that the ramp improvements shown in Figure 3.1 had been built. These improvements were approved in November 2018 by the LA Metro Ad Hoc Congestion, Highway, and Roads Committee (Scauzillo, 2018), and as shown in Chapter 2, they would substantially impact the year 2035 traffic on I-710.

To model the projected growth in SPBP container traffic by 2035, I relied on a report from MERCATOR and Oxford Economics (2016), a technical paper (Leue et al., 2019), and personal communications with SPBP experts. According to these sources, the container traffic at the SPBP is projected to reach 34.5 million 20-Foot Equivalent Units (TEUs) by 2035, up from 14.1 million TEUs in 2012. Containers move out of the SPBP in three different ways: 1) they are loaded directly on-dock (i.e., in rail yards located within the ports) to be moved by rail; 2) they leave the ports by truck to be transloaded at off-dock railyards in the region (i.e., to railyards outside the ports); or 3) they are moved out directly by truck. To quantify the changes of on-dock capacity, I used SCAG's forecast of 8.3 million TEUs in on-dock capacity by 2035. Applying the same assumption detailed in

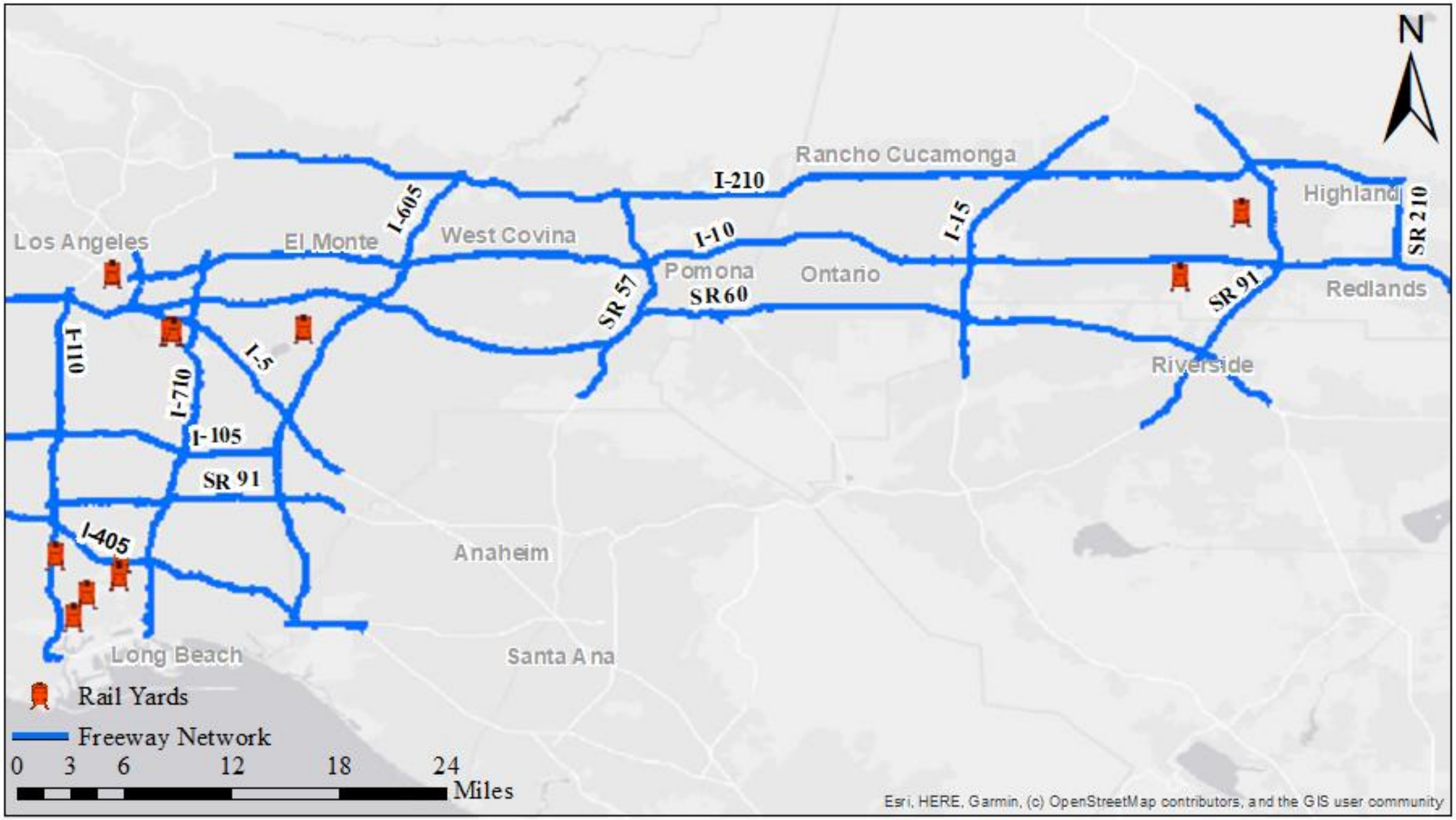


Figure 3.6 Railyards within the study area

Section 2.3.2, I adjusted the demand for all origins and destinations starting or ending at one of the railyards in the region (shown in Figure 3.6).

3.3.2 Environmental and Health Impacts

In Part II of my methodology, I first estimated emissions of CO_2, $PM_{2.5}$, and precursor pollutants to $PM_{2.5}$ using EPA's latest version of its Motor Vehicle Emission Simulator (MOVES3). I focused on $PM_{2.5}$ because, among common air pollutants, it has the greatest adverse health impacts (CARB, 2022b), which include additional cases of asthma, cardiovascular disease, and premature deaths (Kim et al., 2015). In addition, diesel $PM_{2.5}$ contains carcinogenic air toxins (CARB, 2022c). I used MOVES3 instead of EMFAC because only the former allows estimating vehicle emissions based on second-by-second speeds and accelerations generated by TransModeler. I then relied on the Benefits Mapping and Analysis Program - Community Edition (BenMAP-CE) to estimate the health impacts resulting from the contribution of HDDTs to $PM_{2.5}$ concentrations, which were generated using InMAP (Tessum, Hill, & Marshall, 2017).

3.3.2.1 *Emission Estimation*

Changes in CO_2, $PM_{2.5}$, and precursor pollutants to $PM_{2.5}$ (VOC, NO_x, SO_2, and NH_3, i.e., pollutants that can react in the atmosphere to generate additional $PM_{2.5}$) were estimated from second-by-second simulated vehicle trajectories using the vehicle operating mode (OpMode) approach, which relies on modal binning based on vehicle-specific power (*VSP*) or Scaled Tractive Power (*STP*) for heavy-duty vehicles, speed, and acceleration (Claggett, 2009) (see Table 3.1). Given my network's size and the duration of my simulations (24 hours), output trajectories represent approximately 180 GB of data per scenario, so it was impractical to use MOVES directly. *VSP* (in kW/ton) can be calculated from:

$$VSP = \frac{A \cdot v + B \cdot v^2 + C \cdot v^3 + a \cdot g \cdot v \ \cdot sin\theta}{m/m_{fixed}}, \quad (1)$$

where A, B, C, and m/m_{fixed} are parameters that correspond respectively to rolling resistance (kW s/m), rotational resistance (kW s^2/m^2), aerodynamic drag (kW s^3/m^3), and source/fixed mass (ton), which for heavy-duty vehicles this becomes a fixed parameter; v (m/s) is the vehicle's velocity, and a (m/s^2) its acceleration; g (=9.81 m/s^2) is the gravity constant; θ is the road grade. Their values are shown in Table 3.2. Emission rates for twenty-three operating modes (see Table 3.1) came from a project-level analysis, which is one of the three available domains on MOVES3 (US EPA, 2020) for my study area, baseline year (2012) and target year (2035).

For each fuel type in each MOVES vehicle class and for each of 2012 and 2035, I generated a lookup table made up of age-aggregated emission rates for MOVES' twenty-three operating modes (see Table 3.1) using a project-level analysis (US EPA, 2020). I then converted these emission rates to grams/second. To perform the age aggregation, I retrieved the distribution of model years by vehicle class for Los Angeles County in EMFAC2021 v1.0.2 for 2012 and 2035 and entered it in MOVES3. Age distributions by fuel type for HDDTs serving the SPBP in 2012 and 2035 are shown in Figure 3.7.

Table 3.1 Running exhaust operating modes attributes

OpMode ID	Description	VSP_t/STP_t (kW/ton)	Vehicle Speed (u_t, mph)	Median Speed (mph)
0	Idling	-	-	0
1	Low Speed Coasting	-	$-1 \le u_t < 1$	13
11	Cruise/Acceleration	$VSP_t < 0$	$1 \le u_t < 25$	13
12	Cruise/Acceleration	$0 \le VSP_t < 3$	$1 \le u_t < 25$	13
13	Cruise/Acceleration	$3 \le VSP_t < 6$	$1 \le u_t < 25$	13
14	Cruise/Acceleration	$6 \le VSP_t < 9$	$1 \le u_t < 25$	13
15	Cruise/Acceleration	$9 \le VSP_t < 12$	$1 \le u_t < 25$	13
16	Cruise/Acceleration	$12 \le VSP_t$	$1 \le u_t < 25$	13
21	Cruise/Acceleration	$VSP_t < 0$	$25 \le u_t < 50$	37.5
22	Cruise/Acceleration	$0 \le VSP_t < 3$	$25 \le u_t < 50$	37.5
23	Cruise/Acceleration	$3 \le VSP_t < 6$	$25 \le u_t < 50$	37.5
24	Cruise/Acceleration	$6 \le VSP_t < 9$	$25 \le u_t < 50$	37.5
25	Cruise/Acceleration	$9 \le VSP_t < 12$	$25 \le u_t < 50$	37.5
27	Cruise/Acceleration	$12 \le VSP_t < 18$	$25 \le u_t < 50$	37.5
28	Cruise/Acceleration	$18 \le VSP_t < 24$	$25 \le u_t < 50$	37.5
29	Cruise/Acceleration	$24 \le VSP_t < 30$	$25 \le u_t < 50$	37.5
30	Cruise/Acceleration	$30 \le VSP_t$	$25 \le u_t < 50$	37.5
33	Cruise/Acceleration	$VSP_t < 6$	$50 \le u_t$	60
35	Cruise/Acceleration	$6 \le VSP_t < 12$	$50 \le u_t$	60
37	Cruise/Acceleration	$12 \le VSP_t < 18$	$50 \le u_t$	60
38	Cruise/Acceleration	$18 \le VSP_t < 24$	$50 \le u_t$	60
39	Cruise/Acceleration	$24 \le VSP_t < 30$	$50 \le u_t$	60
40	Cruise/Acceleration	$30 \le VSP_t$	$50 \le u_t$	60

For idling (OpMode ID = 0), the acceleration a_t (in mph/s) is such that $a_t \le -2$ or ($a_t < -1$ and $a_{t-1} < -1$ and $a_{t-2} < -1$). Source: US EPA, (2020)

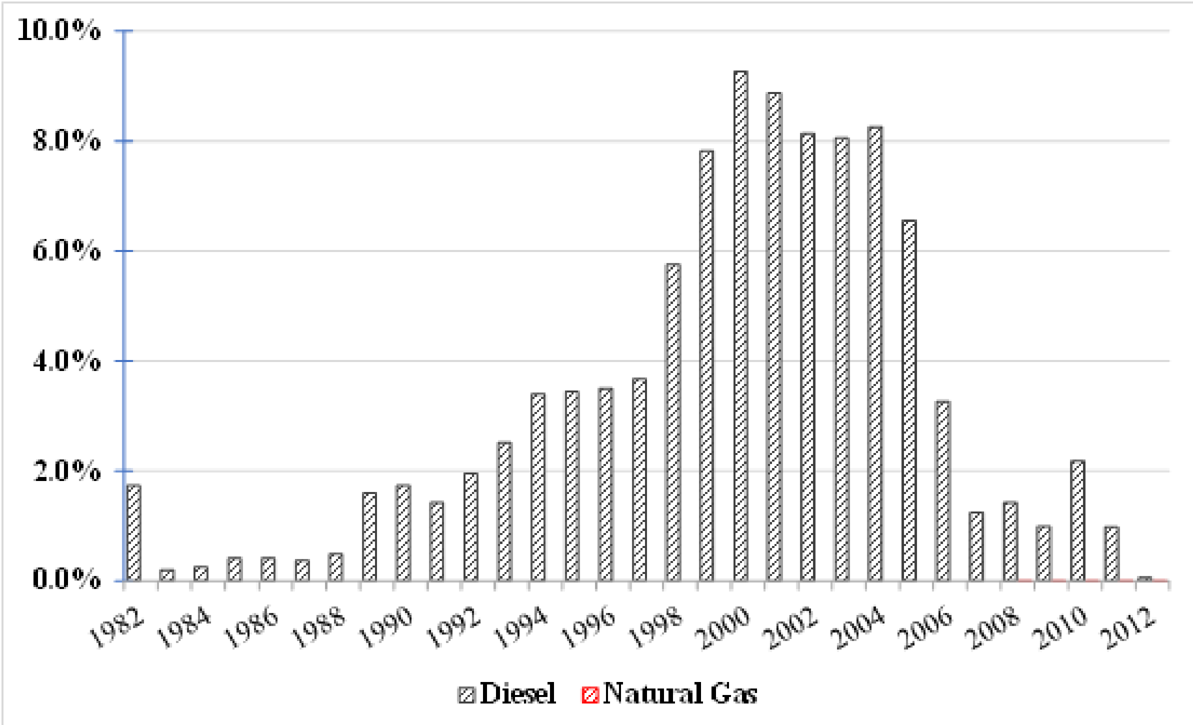
Table 3.2 Default parameters for VSP/STP estimation

ID	Vehicle type	Rolling term A (kW s/m)	Rotating term B (kW s²/m²)	Drag term C (kW s³/m³)	Source mass (tonnes)	Fixed mass (tonnes)
21	Passenger car	0.15646	0.002	0.00049	1.4788	1.4788
31	Passenger truck	0.22112	0.00284	0.0007	1.86686	1.86686
32	Light commercial truck	0.23501	0.00304	0.00075	2.05979	2.05979
51	Refuse truck	1.41705	0	0.00357	20.6845	17.1
52	Single unit short-haul truck	0.56193	0	0.0016	7.64159	17.1
53	Single unit long-haul truck	0.4987	0	0.00147	6.25047	17.1
54	Motor home	0.61737	0	0.00211	6.73483	17.1
61	Combination short-haul truck	1.96354	0	0.00403	29.3275	17.1
62	Combination long-haul truck	2.08126	0	0.00419	31.4038	17.1

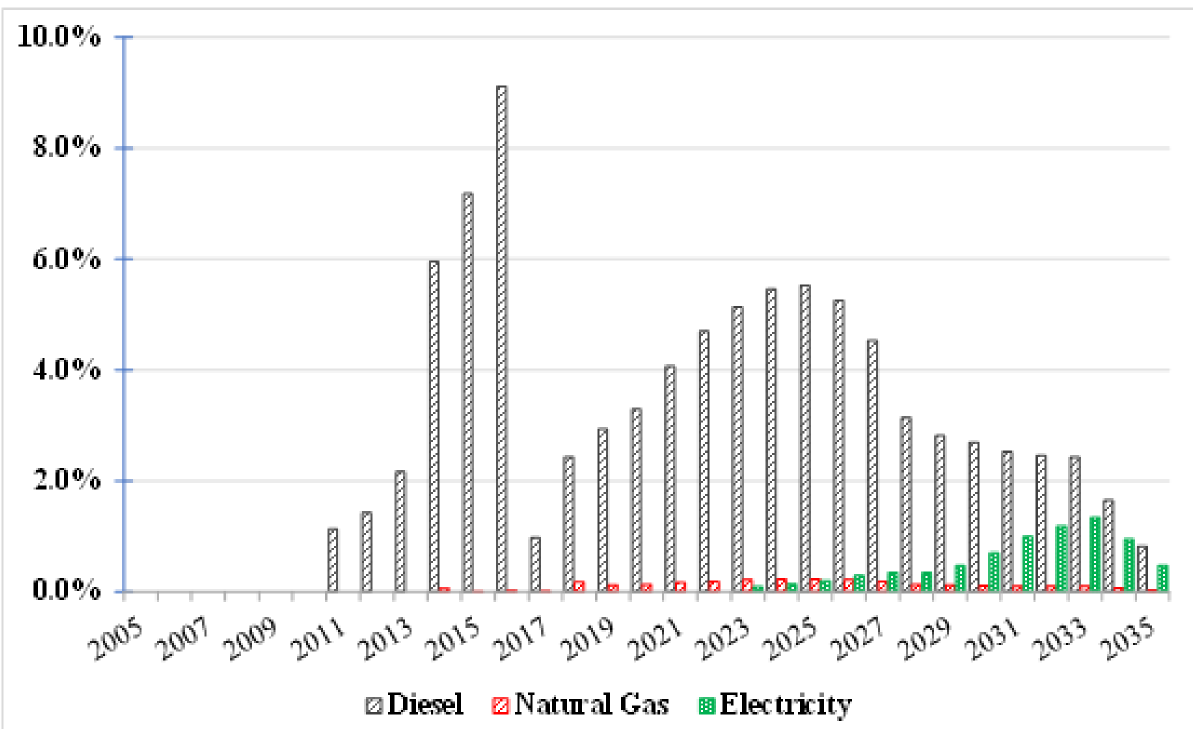
Source: US EPA (2020).

An analysis of the sensitivity of emission rates to temperature and humidity showed that neither significantly impacts emission rates for precursor pollutants in my study area, so I adopted emission rates generated with annual average temperature and humidity.

More stringent standards will shrink emissions of $PM_{2.5}$ and its precursor pollutants by 2035. After comparing 2012 and 2035 emission rates for all vehicle categories in my network, I found that aggregate emission rates are expected to drop by over 80% for $PM_{2.5}$ and approximately 30% for CO_2. Figure 3.8 shows the change in age-aggregated emission rates between 2012 (Panel A) and 2035 (Panel B) for HDDTs in my study area.



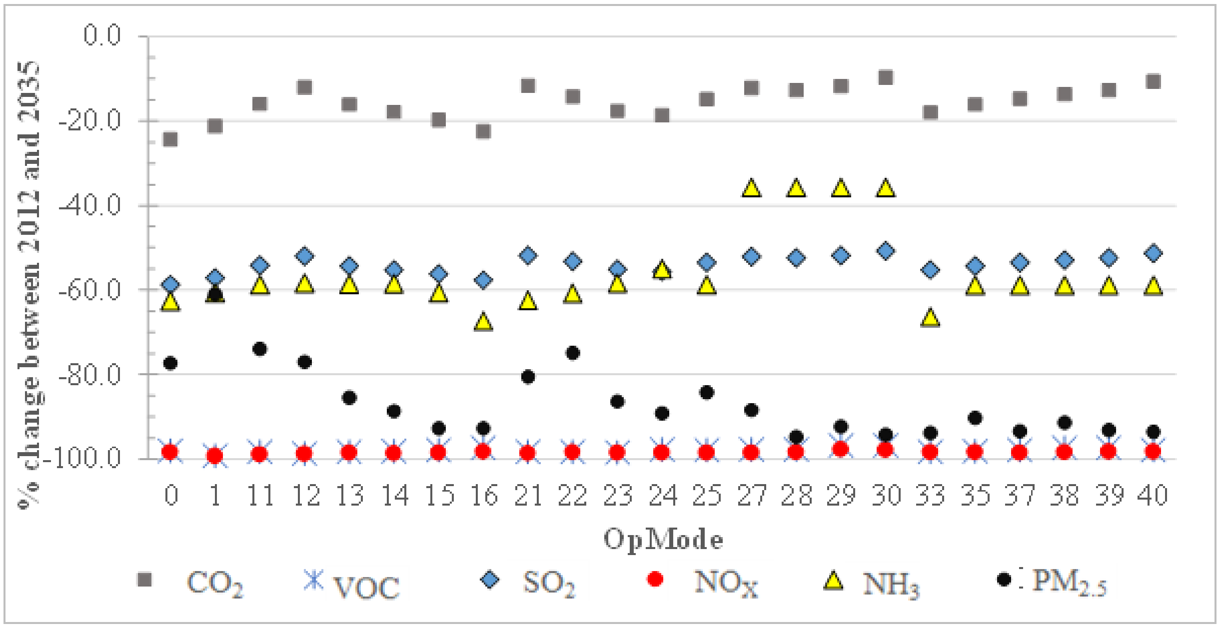
Panel A: 2012 age distribution



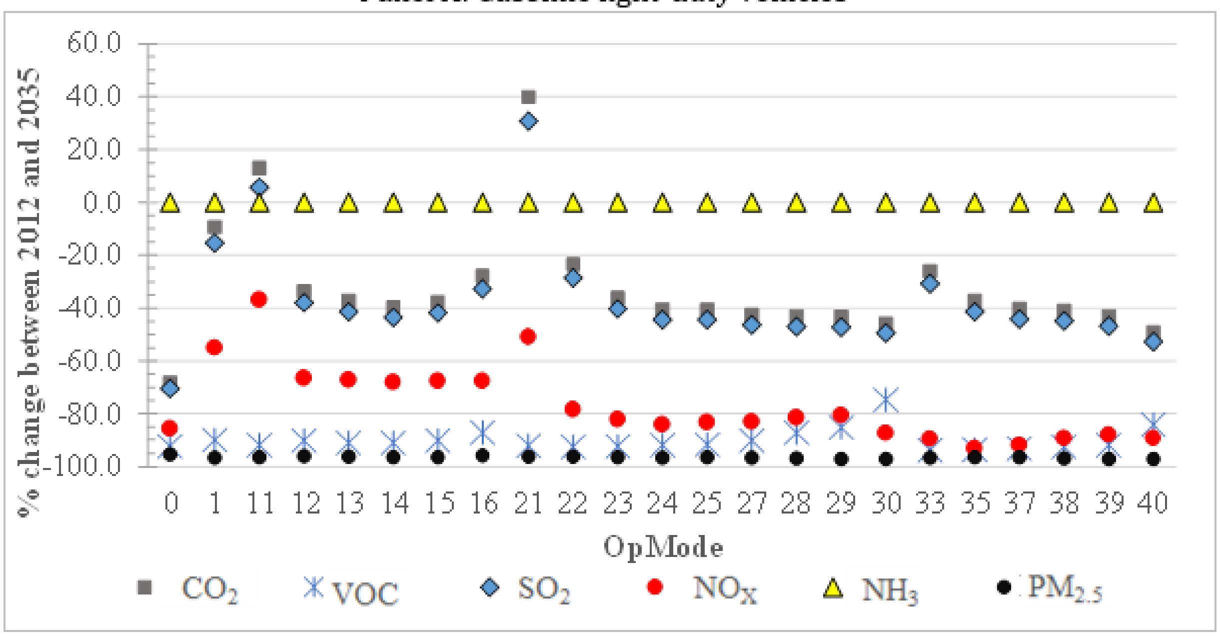
Panel B: 2035 age distribution

Figure 3.7 . Heavy-duty drayage trucks' age distribution

Data are for vehicle category T7 POLA Class 8 in EMFACv1.0.2. In Panel A, the year 1982 includes all previous years (back to 1968).



Panel A: Gasoline light-duty vehicles



Panel B: Heavy-duty diesel trucks

Figure 3.8 Percentage change in aggregated emission rates between 2012 and 2035

OpMode meaning: 0: idling; 1: low speed coasting; 11-16: cruise/acceleration under 25 mph for various VSP ranges; 21-30: cruise/acceleration between 25 and 50 mph for various VSP ranges, 33-40: cruise/acceleration above 50 mph for various VSP ranges.

Table 3.3 Fleet distribution (Source: EMFAC2021)

Vehicle Category (MOVES)	Class	Fuel Type	TransModeler Class	2012 fleet		2035 fleet	
				*	**	*	**
Passenger Car 21	LDA	Gas***	Light Duty Vehicles (LDV)	93.80%	59.39%	93.12%	43.10%
		Diesel			0.28%		0.04%
		Natural Gas			0.00%		0.00%
		Electricity			0.07%		4.94%
Passenger Truck 31	LDT1	Gas***			5.87%		4.06%
		Diesel			0.01%		0.00%
		Natural Gas			0.00%		0.00%
		Electricity			0.01%		0.07%
Light Commercial Truck 32	LDT2	Gas***			19.72%		27.39%
		Diesel			0.01%		0.10%
		Natural Gas			0.00%		0.00%
		Electricity			0.00%		0.79%
Refuse Trucks/Working Trucks 51	MDV	Gas***			14.52%		15.69%
		Diesel			0.06%		0.17%
		Natural Gas			0.00%		0.00%
		Electricity			0.00%		0.74%
Single Unit Short-Haul Truck 52	LHDT1	Gas***	Light Heavy-Duty Trucks (LDT)	1.28%	62.67%	1.27%	38.72%
		Diesel			19.30%		25.13%
		Natural Gas			0.00%		0.00%
		Electricity			0.00%		14.73%
Single Unit Long-Haul Truck 53	LHDT2	Gas***			10.41%		5.63%
		Diesel			7.63%		11.89%
		Natural Gas			0.00%		0.00%
		Electricity			0.00%		3.90%
Refuse Trucks 61	MHDT	Gas***	Medium Heavy-Duty Trucks (MDT)	1.08%	21.55%	1.06%	11.56%
		Diesel			78.23%		65.35%
		Natural Gas			0.22%		1.30%
		Electricity			0.00%		21.78%
Combination Unit Long-Haul Truck	HHDT	Gas***	Heavy Heavy-Duty Trucks (HDT)	3.12%	1.94%	3.09%	0.02%
		Diesel			94.53%		78.35%
		Natural Gas			3.53%		10.11%
		Electricity			0.00%		11.52%
Combination Unit Long-Haul Truck 62	T7 POLA Class 8	Gas***	Heavy-Duty Drayage Trucks (HDDT)	0.74%	0.00%	1.46%	0.00%
		Diesel			99.53%		89.79%
		Natural Gas			0.47%		2.71%
		Electricity			0.00%		7.50%

Notes. *: Fleet distribution from TransModeler's demand. **: Fuel type distribution from EMFAC2021 v1.0.2. ***: a small number of plug-in hybrid vehicles were lumped with gas vehicles due to a lack of emission rate data.

The 2035 projections reflect current regulations and standards, such as the Safer Affordable Fuel-Efficient (SAFE) vehicle standards for light and heavy-duty vehicles, which increase the stringency in CO_2 standards each year for model years 2021-2026. MOVES3 incorporates GHG Phase 1 and Phase 2 standards for heavy-duty vehicles. Moreover, NO_x and $PM_{2.5}$ emission rates reductions for model years 2014-26 and beyond come from lower vehicle weights, lower rolling resistance, and improved truck aerodynamics following Phase 1 and Phase 2 Heavy-duty Greenhouse Gas Regulations, as well as tougher NO_x emission standards.

I used MATLAB to process second-by-second trajectory data into emission estimates after mapping the five vehicle classes simulated (i.e., LDV, LDT, MDT, HDT, and HDDT) into the fifteen vehicle categories selected to represent light, medium, and heavy vehicle classes broken down by fuel type (see Table 3.3). I performed this process in two steps: first, I assigned a vehicle category to each vehicle ID in my network and created a file that lists all simulated vehicle IDs with their corresponding vehicle category. Second, I used that list to separate trajectories by vehicle category in 15-minute increments.

3.3.2.2 *Air Quality Changes*

To estimate air quality changes associated with the deployment of ZE HDDTs, I used the Intervention Model for Air Pollution (InMAP) (Tessum et al., 2017). InMAP is faster and simpler than chemical transport models such as WRF-Chem or CMAQ for estimating annual average primary and secondary $PM_{2.5}$ concentrations, keeping in mind that it was designed to estimate the impacts of marginal emission changes rather than total ambient $PM_{2.5}$ concentrations (Tessum et al., 2017). Compared to other reduced-complexity models such as COBRA, InMAP is more spatially detailed and uses a variable grid that dynamically updates between iterations based on pollutant concentrations and population density

(Tessum et al., 2017).

InMAP estimates annual average $PM_{2.5}$ concentrations in each grid cell from reduced-form equations that account for secondary $PM_{2.5}$. $PM_{2.5}$ concentrations can be estimated for various geographic resolutions (from 1x1 km to 48x48 km). For simplicity, I opted for a constant grid at the highest resolution available (1 km x1 km), resulting in a grid with 51,168 cells that cover the South Coast Air Basin.

My study area for air quality analysis covers the intersection of the South Coast Air Basin with Los Angeles, San Bernardino, Riverside, and Orange Counties, as shown in Figure 3.9. This area was selected based on the simulated freeways and adjacent subareas to include background emissions from sources that contribute to the formation of secondary $PM_{2.5}$. All other sources of natural and anthropogenic background emissions came from CARB (CEPAM 2019 SIP v1.01). Geographic locations can be specified as shapefiles that serve as inputs for annual average emissions as polygons, point, or line sources.

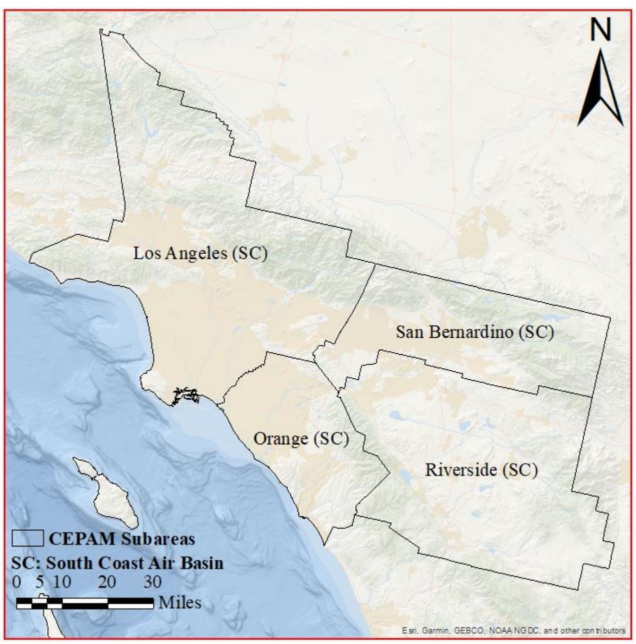


Figure 3.9 CEPAM subareas for background emissions

3.3.2.3 ***Health Benefits***

To estimate the mortality and morbidity associated with $PM_{2.5}$ emissions from SPBP HDDTs and their associated valuation, I relied on the EPA's Environmental Benefits Mapping and Analysis Program (BenMAP) (US EPA, 2022) because it is widely used for health impact analysis thanks to its versatility for handling user-specified grids and health impact functions. My user-defined inputs consisted of two 1x1 km grids of 51,168 cells each (one for all vehicles and the other for all vehicles without SPBP HDDTs), plus a grid with age-stratified population projections.

BenMAP can estimate health outcomes caused by changes in the concentration of an air pollutant using age-stratified population data and concentration-response (C-R) functions. Whenever possible, I used California C-R functions (see Table 3.4).

Given the small diameter of $PM_{2.5}$ ($\leq$2.5 micrometers), it has the potential to penetrate deep into the lungs and from there into the bloodstream, causing various respiratory and cardiovascular diseases, resulting in hospital admissions or even premature death. People at greater risk from PM exposure include older adults with chronic lung and heart conditions, asthmatics, children, and infants as they inhale more air per pound of body weight than adults (CARB, 2022c; Slaughter et al., 2005).

Since BenMAP needs incidence rates to estimate health outcomes, I used California-specific rates from BenMAP's default U.S. dataset. For valuing mortality and various morbidity endpoints (e.g., asthma hospitalization), I relied on BenMAP data. To calculate the Value of a Statistical Life (VSL) in 2012 and 2035, I used the equation (US DOT, 2021):

$$VSL_{\text{x}} = VSL_{1990} * \frac{CPIU_{\text{x}}}{CPIU_{1990}} * \frac{RI_{\text{x}}}{RI_{1990}}, \tag{1}$$

where VSL_{x} is the U.S. VSL value for year *x*, $CPIU_{\text{x}}$ is the U.S. Consumer Price Index for all urban consumers for year *x*, and RI_{x} is the real income for year *x* (measured using median usual weekly earnings), with VSL_{1990}=\$4.8 million (1990\$) (US EPA, 2022), $CPIU_{1990}$=130.7, and $CPIU_{2022}$=296.3. As a result, VSL_{2012}=\$11.43 million and VSL_{2035}=\$12.03 million, both in \$2022. Valuation estimates for the other health endpoints I considered were converted to \$2022 using the same approach.

Table 3.4 Selected concentration-response functions

Health endpoint	Health impact function reference	$PM_{2.5}$ range (μg/m^3)	Location	Age range (years)
Mortality				
All causes	Krewski et al., (2009)		Los Angeles, CA	30-99
Hospital Admissions				
All cardiovascular	Moolgavkar (2000)	4 - 86	Los Angeles, CA	18-64
All cardiovascular	Zanobetti et al., (2009)	6.1 - 24	26 U.S. Communities	65-99
Asthma	Babin et al., (2007)	Not reported	Washington D.C.	0-17
Asthma – ER visits	Slaughter et al., (2005)	5 - 60	Seattle, WA	0-99
Chronic lung disease (excl. asthma)	Moolgavkar, (2000)	4 - 86	Los Angeles, CA	18-64
All respiratory	Zanobetti et al., (2009)	6.1 - 24	26 US Communities	65-99
Asthma				
Exacerbation, Asthma Attacks	Ostro et al., (2001)		Los Angeles, CA	6-18

3.3.2.4 *Climate Impacts*

To estimate the global climate impacts of SPBP HDDTs, I multiplied their calculated annual CO_2 emissions by the social cost of CO_2, i.e., an estimate of the present value of damages from emitting an additional metric ton of CO_2. Since the social cost of carbon depends on how future damages are discounted, how the climate will change, and how this will affect future economic outcomes, its value is highly uncertain.

Following the report of the Interagency Working Group on the Social Cost of Greenhouse Gases (2016), I adopted a range of [$33,$53] for the 2012 social cost of CO_2 ($2007), which corresponds to [$47.15,$75.73] in $2022 based on historical inflation rates. Similarly, following the recommendations of the report of Interagency Working Group on Social Cost of Greenhouse gases (2021), I adopted a range of [$67, $96] for the 2035 social cost of CO_2 ($2020), which corresponds to [$75.55, $108.25] in $2022 assuming inflation rates of 4.7% and 7.7% for 2021 and 2022 respectively (IMF, 2022). This range corresponds to the average cost of CO_2 for discount rates of 3% and 2.5%, respectively.

3.3.3 Population Changes Between 2012 and 2035

To estimate 2012 population characteristics, I relied on 2012 age-stratified estimates from the American Community Survey (ACS) at the census tract level (US Census, 2012). Similarly, for 2035 I relied on age-stratified population projections at the census tract level from Geolytics (Geolytics, n.d.). Population projections by age group at the census tract level were adjusted to ensure county totals match official projections (Department of Finance, 2017).

Panel A. 2012

Panel B. 2035

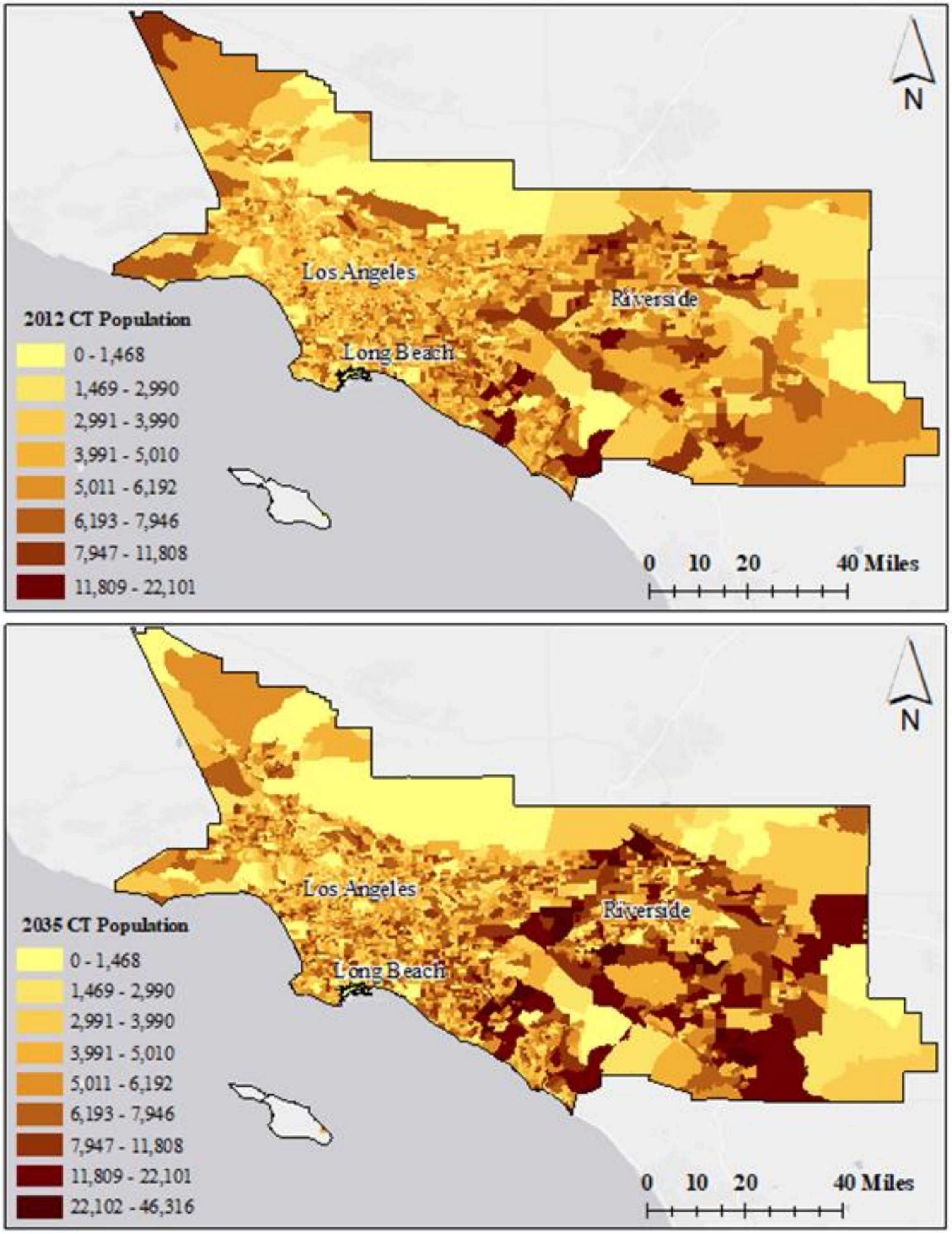


Figure 3.10 2012 and 2035 population

Figure 3.10 shows census tract population data in 2012 and 2035 for all census tracts within the South Coast Air Basin (SCAB). Overall, the SCAB population is expected to increase by 2.0 million between 2012 and 2035 (from 15.8 to 17.8 million). Of importance for my health calculations, the number of children under 17 years is projected to decrease slightly, while the number of people over 65 (who are particularly vulnerable to $PM_{2.5}$ exposure) is projected to increase by 1.9 million.

3.3.4 Environmental Justice (EJ) Implications

To explore the EJ impacts of HDDT operations in my study area, I relied on CalEnviroScreen 4.0, which in mid-2022 was the latest version of the screening tool created by CalEPA to identify communities disproportionately burdened by multiple sources of pollution (OEHHA, 2021).

Although environmental quality in California has improved over the last few decades, many communities (often referred to disadvantaged) continue to bear a disproportionate share of pollution from multiple sources. To identify these communities, CalEPA's methodology multiplies two census tract indexes, each between 0 and 10, to obtain an overall 0-100 score: the first index reflects the pollution burden from many sources, and the second index captures population characteristics that make a community more sensitive to pollution (OEHHA, 2021).

The pollution burden index has two components: an exposure indicator and an environmental effects indicator. To capture potential human exposure, CalEnviroScreen uses eight factors relating to pollution sources, releases, and environmental concentrations (two of which are directly related to transportation: diesel PM emissions and traffic density in vehicle-km per hour per road length). The environmental effects indicator, which is based on five factors, reflect adverse environmental conditions caused by pollutants (e.g., toxic cleanup sites).

The population characteristics index serves as a modifier to the pollution burden index. It combines a sensitive populations indicator and a socioeconomic factors indicator. The former reflects that some groups have physiological conditions (e.g., genetic factors) that increase their vulnerability to pollution; it is based on three factors. The socioeconomic factors indicator, built from five factors, reflects community characteristics that heighten vulnerability to pollutants.

Each factor in a census tract is assigned a percentile based on its statewide rank order, and percentiles are averaged over the factors that make up each component. The pollution burden score is calculated by weighting twice as much the average of the exposure factors as the environmental effects average, finding the corresponding percentile, and scaling it between 0 and 10. The population characteristics score is obtained similarly, with equal weights for the sensitive population and the socioeconomic factors averages. A California census tract is then classified as a disadvantaged community (DAC) by CalEPA if its CalEnviroScreen score is in the upper quartile. Figure 3.11 shows census tracts designated as DACs in my study area.

One challenge when conducting an environmental justice analysis in the future is the lack of official projections for the location of disadvantaged communities because of the comprehensive nature and the geographic coverage (statewide) of the data required to calculate CalEnviroScreen scores. For simplicity and given my relatively short time horizon, I assumed that the DACs identified by CalEnviroScreen 4.0 would change little by 2035.To

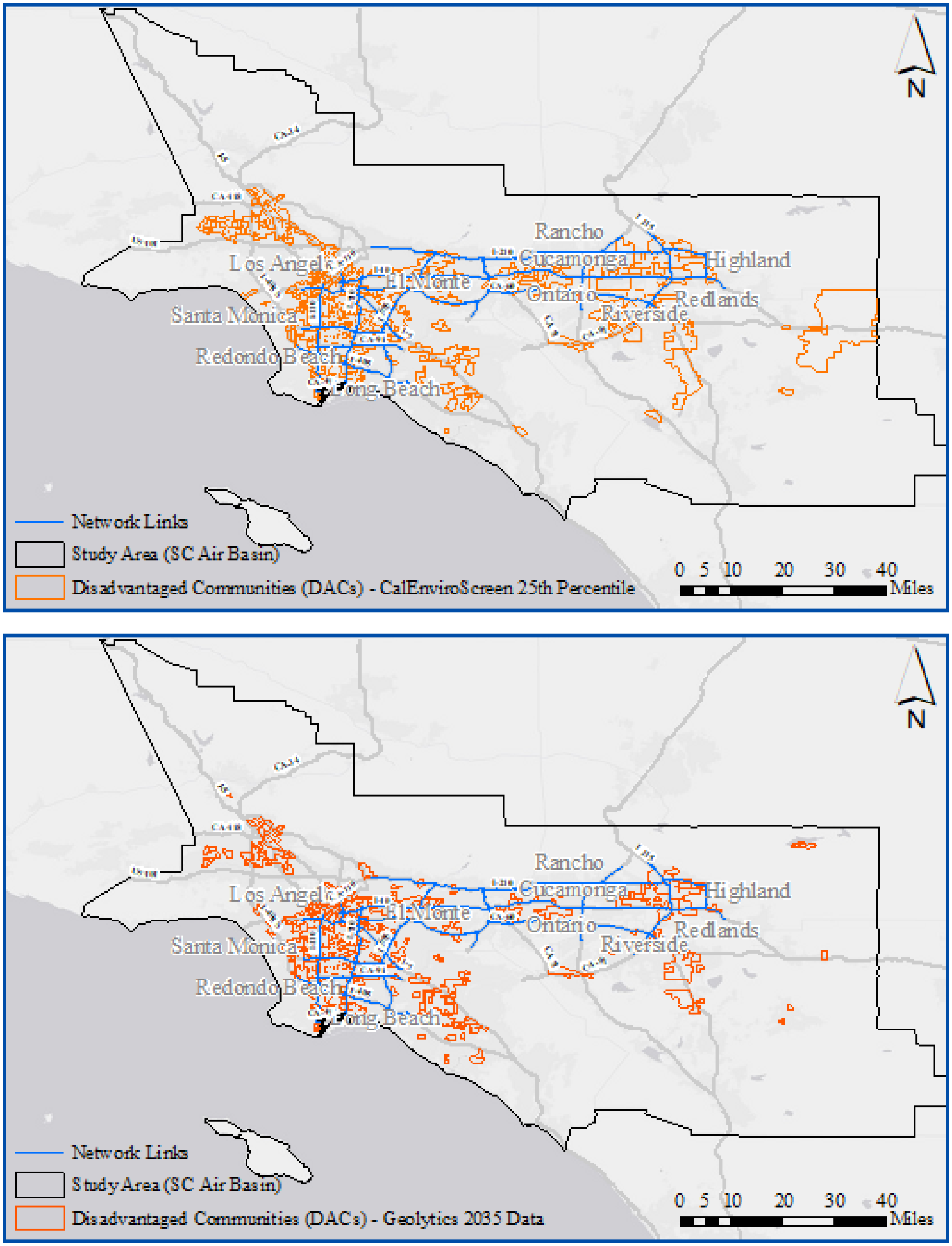


Figure 3.11 CalEnviroScreen and Geolytics DAC designation

complement the environmental justice analysis, I estimated a new 2035 DAC designation based only on the 2035 population and income projections from Geolytics (Geolytics, n.d.). First, I ranked all census tracts in California based on their share of minority population, identified as the non-white population. Then, I created a second rank for all census tracts in California based on the share of households below the 2035 median income for Los Angeles County, $75,000. Then, I estimated the percentile of both rankings and adjusted it to have two 0-10 scores for both the minority and household income indicators. Lastly, both scores were multiplied by each other to get a final DAC 0-100 score and ranked. Figure 3.11 shows the top quartile of the DAC designation in 2035; compared to the CalEnviroScreen DAC designation, I can see that there is little variation in 2035 despite the omitted indicators.

3.4 Results

3.4.1 iDTA Results

Initially, I loaded an empty network using 15-minute demand for each vehicle class (LDV, HOV, LDT, MDT, HDT, and Port HDT). I started using a demand factor of 25%, a convergence gap of 3%, and 100 maximum iterations. I used historical travel times and turning delays from the converged 25%, 50%, and 75% demand factor DTA as input to start the next step of iDTA. Figure 3.12 shows iDTA convergence under the different demand factors.

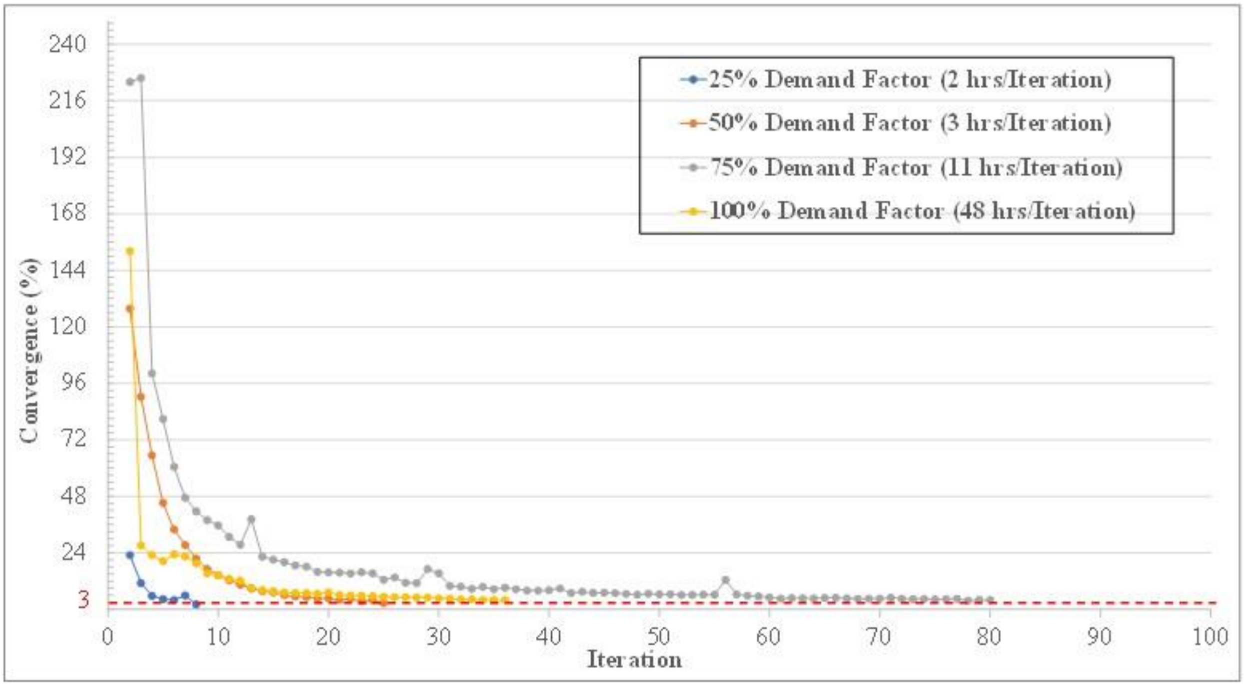


Figure 3.12 iDTA Convergence and computational time per iteration

3.4.2 DTA2 Results

After iDTA, I ran a 24-hour simulation using historical travel times from the 100% demand factor iDTA. The first simulation resulted in ~20% of the vehicles queuing outside the network by 18:00. This prevented demand from the last six hours of the day from loading into the network. Thus, as an initial adjustment, I remove all vehicles queued outside of the network before calibration as this would provide a more accurate representation of the difference between observed and simulated flows. The total number of vehicles after this process was ~7.3 million vehicles. I then started the second round of Dynamic Traffic Assignment at 100% demand factor using the same convergence criteria as in iDTA.

The calibration process consisted of fifteen iterations: one using historical travel times from DTA2, one with calibrated demand for the first 18 hours of the day, a second and third calibration iteration for hours 12-18, and a fifth one to calibrate hours 12-24 of the day. Ten additional iterations consisted of 24-hour calibration of loading segments and a final iteration to remove remaining vehicles queued outside the network (~1.5%) during individual 15-minute periods. This process could have been extended to more iterations to improve GEH convergence. However, given the size of the network and the computational times of an iteration run (~16 hours), it was not essential to continue the process with extremely time-consuming iterations. After calibration, approximately 65% of the 1,189 stations in my network had GEH values under 10, which can be considered a good match due to the size of the network and the number of observations (114,144). However, the convergence of loading segments significantly improved after calibration to ~75% of the loading segment observations having a GEH value under 5, and ~86% of the loading segment observations having a GEH value under 10. After this process, there were ~6.5 million vehicles in my simulation model.

After cleaning up the data from healthy loop detectors to exclude detectors with missing records, the variation in speed errors resulting from the remaining 716 stations (68,736 observations) was found to be+/-3 mph or less for ~80% of the 68,736 observations, and +/- 5 mph or less for ~90% of the observations, which gave me additional confidence in my results.

3.4.3 Emissions

Table 3.5 presents emissions of CO_2, $PM_{2.5}$, and NO_x (as a precursor to $PM_{2.5}$). Comparing 2035 to 2012, I observe emission drops of 94.6% for $PM_{2.5}$ and 90.6% for NO_x, which results from more stringent emission standards and the appearance of ZE vehicles. CO_2 emissions also decrease, but only by 33.1%. The drop in $PM_{2.5}$ and NO_x emissions is slightly lower for SPBP HDDTs (92.1% for $PM_{2.5}$ and 76.5% for NO_x), because of the projected 145% cargo growth in 2035 compared to 2012, which drives up CO_2 emissions of SPBP HDDTs by 16.3%. The share of CO_2, $PM_{2.5}$, and NO_x emissions from SPBP HDDTs as a percentage of all vehicles in my study area increases respectively from 6.9%, 16.9%, and 13.8% to 11.9%, 24.5%, and 34.3%.

Estimated emissions from simulation trajectories represent average daily emissions for a typical weekday. To estimate the annual average on-road emission, I used the California Air Resource Board mobile emission projections (CEPAM 2019 SIP v1.02) as a baseline for on-road projections. Thus, emission outputs from my simulation were used to 1) adjust daily emissions to annual weekday emissions in tons/year (=Daily emissions ×Annual number of weekdays); and 2) replace annual weekday emissions from CEPAM mobile background emissions. I assumed that the remaining mobile emissions from CARB's inventory include vehicle classes excluded from my model (i.e., motorcycles, buses), arterial road traffic, and weekend traffic.

Table 3.5Daily CO2, PM2.5, and precursor emission results

	CO_2 (tonnes)	**$PM_{2.5}$ (tonnes)**	**NO_x (tonnes)**
Yr2012 all vehicles	127,197	24.747	696.550
Yr2012 all vehicles except SPBP HDDTs	118,467	20.566	600.514
Yr2012 SPBP HDDTs only	8,730	4.181	96.036
Yr2035 all vehicles	85,063	1.345	65.666
Yr2035 all vehicles except SPBP HDDTs	74,908	1.015	43.110
Yr2035 SPBP HDDTs only	10,155	0.33	22.556
Percentage changes			
(Yr2035-Yr2012)/Yr2012 (all vehicles)	-33.1%	-94.6%	-90.6%
(Yr2035-Yr2012)/Yr2012 (SPBP HDDTs)	16.3%	-92.1%	-76.5%
Yr2012 HDDTs as a % of Yr2012 total	6.9%	16.9%	13.8%
Yr2035 HDDTs as a % of Yr2035 total	11.9%	24.6%	34.4%

Note: percentage changes are calculated as (target-baseline)/baseline.

A check of ,my calculated emission rates against published values by the EPA for specific model years of heavy-heavy-duty trucks (EPA, 2020) suggests that while there are some variations between my results and the examples presented in the MOVES3 technical documentation, my emission rates are within the range presented in the Exhaust Emission Rates for Heavy-Duty On-road Vehicles technical report.

3.4.4 Changes in $PM_{2.5}$ Concentrations

Figure 3.13 displays ground-level $PM_{2.5}$ concentrations in μg/m^3 due to HDDTs. Differences in $PM_{2.5}$ concentrations for 2012 (Panel A) range from 0 to 7.24 μg/m^3, with a mean value of 0.145 μg/m^3. $PM_{2.5}$ concentrations within the DACs in my study area are similar, although the mean difference for these census tracts increases to 0.257 μg/m^3.

Concentrations of $PM_{2.5}$ due to SPBP HDDTs in 2035 (Panel B) show larger values near the SPBP, with overall $PM_{2.5}$ concentrations ranging from 0 to 1.37 μg/m^3, and a mean of 0.024 μg/m^3. DACs $PM_{2.5}$ concentrations are similar, although their mean increases to 0.042 μg/m^3.

Panel A. 2012

Panel B. 2035

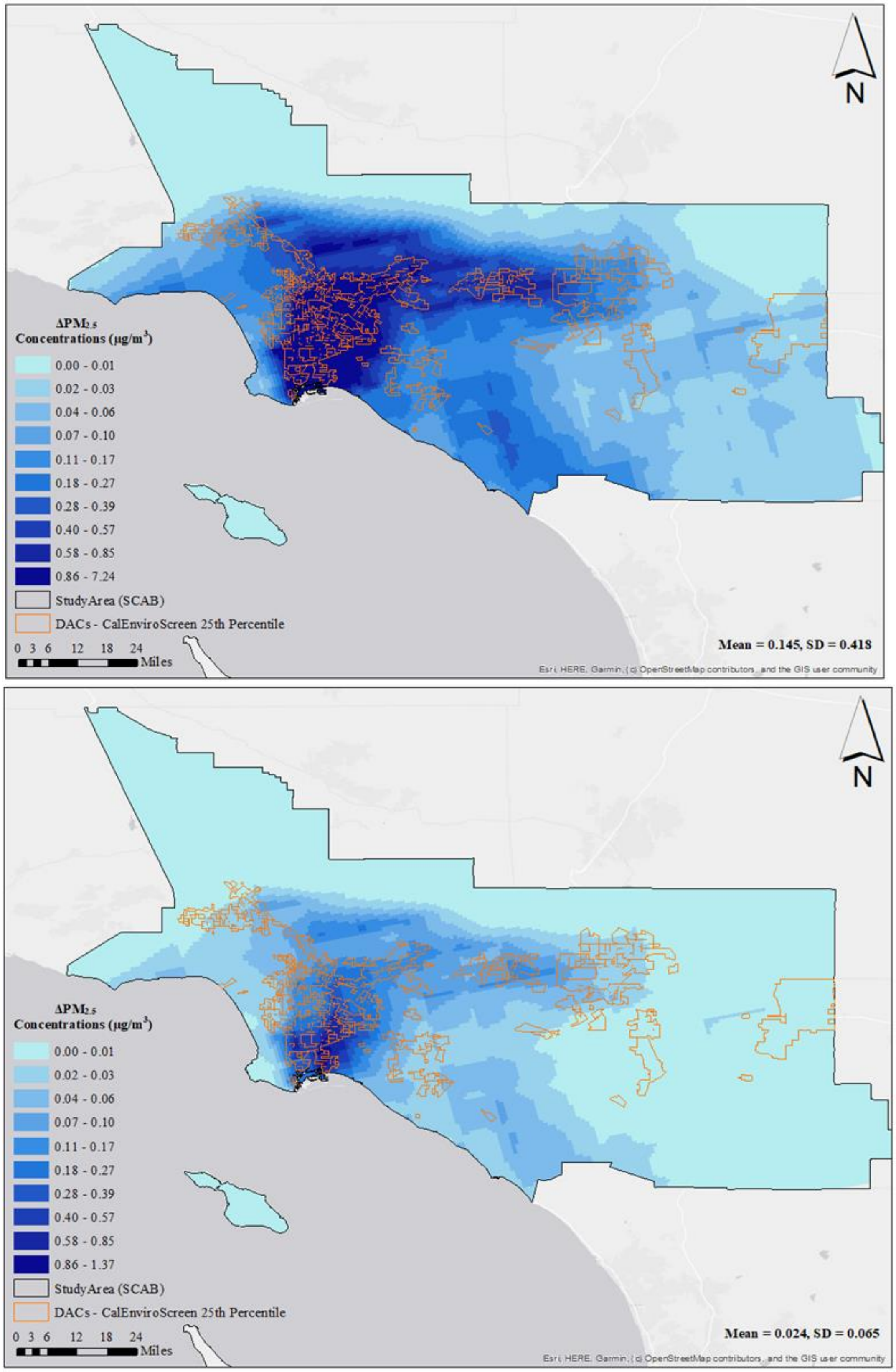


Figure 3.13 Annual average contribution of HDDT freeway traffic to PM2.5 concentration

3.4.5 Health Benefits

Table 3.6. shows estimates of selected annual health benefits from eliminating $PM_{2.5}$ emissions from HDDTs in 2012 and 2035.

Table 3.6 Study area and DAC health benefits for 2012 and 2035

Health Endpoint	Incidence		Valuation ($2022 million)	
	2012	2035	2012	2035
Study area				
Mortality	483	106	$5,588.31	$ 1,308.00
Hospital Admissions, Respiratory♦	128	37	$5.02	$1.67
Hospital Admissions, Cardiovascular♣	139	38	$7.14	$2.15
Emergency Room Visits, Respiratory♠	140	23	$0.09	$0.02
Asthma Exacerbation●	15,468	2,142	$1.21	$0.18
DACs (CalEnviroScreen 4.0)				
Mortality	343	72	$3,968.50	$888.50
Hospital Admissions, Respiratory♦	93	25	$3.60	$1.14
Hospital Admissions, Cardiovascular♣	101	26	$5.20	$1.49
Emergency Room Visits, Respiratory♠	111	17	$0.07	$0.01
Asthma Exacerbation●	12,544	1,671	$0.98	$0.14

♦: Hospital admissions for respiratory causes include asthma, chronic lung disease, and all other respiratory conditions for ages 0-to 99 (Babin et al., 2007; Moolgavkar, 2000; Zanobetti, Franklin, Koutrakis, & Schwartz, 2009).

♣: Hospital admissions for cardiovascular causes include all cardiovascular incidences from ages 18-to 99 (Moolgavkar, 2000; Zanobetti et al., 2009).

♠: Asthma-related emergency room visits are for ages 0-99 (Slaughter et al., 2005)

●: Asthma Exacerbation attacks are for ages 6-18 (Ostro et al., 2001)

As expected, avoided premature mortality dominates health benefits with 483 cases in 2012, which are valued at over $5.59 billion (2022$). Hospital admissions for cardiovascular and respiratory reasons stemming from air pollution are far below mortality in terms of cases and value. While asthma exacerbation has comparatively a low dollar value, it affects many more Southern California residents (15,468 per year).

For DACs, the 2012 health costs of HDDTs operating on freeways in my study area exceed \$3.97 billion, which is 71% of calculated health costs. DACs also incurred over 81% of avoided annual asthma exacerbation cases among 6–18 year olds, which highlights that DACs incurred a disproportionate share of the air pollution burden from drayage operations.

In 2035, despite technological advances that substantially cleaned up HDDTs, the projected number of avoided premature mortality cases is still substantial (106 versus 483) partly because of the population increase in my study area but mostly because of the sharp increase in drayage operations in 2035 compared to 2012. These 106 cases, which is ~7.5% of the number of avoided premature mortality cases from decarbonizing California's transportation sector reported in Brown et al. (2021), are valued at over \$1.31 billion. I note, however, that my analysis excludes arterial traffic and focuses on SPBP drayage trucks, which represent only 21% of HDTs in my study area. Moreover, Brown et al. (2021) made different assumptions about the penetration of ZE vehicles (e.g., ~20% to 25% of HDTs), used a much coarser approach for modeling traffic emissions, and did not consider all known regulations that could decrease transportation emissions by 2035. Asthma exacerbation again affects many more Southern California residents (2,142 in 2035.)

Strikingly, DACs are still projected to be disproportionately affected by HDDT $PM_{2.5}$ emissions in 2035 because the \$888.5 million (2022\$) in health costs from HDDT $PM_{2.5}$ emissions in 2035 represents ~68% of total health benefits. Moreover, DACs are projected to bear 78% (1,671/2,142) of annual asthma exacerbation cases among 6-18 year-olds.

3.4.6 GHG Emissions

Daily CO_2 emissions from SPBP HDDTs in 2012 in my study area is 8,730 tonnes. Assuming drayage trucks operate 5.5 days a week on average (287 days per year), daily CO_2 savings translate into 2,505,510 tonnes of CO_2 for 2012. The (rounded) value of these emissions for my [$47.15, $75.73] range for the 2012 social cost of carbon is [$118 million, $190 million].

Similarly, with my assumptions, SPBP HDDTs would emit 10,155 tonnes of CO_2 in 2035 in my study area. With the same operating assumptions as in 2012, this would correspond to 2,914,485 tonnes of CO_2 for the year. The value of these emissions for my [$75.55, $108.25] range for the 2035 social cost of carbon is [$220 million, $316 million] in $2022.

3.5 Discussion

My results show that the health and environmental benefits from replacing non-ZE HDDTs serving the SPBP with ZE HDDTs exceed $1.5 billion ($1.31 billion for health and at least $220 million from avoided GHG emissions) in 2035 in my study area alone, and only from freeway operations. How do the costs compare? In this section, all calculations are in $2022.

As can be seen from Panel B of Figure 3.7, CARB is projecting that almost 90% of HDDTs will still run on diesel in 2035 (and <3% on natural gas). Much remains to be done to reach ZE road freight operations by 2035, as requested in June 2017 by the mayors of Los Angeles and Long Beach. Obstacles to overcome include the availability and the cost of ZE HDDTs, the cost of the charging infrastructure, and concerns about adopting new technologies.

3.5.1 Zero Emission Heavy-Duty Drayage Trucks (ZE HDDTs)

Let us start with HDDTs. The first source of uncertainty comes from the size of the drayage fleet serving the SPBP. In 2020, approximately 22,000 drayage trucks were on the SPBP Drayage Truck Registry (Port of Long Beach, 2020), but CARB staff calculated that only 13,951 different California drayage trucks visited the ports in 2019; they also projected 19,881 different California drayage trucks for 2035, of which 18,446 would be non-ZE. The difference between registered HDDTs and EMFAC2021 numbers corresponds to trucks that either belong to a lower weight class, visit too unfrequently, or are registered out-of-state (CARB, 2021b).

Let us assume for simplicity that the retail price of a new diesel Class 8 day cab truck in 2035 is $150k and that its value drops on average by $5000 per year. After 20 years, it would still be worth $50k, which is generous compared to the asking price for 20-year-old diesel Class 8 day cabs on used trucks websites. With this assumption, the fair market value of the entire fleet of 18,446 non-ZE HDDTs in 2035 (using the age distribution of "T7 POLA" in EMFAC2021) would be $1.55 billion. A good case could be made that California should compensate the owners of non-ZE HDDTs if it decides that all HDDTs serving the SPBP should be ZE by 2035.

The cost of ZE HDDTs may also appear to be a serious issue, but not their commercial availability, as manufacturers are already offering dozens of models of Class 8 ZE day cab tractors as of mid-2022 in the U.S. or the E.U. (Sharpe & Basma, 2022), although commercial production barely started. Currently, the retail price of Class 8 ZE trucks varies widely (between $200k and close to $1 million) depending on driving range, and there is a dearth of public data on the projections of costs of heavy-duty ZE trucks (Sharpe & Basma, 2022).

To circumvent that problem, Anculle et al. (2021) built a BE day cab with a 600 kWh battery pack, which would provide a range of over 275 mi, sufficient for SPBP drayage operations. Building on Anculle et al. (2021), Buysse (2022) calculated that, after adding a 36% markup for all trucks plus a 10% markup for ZE trucks to cover additional R&D and retooling costs, the retail price of a BE Class 8 day cab could be 1.5 times more than a similar diesel Class 8 day cab in 2030 (e.g., $200k versus $135k), down from 2.8 times more in 2020.

However, the relevant metric in this context is the total cost of ownership (TCO), which includes direct costs (purchase price, fuel, operation and maintenance, driver wages and benefits, insurance, permit costs, and tolls), and indirect costs (refueling/recharging dwell time, and lost payload capacity) (Hunter et al., 2021). Performing a rigorous TCO is a complex undertaking beyond the scope of my analysis. I simply note that in their TCO analysis, Hunter et al. (2021) concluded that heavy-duty trucks with battery and fuel cell electric powertrains could be economically competitive with diesel powertrains as early as 2025 (they did not analyze 2035) for shorter-range applications (<500 mi) if diesel prices are sufficiently high (> $3/gal, which has been the case in California since 2016; EIA, 2022), electricity/hydrogen prices are sufficiently low (fuel costs make up half of the TCO for Class 8 diesel trucks; Moore and Bullard, 2020), and there are no dwell times. For BE HDDTs, the last condition requires a battery pack capable of lasting a whole day. This means that before 2035, ZE HDDTs will very likely be more attractive to operators than diesel HDDTs, so ZE HDDTs buying subsidies will no longer be needed.

3.5.2 Charging Infrastructure

The driving cycle of HDDTs and the distribution of battery sizes in the battery electric HDDT fleet determine their demand for charging infrastructure. By nature, the daily mileage of HDDTs is limited; they return to a home base daily and spend much time creeping and idling (Tanvir et al., 2021). For the HDDTs serving the SPBP, Tanvir et al. (2021) reported an average daily mileage of 185 mi, with a maximum of 271 mi and an average tour of 60 mi; they also found that 95% of the HDDTs they analyzed could complete their daily assigned tours with a 400kWh battery without recharging. In that case, all HDDTs could be fully charged overnight using 100 kW depot chargers, with a small number (say 2.5% of the 18,500 HDDTs, or 463 chargers) of public mega (1 MW) chargers for peace of mind.

Minjares et al. (2021), who analyzed the infrastructure needed to support a fleet of 100% ZE tractor-trailers in the U.S., argued that most new owners of ZE short-haul tractor-trailers will purchase overnight (100 kW) chargers to minimize energy costs, although some independent owner-operators will not have the resources to do so and will depend on public chargers.

Let us assume that 20% of the 18,500 BE HDDTs in 2035 will need public overnight chargers. If I combine the cost assumptions from Minjares et al. (2021) with the IMF (2022) projections for inflation, which results in $44.4k for an overnight charger and $277k for a mega charger purchased and built in 2025, the total cost of buying and installing 3,700 overnight and 463 mega chargers in 2025 (10 years before all are needed to stimulate the purchase of ZE HDTs) would be under $280 million. Minjares et al. (2021) assume that they would need to be replaced every ten years, but the price of electricity could cover their recurring cost.

The other piece of the charging infrastructure puzzle is the impact on the electric grid of HDDT electrification. After investigating the distribution systems upgrades needed for depot (or overnight) charging, Borlaug et al. (2021) found that, despite local variability in the state of the electric grid, ~90% of the electric substations they studied could accommodate charging of fleets of 100 trucks using 100 kW chargers if charged at their slowest rate.

3.5.3 The Road to ZE HDDTs

To foster the development and lower the cost of BE heavy-duty trucks, subsidies should continue until BE HDDTs are economically more advantageous than diesel HDDTs, which could start in 2025 if the right conditions are met (Hunter et al., 2021). After that date, subsidies for BE HDDTs should be removed. To alleviate concerns about the long-term performance of batteries, a leasing program could be considered. It could be restricted to small and medium owner-operators, which would allow them to operate BE HDDTs at a competitive price.

Over the next few years, the public charging infrastructure should be built to affirm the public commitment to clean drayage operations.

Ignoring the costs of upgrading the electric grid and of cleaning up diesel stations in my study area, the main public expense from switching to ZE-HDDTs by the end of 2035 would be the cost of the scrappage program for non-ZE HDDTs. In sub-Section 3.5.1, I estimated it at approximately $1.55 billion, which is equivalent to the health and environmental costs of the projected fleet of SPBP HDDTs in 2035. Keeping in mind that I under-estimated these costs because I did not consider $PM_{2.5}$ and CO_2 emissions at the SPBP, railyards, and warehouses served by SPBP HDDTs, my results strongly suggests that it makes economic sense for the state of California, working together with the SPBP, the City of Long Beach and the City of Los Angeles to make drayage operations emissions free by 2035. This is especially important because the bulk of the environmental and health costs from drayage operations has been borne by DACs, and they would benefit disproportionately from ZE HDDTs.

However, implementing a scrappage program for non-ZE HDDTs will require removing the provision in California Senate Bill 1 (SB1; signed into law in 2017), which prohibits new state requirements to replace, retire, repower, or retrofit heavy-duty trucks before they reach 800k mi or 18 years on their engine model year. SB1 requires CARB to weigh in on this provision by January 1, 2025. I hope that this study will factor into CARB's assessment.

3.6 Conclusions

In Chapter 3, I proposed an integrated methodology to assess the health and environmental costs from drayage operations on a regional freeway network that connects the San Pedro Bay Ports to railyards and warehouses in the Inland Empire. I analyzed these costs for two years (2012 and 2035) that have been widely used for regulatory purposes and discussed how to achieve zero emission drayage operations by 2035. My analysis accounts for projected cargo growth, population changes, technology improvements, and foreseeable regulatory changes.

I found that despite improvements in vehicle technology and increasingly stringent emission standards, freeway operations of HDDTs in 2035 would still result in ~\$1.31 billion in premature mortality due to $PM_{2.5}$ (compared to ~\$5.59 billion in 2012), and 2,142 asthma attacks (compared to 15,468 cases in 2012), not to mention at least \$220 million in climate costs. Moreover, 68% of premature mortality cases and 78% of asthma cases would accrue to disadvantaged communities in my study area. These results highlight that despite substantial progress, diesel HDDT will likely continue to seriously harm vulnerable segments of the population in the current regulatory and policy framework. In addition, my results show that the contribution of drayage operations to GHG emissions will likely continue to increase by 2035, making it more difficult for California to reach its GHG reduction goals. However, my discussion strongly suggests that it makes economic sense for the state of California, working together with the SPBP, the City of Long Beach and the City of Los Angeles to make drayage operations emissions free by 2035 by buying back non-ZE HDDTs by 2035 and building the infrastructure needed to encourage drayage firms to switch to ZE HDDTs.

My results are only as good as my assumptions, particularly as they relate to travel demand in 2035, population projections, technological change, and the calibration of the many sub-models in my simulation software. Two additional limitations need to be mentioned, but they both contribute to under-estimating the true health and environmental costs of drayage operations in my study area. First, my simulations are accident-free, so they tend to underestimate congestion and, therefore, on-road emissions. Second, my simulations leave out arterial traffic and truck idling at the SPBP gates and nearby railyards or warehouses because of the complexity of reliably simulating these features given publicly available data.

There are multiple avenues for future work. In addition to addressing the limitations mentioned in the paragraph above, they include refining and updating a TCO analysis for drayage trucks serving the SPBP; explicitly accounting for cost and technological uncertainty in the decision of both CARB and drayage truck operators to switch to ZE HDDTs; and analyzing the costs of upgrading the electric grid in support of ZE HDDTs.

CHAPTER 4 LANE MANAGEMENT STRATEGIES IN A CONNECTED ENVIRONMENT

4.1 Introduction

The advent of vehicle connectivity in transportation systems promises to improve road safety, mitigate congestion, and create opportunities to manage traffic more efficiently as communication technology enables real-time freeway traffic management. One of the possible applications of traffic management is managed lanes. Variable lane eligibility based on known demand (i.e., vehicle position and classification recorded from the connected environment) can potentially support the deployment of Connected and Autonomous Vehicles (CAVs), even at low market penetration. More specifically, lane management could support the deployment of vehicles equipped with Cooperative Adaptive Cruise Control (CACC) (SAE Level 1) to enhance safety, add capacity, and improve performance by coordinating their deployment on dedicated lanes during selected periods.

While the deployment of connected and autonomous vehicles is typically impeded by infrastructure and technology requirements, level 1 CAVs could be deployed with existing infrastructure without major improvements. Some of the technologies that can support lane management or that can benefit from having CACC-equipped vehicles drive on dedicated lanes for selected periods are 1) variable-message signs (VMS) (which can support variable lane eligibility during early deployment stages); 2) cellular vehicle to everything (C-V2X) communication (i.e., communication with other vehicles, infrastructure, pedestrians, and the cloud, enabled by 3rd Generation Partnership Project

(3GPP) frequency bands); and 3) contactless in-lane charging, which may be convenient for Zero-Emission (ZE) CACC-equipped trucks on dedicated lanes.

Combining these technologies is attractive for Southern California freeways, which are increasingly congested as the regional population continues to grow. This is particularly the case for I-710, which connects the country's largest port complex with regional warehouses and logistics centers. Caltrans, Gateway Cities, community organizations, and environmental justice activists have clashed for years over how to manage increasing freight traffic on I-710 and the resulting air pollution, congestion, and accidents. However, to my knowledge, little research has been done on the system-wide impacts of deploying CACC-enabled vehicles with lane management. This study aims to start filling this gap.

My main objective is to realistically simulate the system-wide impacts of deploying CACC-enabled vehicles jointly with lane management to explore if this approach could absorb the 2035 projected growth in cargo demand on I-710 and other freeways connecting the San Pedro Bay Ports (SPBP, i.e., the ports of Los Angeles and Long Beach) to the Inland Empire, which houses large warehouse complexes. Because of its critical role in regional freight movements, I focused on I-710 to implement lane management with an emphasis on drayage trucks. Figure 4.1 shows my simulation network (the same network presented in the previous Chapter 3) and the segments utilized to test the lane management strategies. I considered three scenarios for 2035, including a baseline scenario where I deployed CACC-enabled vehicles under mixed traffic conditions. Performance indicators such as travel time and average speed by vehicle class shed some light on the potential importance of connectivity and automation in road infrastructure planning and the deployment of CAVs. As previously mentioned, to the best of my knowledge, my regional network, which spans most of the South Coast Air Basin, is one of the largest microscopic simulation networks in the literature. While I only implemented lane management strategies on I-710, I used a regional network to estimate potential traffic spillage onto surrounding freeways.

In Section 4.2, I review background information and selected papers relevant to my analysis. In Section 4.3, I present my study area, methodology, and the selected scenarios. In Section 4.4, I summarize my results before concluding in Section 4.5.

4.2 Background

4.2.1 Some Key Definitions

The Society of Automotive Engineers (SAE, 2021) classifies automated vehicles using a scale that ranges from level 0 (no automation) to level 5 (full automation, where onboard systems perform all driving functions under all conditions.) The focus of this study is on port heavy-duty drayage trucks (HDDT) connected via Cooperative Adaptive Cruise Control (CACC), i.e., trucks whose longitudinal motion, braking, and acceleration are controlled by onboard systems when their driving is synchronized with a leading CACC-enabled HDDT using short-range wireless communication (a C-V2X technology); a human driver handles all other driving tasks. While CACC-enabled trucks travel in a string by maintaining a constant time gap, they can be distinguished from vehicles traveling in a platoon, where consecutive vehicles strive to maintain a fixed distance between themselves (Shladover et al., 2015). The formation of CACC-enabled vehicle strings is bounded by opportunity as vehicles equipped with CACC or other radio access communications could potentially cluster together based on their location (Mavromatis et al., 2018). Alternatives to short-range radio signals include establishing communication between vehicles using other devices, the surrounding infrastructure, or the internet (Mavromatis et al., 2018). By taking advantage of the widespread deployment of LTE cellular technology, Cellular Vehicle-to-Everything (C-V2X) technology offers a roadmap to the deployment of connected vehicles. By communicating with the network (V2N), transportation authorities would be able to broadcast safety and traffic conditions to the vehicles and manage traffic in real-time (Demler, 2020).

4.2.2 Expected Benefits and Challenges of CACC-enabled Vehicles

A fully connected transportation system is expected to enhance the safety of US roads substantially and thus decrease the external costs of using motor vehicles, which reached $242 billion or 1.6 percent of the US Gross Domestic Product in 2010 ($836 billion if the value of the quality of life is included) from fatalities, injuries, and damages to vehicles. Approximately 12% ($28 billion) of this cost corresponds to congestion which accounts for travel delays, added fuel usage, and adverse environmental impacts (Blincoe, Miller, Zaloshnja, & Lawrence, 2015).

By organizing trucks in platoons, connected and automated technologies promise fuel efficiency improvements, a potential benefit that has already been widely analyzed (Boysen et al., 2018; Larson et al., 2015; Liang et al., 2013; Rios-Torres & Malikopoulos, 2017; Van De Hoef, Johansson, & Dimarogonas, 2015). Moreover, engine propulsion changes and aerodynamic drag reductions could help reduce carbon emissions. A third motivation for introducing CAVs is congestion relief, which is my main focus here.

Congestion reduction relies on a significant number of CACC-enabled vehicles and the formation of stable platoons (Ploeg, Serrarens, & Heijenk, 2011).

The feasibility and the potential safety and fuel efficiency benefits of CACC-enabled vehicles have already received much attention (Bishop, Bevly, Humphreys, Boyd, & Murray, 2017; Kunze, Ramakers, Henning, & Jeschke, 2009; Lu & Shladover, 2014b; Ramezani, Shladover, Lu, & Chou, 2018b). A number of studies have also relied on simulation to assess how the characteristics of various control systems for trucks could impact vehicle interactions, traffic flow, and traffic management (Guériau et al., 2016; Ramezani et al., 2018b; Talebpour & Mahmassani, 2016; Talebpour et al., 2017; van Arem et al., 2006; Yang, Kuijpers, Dane, & der Sande, 2019), but to my knowledge, these are almost exclusively modeled as one-directional stretches and during relatively short periods (1-3 hours). While these studies had different objectives, their results suggest that connected truck technologies are likely to positively impact traffic flow, although the magnitude of this impact depends on market penetration and how platooning is implemented. For example, excessive platoon size and intensity could block merging and diverging areas, cause unnecessary lane changes, or result in other vehicles missing an off-ramp.

While the technical, societal, and institutional challenges of autonomous vehicles are prevalent (Colonna, 2013; Dawid & Muehlheusser, 2019; Duffy & Hopkins, 2013; Hevelke & Nida-Rümelin, 2015; Marchant & Lindor, 2012; Pöllänen, Read, Lane, Thompson, & Salmon, 2020; Taeihagh & Lim, 2019), particularly as relating to liabilities (Geistfeld, 2017; Noussia, 2020; Seuwou et al., 2020), the deployment of CACC-enabled vehicles, which only utilize the lowest level of autonomy and require a human driver on board, is mostly bounded by the infrastructure requirements needed to maximize their expected benefits.

4.2.3 Lane Management Opportunities

While performance improvements and optimal strategies for managed lanes have received much attention over the years (Ansari Esfeh & Kattan, 2019; Sajjadi & Kondyli, 2017; Sisiopiku & Cavusoglu, 2008; Song, Yin, & Lawphongpanich, 2015; Thomson, Liu, Wang, Schroeder, & Rouphail, 2012), inquiries of system-wide operational improvements associated with the implementation of managed lanes in a connected environment have been more limited. Several studies have analyzed the impacts of managed lanes under a connected environment with different objectives such as tolling, safety, and lane-changing behavior (Abdel-Aty, Wu, Saad, & Rahman, 2020; Guo, Peng, Ashraf, & Burris, 2020; Zhu & Ukkusuri, 2015). Furthermore, a microscopic simulation study modeled three hours of traffic on a segment of a Florida freeway to test the deployment of connected vehicles under different lane management strategies. However, the objective of this study was safety improvements by quantifying the reduction in the number of traffic conflicts (Abdel-Aty, Wu, Saad, & Rahman, 2019). To the best of my knowledge, little research has been conducted on system-wide performance improvements resulting from their adoption to support the deployment of CACC-enabled vehicles, which is a key contribution of my dissertation.

4.3 Data and Methods

As a baseline for my study area traffic conditions, I calibrated a regional microscopic simulation model with the projected year 2035 freeway traffic conditions. I selected 2035 because it has been used to forecast the region's cargo growth (California Department of

Transportation & Los Angeles County Metropolitan Transportation Authority, 2012; MERCATOR & Oxford Economics, 2016; SCAG, 2013). My aim focus here is to test the impact of CACC-enabled vehicles and managed lanes on absorbing the 2035 projected cargo growth from the SPBP. I then recalibrated my network to simulate connected and autonomous drayage trucks driving under mixed and restricted traffic conditions in response to historical traffic data. I assumed that simulated trajectories represent average weekday traffic flows for my purposes. More specifically, I studied the operational impact of CACC-enabled vehicles driving under mixed and restricted traffic conditions for different lane management strategies. I evaluated performance based on speed improvements, vehicle hours saved, and overall system speed.

4.3.1 Study Area

My study area (see Figure 4.1) includes parts of 13 freeways in the Southern California Association of Governments (SCAG) region. I selected these 13 freeways because they have the highest concentration of container truck traffic based on sensor data from the Truck Activity Monitoring System (Tok et al., 2017). Using data from a representative month (July of 2017), I identified Interstate 710 (I-710), State Route 60 (SR 60), Interstate 110 (I-110), Interstate 10 (I-10), and Interstate 605 (I-605), Interstate 210 (I-210), State Route 57 (SR 57), and Interstate 5 (I-5) as the busiest in the region for heavy-duty traffic. I completed my freeway network by including intersecting freeways—details on the calibration and validation of the freeway network in Section 3.3.1.

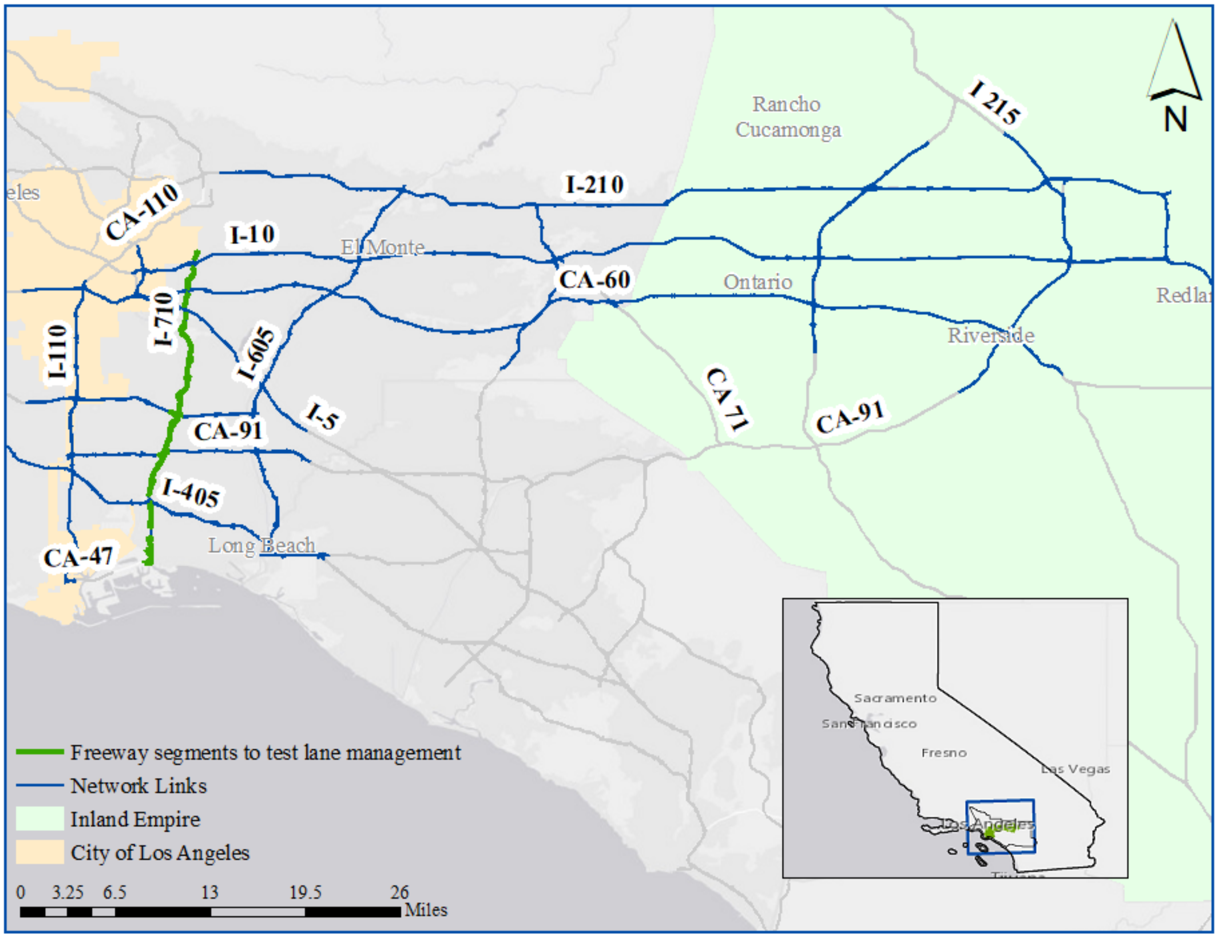


Figure 4.1 Study area

4.3.2 Lane Management

To test the effects of lane management in a connected environment, I analyzed the patterns of HDDT traffic on I-710. The data processing of I-710 trajectories was conducted outside of TransModeler using Python to determine lane eligibility criteria for each segment and every 15 minutes considered. Standard hours of operation at the Long Beach port are 7:00 to 17:00 and 19:00 to 4:00. Standard hours of operation at the Los Angeles port are similar, with one additional hour in the AM shift. Truck traffic in the northbound direction accounts for 10% - 15% during most of the day. Similarly, truck traffic in the southbound direction of I-710 accounts for 4% - 6% during most of the day. As expected, the flow of

HDT is higher during peak periods. As shown in Figure 4.2, I identified the period between 9:00 and 18:00 as the period of highest HDDT flows.

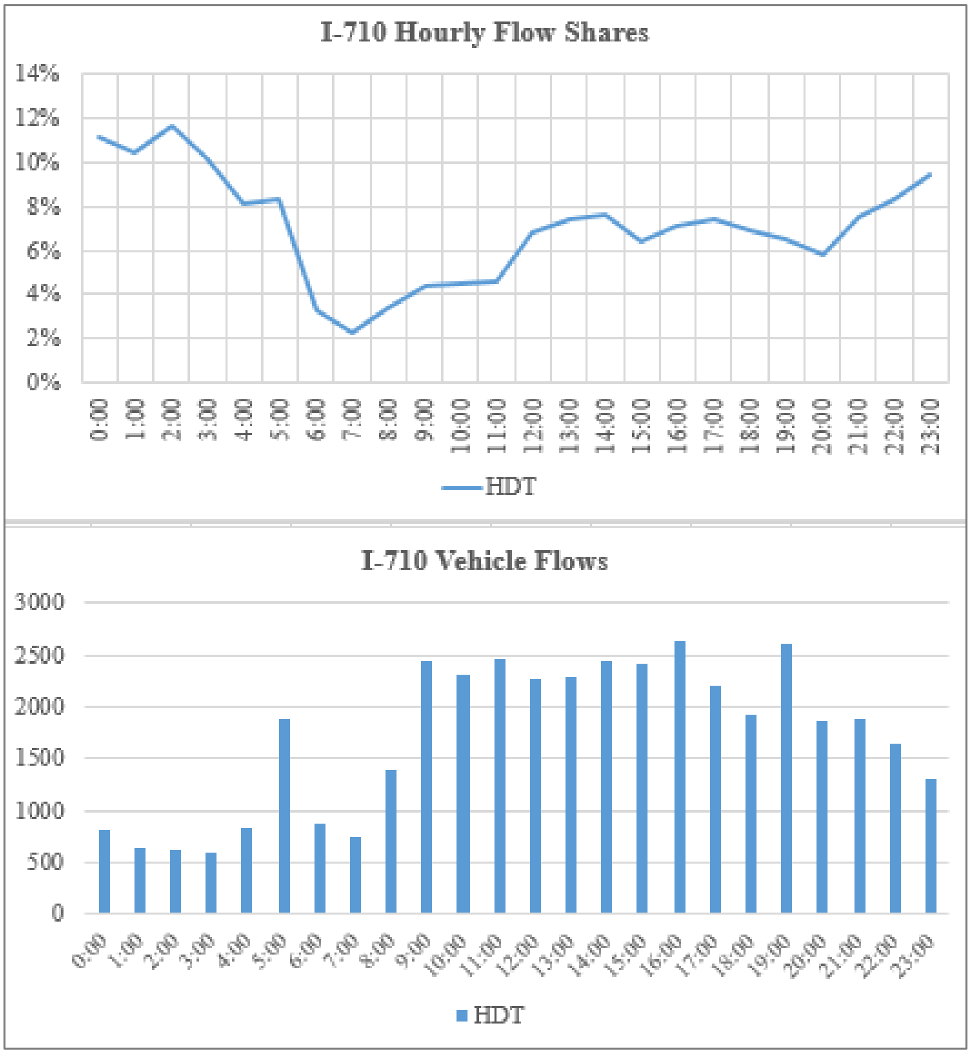


Figure 4.2 I-710 HDT share and flow over all segments
Source: I-710 vehicle trajectories from simulation (one second time step).

In this context, I considered three 2035 scenarios (defined below), including a baseline where CACC-enabled vehicles drive under mixed traffic conditions and two lane management scenarios.

4.3.3 Scenarios

As depicted in Figure 4.3, I considered three scenarios for testing, including a baseline scenario where I deployed CACC-enabled vehicles under mixed traffic conditions :

- **Baseline Scenario**: I restricted heavy-duty trucks to the two outer lanes of freeways as per California regulations; I deployed CACC-enabled vehicles under mixed traffic conditions.
- **Dedicated First Lane Scenario (Restricted Access)**: I reserved the first lane (left-most lane) for CACC-enabled vehicles; I restricted CACC vehicles from using any other lane (except for access and egress).
- **Dedicated First Lane Scenario (Optional Access)**: I reserved the first lane (left-most lane) for CACC-enabled vehicles; CACC vehicles are free to use any other lane as well (similar to an HOV lane).

The selection of periods to test lane management only considered the number of port-related HDDT on I-710 to identify the periods with the most slow-moving trucks. Thus, based on the distributions of port HDDTs over the 24 hours simulation, I decided to apply lane management strategies during the following peak periods: NB & SB: from 9:00 to 12:00 and from 15:00 to 18:00. Additionally, I implemented lane management strategies for the consecutive nine hours between 9:00 and 18:00.

To test lane management, I configured lane sets to identify I-710's first lane (left-most lane) and other I-710 lanes to apply the different lane configurations (see Figure 4.3). I applied lane restrictions as reserved and restricted access by vehicle categories in TransModeler.

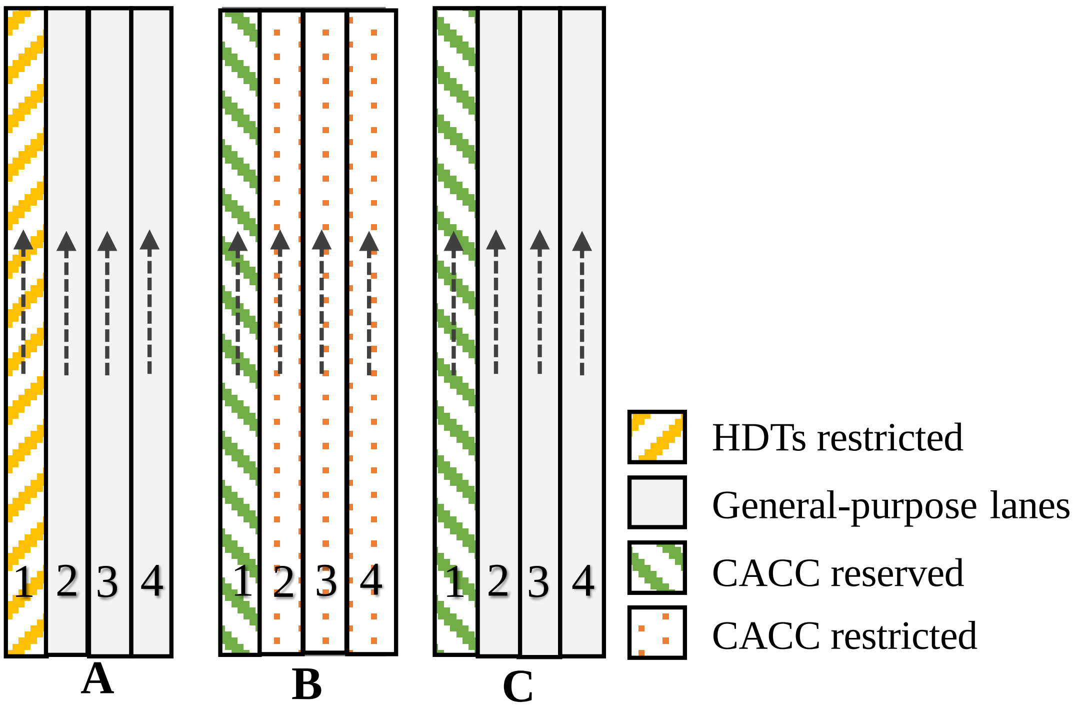


Figure 4.3 Lane configuration

In addition to the scenarios illustrated above, I tested the deployment of CACC-enabled vehicles with the third lane (second to last lane) designated for CVs. The addition to the second to last lane to my analysis came from illustrations from the San Diego Association of Governments (SANDAG) 2021 Regional Plan, which proposes a vision for Complete Corridors that incorporates managed lanes and demand management to support the deployment of emerging technologies such as connected vehicles (SANDAG, 2019). However, as expected, allowing the formation of platoons on the third lane (second to last lane) substantially decreased the network's performance. Thus, I omitted the third (second to last) lane as a dedicated CACC lane simulation runs from my analyses.

4.3.4 Data Processing

Outputs from the 24-hour simulation of each scenario account for ~180 GB and ~4 billion rows of vehicle trajectories. I processed these outputs to estimate performance metrics by facility type at the link level. First, I split vehicle trajectories into 15-minute bins by vehicle class (i.e., LDV, LDT, MDT, HDT, PHDT, and CLDV). I estimated average speeds by vehicle class from each 15-minute bin by dividing VMT by VHT after aggregating for all vehicles in 15-minute increments. This approach can also be applied to specific facilities by filtering 15-minute trajectories. I then calculated trip statistics at the network level to estimate performance metrics such as changes in average speed and travel time-saving at the network level.

4.4 Results

I ran 24-hour simulations to test the above scenarios for the nine hours of highest HDDT traffic and peak period regimes. I also tested performance improvements when only HDDTs were CACC-enabled and when HDDTs and a share of passenger vehicles were CACC-enabled. Some network-wide statistics are presented in Table 4.1.

Selected results are discussed below, starting with network-wide improvements for CACC HDDT, followed by results when a percentage of passenger vehicles are also CACC-enabled. Similarly, I explored I-710 improvements separately as I tested lane management strategies on I-710 segments only for HDDTs and for the scenario where HDDTs and a share of the passenger vehicles are CACC-enabled.

4.4.1 CACC Performance Improvements

Let us first explore performance improvement after setting up lane management strategies when only HDDTs are CACC-enabled and when HDDTs and a share of passenger vehicles are CACC-enabled. I tested both strategies using the three previously described scenarios during peak periods and for the nine hours of peak HDDT traffic.

4.4.1.1 *Network-wide improvements*

Table 4.1 shows network-wide trip statistics. For managed lanes scenarios with only CACC-enabled HDDTs, I observed speed decreases for the scenario when I restricted CACC HDDTs to the first lane (left-most lane) (Scenario B) and only marginal improvements when I designated the first lane to CACC HDDTs with optional access (Scenario C). While the first lane with optional access scenario (Scenario C) only showed minor speed improvements on all vehicles simulated, ~1% for the peak period and 9-hour implementation of lane management scenarios, the restricted first lane scenario showed speed decreases of 4.5% for the peak periods, and 6.8% for the nine consecutive hours of highest HDDTs flows.

When I tested the managed lanes scenarios with CACC-enabled HDDTs and 10% of the passenger vehicles simulated, the results were similar when looking at network-wide speed changes. I observed speed decreases for both scenarios when I restricted CACC HDDTs to the first lane (Scenario B) as a dedicated lane for CACC-enabled vehicles and,

Table 4.1 Network-wide trip statistics

			Scenario A				Scenario B				Scenario C			
			Veh. count	*VMT*	*VHT*	*Speed*	*Veh. count*	*VMT*	*VHT*	*Speed*	*Veh. count*	*VMT*	*VHT*	*Speed*
100% HDDTs are CACC-enabled	*9:00 - 12:00 & 15:00 - 18:00*	*LDV*	6,199,394	55,995,352	1,121,570	49.9	6,198,530	55,990,314	1,150,542	48.7	6,199,636	56,016,849	1,119,833	50.0
		LDT	83,868	853,232	16,965	50.3	83,949	852,114	17,671	48.2	84,300	860,516	17,043	50.5
		MDT	71,088	699,079	13,694	51.1	71,093	696,519	14,300	48.7	70,904	698,624	13,603	51.4
		HDT	206,432	2,938,760	60,039	48.9	206,052	2,925,100	59,555	49.1	205,747	2,926,328	59,444	49.2
		Port HDT	96,786	1,429,088	66,666	21.4	94,141	1,487,449	97,968	15.2	97,383	1,440,408	55,487	26.0
	9:00 - 18:00	*LDV*	6,199,394	55,995,352	1,121,570	49.9	6,199,636	56,016,849	1,119,833	50.0	6,199,931	56,028,922	1,116,908	50.2
		LDT	83,868	853,232	16,965	50.3	84,300	860,516	17,043	50.5	84,241	852,361	16,972	50.2
		MDT	71,088	699,079	13,694	51.1	70,904	698,624	13,603	51.4	71,024	695,305	13,658	50.9
		HDT	206,432	2,938,760	60,039	48.9	205,747	2,926,328	59,444	49.2	205,808	2,911,466	58,702	49.6
		Port HDT	96,786	1,429,088	66,666	21.4	97,383	1,440,408	55,487	26.0	97,024	1,441,312	57,404	25.1
100% HDDTs and 10% of LDVs are CACC-enabled	*9:00 - 12:00 & 15:00 - 18:00*	*LDV*	6,197,708	55,970,296	1,126,277	49.7	6,197,826	56,062,888	1,151,580	48.7	6,198,712	55,991,575	1,128,812	49.6
		LDT	84,504	857,441	17,226	49.8	83,712	851,416	17,840	47.7	83,910	857,714	17,242	49.7
		MDT	70,893	698,144	13,773	50.7	70,629	690,811	14,297	48.3	70,741	694,373	13,719	50.6
		HDT	205,770	2,919,724	59,776	48.8	206,037	2,933,812	59,403	49.4	206,216	2,940,191	60,111	48.9
		Port HDT	97,051	1,440,116	68,609	21.0	93,110	1,442,200	106,390	13.6	97,464	1,445,869	55,545	26.0
	9:00 - 18:00	*LDV*	6,197,708	55,970,296	1,126,277	49.7	6,194,470	56,113,534	1,191,314	47.1	6,199,040	55,979,630	1,122,678	49.9
		LDT	84,504	857,441	17,226	49.8	84,085	854,699	18,870	45.3	84,241	861,493	17,069	50.5
		MDT	70,893	698,144	13,773	50.7	71,087	696,009	15,251	45.6	70,435	690,459	13,425	51.4
		HDT	205,770	2,919,724	59,776	48.8	205,991	2,929,458	59,394	49.3	205,804	2,927,092	59,325	49.3
		Port HDT	97,051	1,440,116	68,609	21.0	88,315	1,384,561	125,823	11.0	97,670	1,458,455	54,214	26.9

Scenario A: CACC-enabled vehicles drive under mixed traffic conditions.
Scenario B: I reserved the first lane (left-most lane) for CACC-enabled vehicles. CVs are restricted only to using the designated lane.
Scenario C: I reserved the first lane (left-most lane) for CACC-enabled vehicles. Access to the designated lane is optional.

again, only marginal improvements when I designated the first lane to CACC-enabled vehicles with optional access (Scenario C). While the first lane with optional access scenario (Scenario C) only showed minor speed improvements on all vehicles simulated, ~1% for the peak periods and 9-hour implementation of lane management scenarios, the restricted first lane scenario (Scenario B) showed speed decreases of 4.6% when I implemented lane management during peak periods and 9% when I implemented it during the nine consecutive hours of highest HDDTs flows.

While my results suggest that lane management strategies do not significantly improve traffic conditions despite the deployment of a significant number of CACC-enabled vehicles, this finding contradicts the expectation of SANDAG's regional plans to accommodate traffic congestion in the future. SANDAG's 2021 Regional Plan incorporates managed lanes and active demand management as part of their vision for Complete Corridors, which would incorporate vehicle connectivity to manage traffic more effectively to reduce traffic congestion (SANDAG, 2019).

However, given the size of my network and that lane management scenarios were only implemented on I-710, I further explored I-710 speed improvements for all vehicles and for CACC-enabled vehicles separately to assess local improvements and, more specifically, the impact on accommodating the expected HDDT demand increase in 2035. An indication of this is the reduction of vehicle miles traveled. While the implementation of lane management did not appear to have a significant impact on overall network performance, HDDT vehicle hours saved for the best-case scenario were significant (i.e., up to a 21% decrease in vehicle hours traveled by HDDTs) when I designated the first lane for

CACC vehicles with optional access. These results suggest that lane management could potentially support the projected cargo growth for 2035.

4.4.1.2 *I-710 speed improvements*

When examining local speed improvements after the implementation of lane management strategies, I look only at the scenario with the best results based on network-wide results. The first lane with optional access (Scenario C), reserved for CACC-enabled vehicles, was the only scenario that contributed to speed improvements when only HDDTs were CACC enabled and when HDDTs and a percentage of passenger vehicles were CACC enabled.

Figure 4.4 compares I-710 15-minute speeds over all NB segments and all vehicles (Panel A) and for HDDTs (Panel B) after implementing lane management strategies when only HDDTs are CACC enabled. My results show that while the speed of both HDDTs and the average speed of all vehicles increased significantly during the lane management periods, off-peak evening traffic due to the night shift gate hours at the SPBP does not improve. I-710 15-minute speeds over all SB segments and all vehicles (Panel C) and for HDDTs (Panel D), where HDDTs are about 20% smaller than on NB segments, speed drastically improves for HDDTs and also for all vehicles during selected periods.

HDDTs on NB speed increase on average by 20 mph (95% improvement) during lane management periods when implemented during peak periods (9:00 – 12:00 & 15:00 – 18:00), with peaks of up to 38 mph (193%) improvements taking HDDT speeds from 19 mph to 57 mph during selected periods. Moreover, I observed an average increase in HDDT speeds of 20 mph (83%) during lane management periods when implemented during the nine hours of highest HDDT traffic (9:00 –18:00), with peaks of up to 40 mph

(204%) improvements taking HDDT speeds from 18 mph to 59 mph. I-710 SB HDDT speeds are more significant given the smaller share of HDDTs. Thus, on SB segments, speed increases to over 50 mph during most of the implementation period, making the scenario with nine hours of consecutive implementation the preferred alternative as it can increase speeds from as low as 18 mph to up to up to 55 mph during selected periods.

Likewise, the average speed of all vehicles on I-710 NB increased on average by 4 mph (8%) when implemented during peak periods (9:00 – 12:00 & 15:00 – 18:00), with peaks of up to 12.5 mph (168%) improvements taking average speeds from 44 mph to 56.5 mph during selected periods. The average increase was 5 mph (11%) during lane management periods when implemented during the nine hours of highest HDDT traffic (9:00 –18:00), with peaks of up to 14.4 mph (32%) improvements taking average speeds from 45 mph to 59.4 mph during selected periods. The average speed of all vehicles on I-710 SB increased on average by 7 mph (19%) when implemented during peak periods (9:00 – 12:00 & 15:00 – 18:00), with peaks of up to 20 mph (52%) improvements taking average speeds from 38 mph to 58 mph during selected periods. The average increase was 3.4 mph (9%) during lane management periods when implemented during the nine hours of highest HDDT traffic (9:00 –18:00), with peaks of up to 20 mph (53%) improvements taking average speeds from 38 mph to 58 mph during selected periods.

Then, I tested the impact of a share of passenger vehicles that are also CACC-enabled. I did this by implementing 10%, 20%, 30%, 40%, and 50% of passenger vehicles with connectivity capabilities to the best-case scenario based on the previous analysis (inner lane reserved with optional access during the nine hours of highest HDDT traffic). Figure 4.5 shows the impact on all vehicles on I-710 NB segments when 10% - 50% of passenger vehicles are CACC-enabled in addition to all HDDTs (Panels A – E, respectively), and the inner lane scenario with optional access is compared against the baseline where all CACC HDDTs and passenger vehicles drive under mixed traffic conditions. I found that the impact of the reserved lane does not seem to degrade as the share of passenger vehicles that are CACC enabled increased, likely due to the level of congestion due to HDDTs in the NB direction. However, the reserved lane increased speeds from 45 to 60 mph during implementation.

Similarly, Figure 4.6 shows the impact on HDDT speeds on I-710 NB segments when 10% - 50% of passenger vehicles are CACC-enabled in addition to all HDDTs (Panels A – E, respectively); once again, the impact of the reserved lane does not seem to degrade as the share of passenger vehicles that are CACC enabled increased, likely due to a larger share of HDDTs on NB segments. Thus, restricting the number of CACC passenger vehicles that access the reserved lane. However, the reserved lane increased speeds from 20 to 60 mph during implementation.

Figure 4.7 shows the impact on all vehicles on I-710 SB segments when 10% - 50% of passenger vehicles are CACC-enabled in addition to all HDDTs (Panels A – E, respectively), and the inner lane scenario with optional access is compared against the baseline where all CACC HDDTs and passenger vehicles drive under mixed traffic conditions. I found that the impact of the reserved lane reached the best output when all HDTTs and 30% of passenger vehicles were CACC-enabled, bringing speeds from as low as 25 mph to speeds over 50 mph during the implementation period. However, when 40% and 50% of passenger vehicles were CACC-enabled, the speeds of all vehicles degraded below the baseline. Similarly, Figure 4.8 shows the impact on HDDT speeds on I-710 SB segments when 10% - 50% of passenger vehicles are CACC-enabled in addition to all HDDTs (Panels A – E, respectively); once again, the impact of the reserved lane reached the best output when all HDTTs and 30% of passenger vehicles were CACC-enabled bringing speeds from as low as 20 mph to speeds over 55 mph during the implementation period. Further, when 40% and 50% of passenger vehicles were CACC-enabled, speed improvements are more conservative, but baseline speed continues to increase as passenger vehicle share increases.

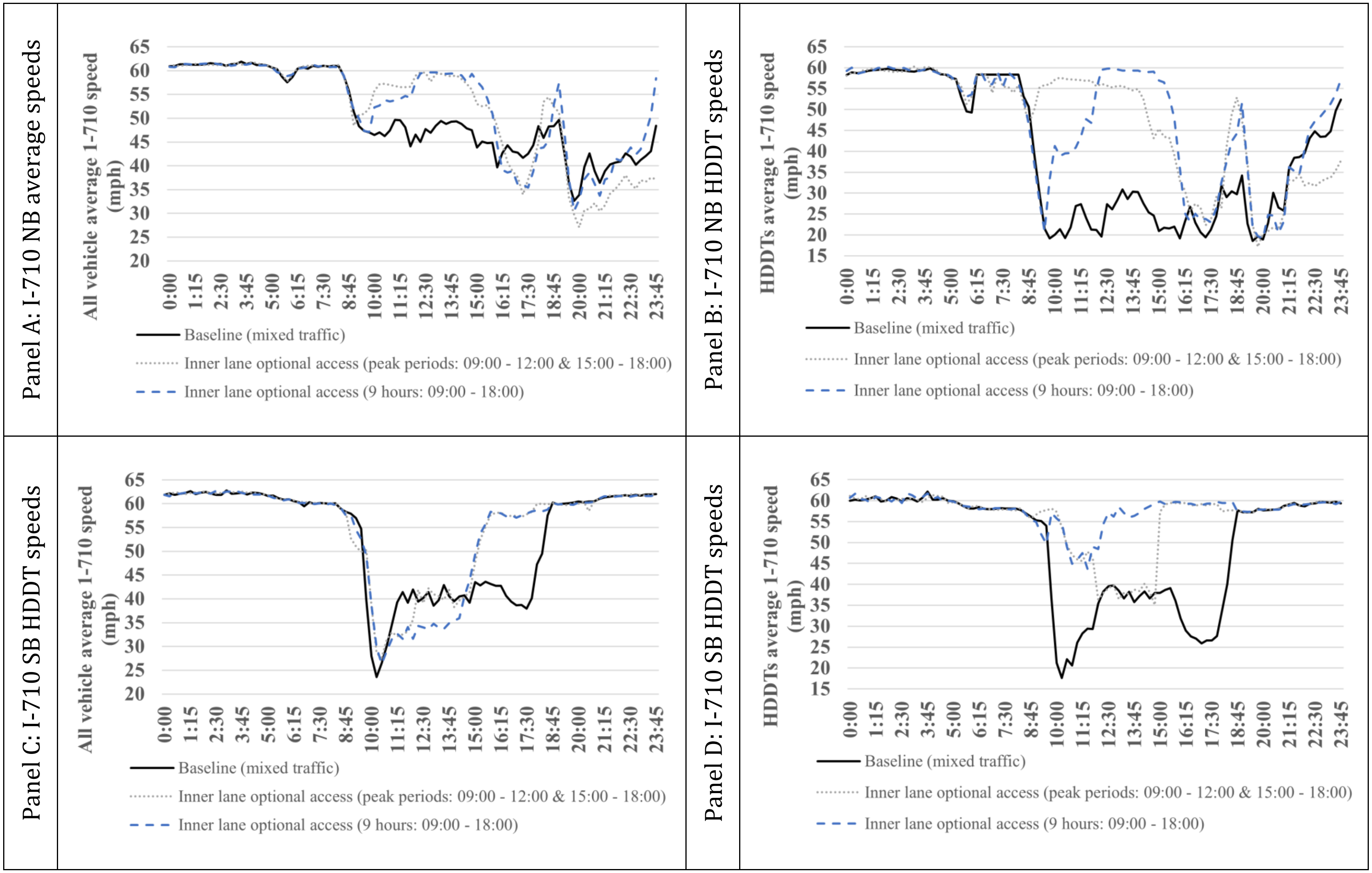
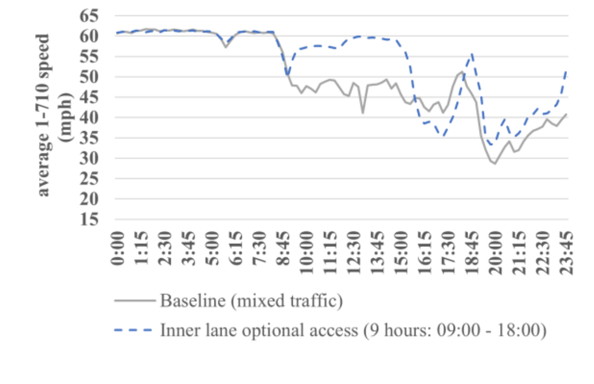
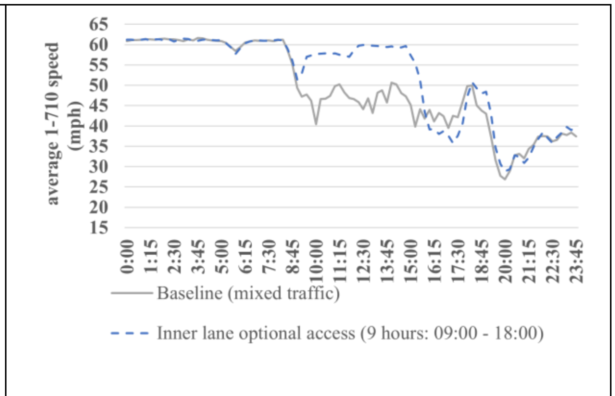


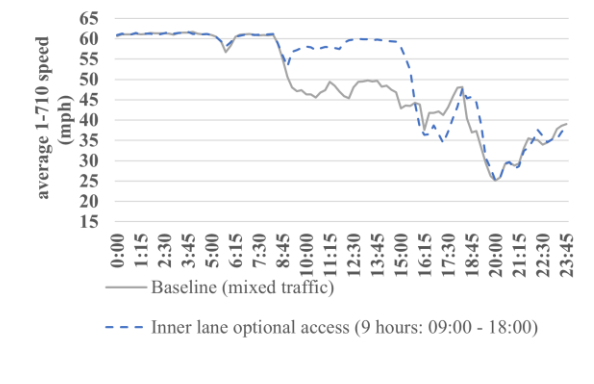
Figure 4.4 I-710 speed variations after I deployed CACC HDDTs with a reserved lane



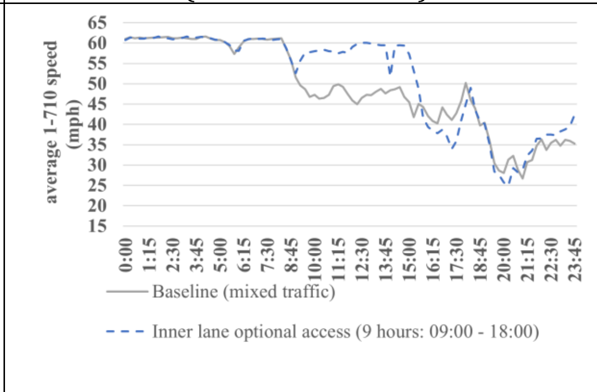
Panel A: I-710 NB average speeds (10% CACC LDVs)



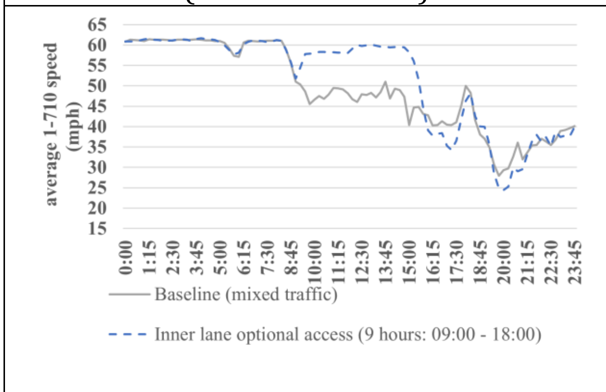
Panel B: I-710 NB average speeds (20% CACC LDVs)



Panel C: I-710 NB average speeds (30% CACC LDVs)

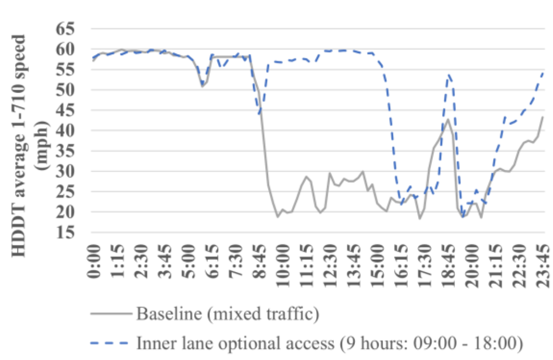


Panel D: I-710 NB average speeds (40% CACC LDVs)

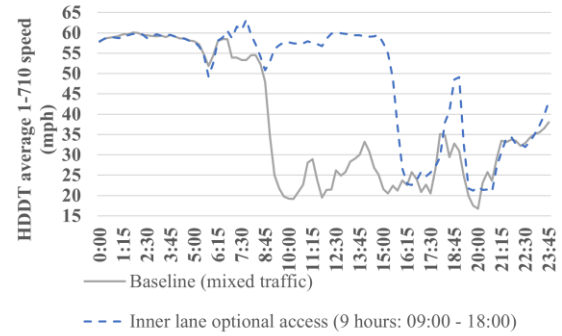


Panel E: I-710 NB average speeds (50% CACC LDVs)

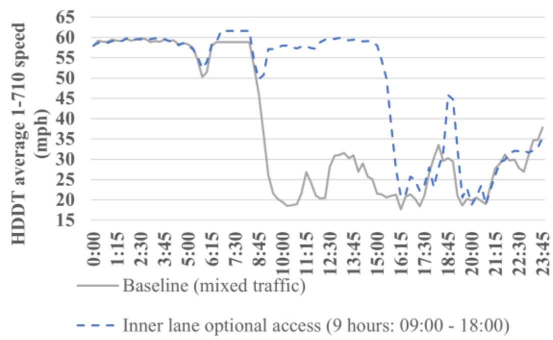
Figure 4.5 I-710 NB speed variations after I deployed CACC HDDTs and a share of passenger vehicles (10% - 50%) with a reserved lane



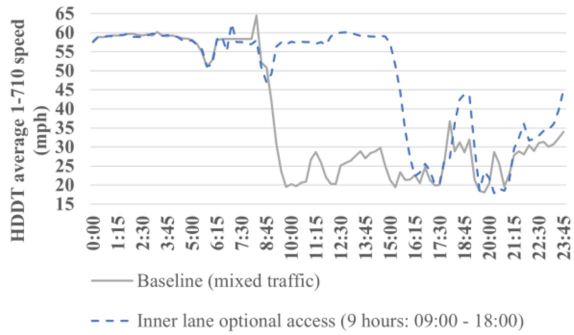
Panel A: I-710 NB HDDT speeds (10% CACC LDVs)



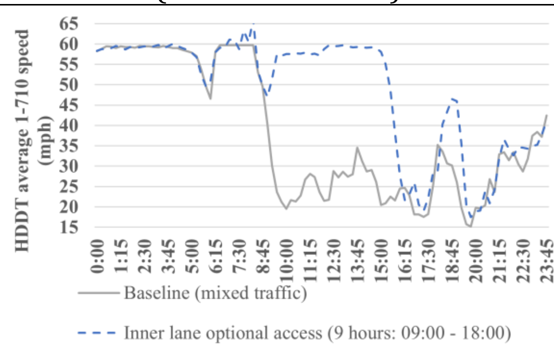
Panel B: I-710 NB HDDT speeds (20% CACC LDVs)



Panel C: I-710 NB HDDT speeds (30% CACC LDVs)

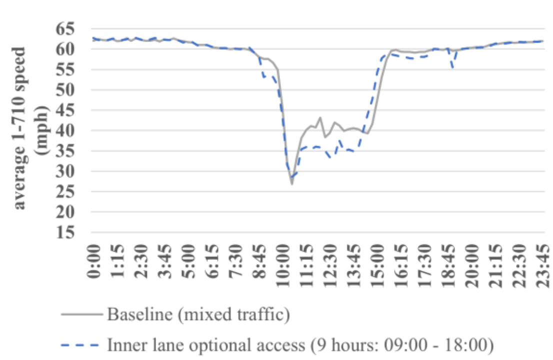


Panel D: I-710 NB HDDT speeds (40% CACC LDVs)

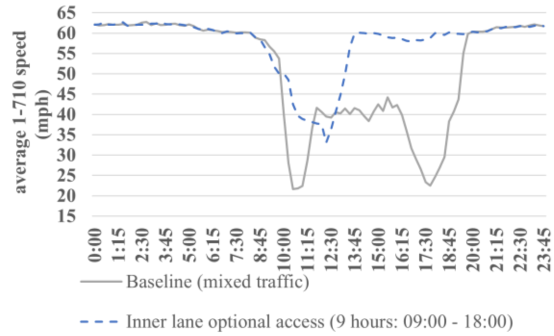


Panel E: I-710 NB HDDT speeds (50% CACC LDVs)

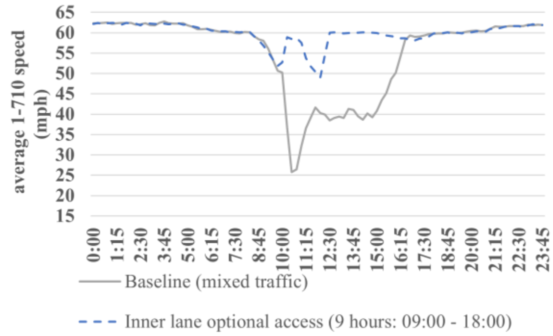
Figure 4.6 I-710 NB HDDT speed variations after I deployed CACC HDDTs and a share of passenger vehicles (10% - 50%) with a reserved lane



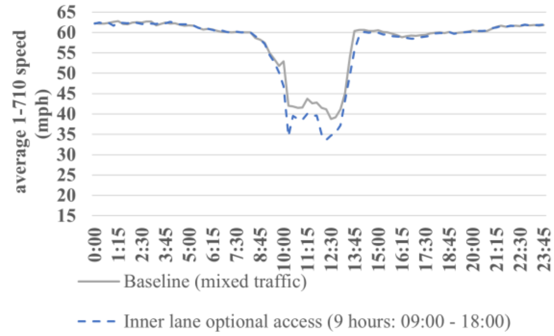
Panel A: I-710 SB average speeds (10% CACC LDVs)



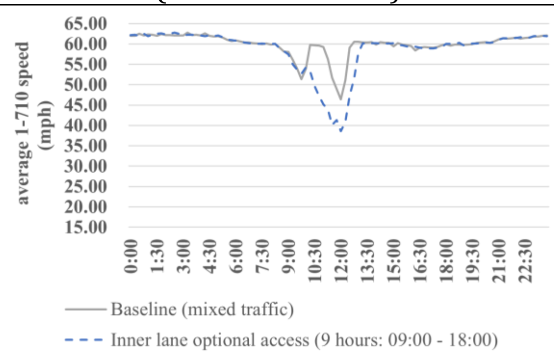
Panel B: I-710 SB average speeds (20% CACC LDVs)



Panel C: I-710 SB average speeds (30% CACC LDVs)

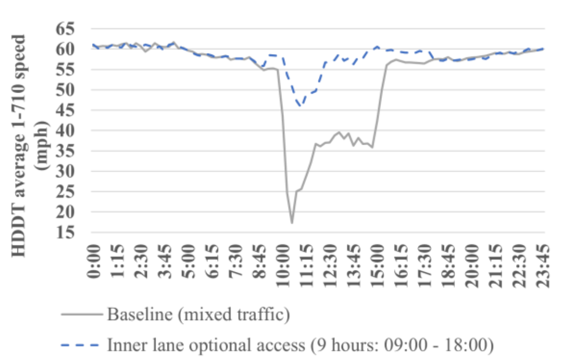


Panel D: I-710 SB average speeds (40% CACC LDVs)

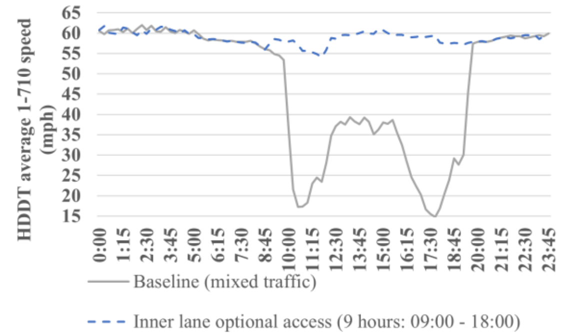


Panel E: I-710 SB average speeds (50% CACC LDVs)

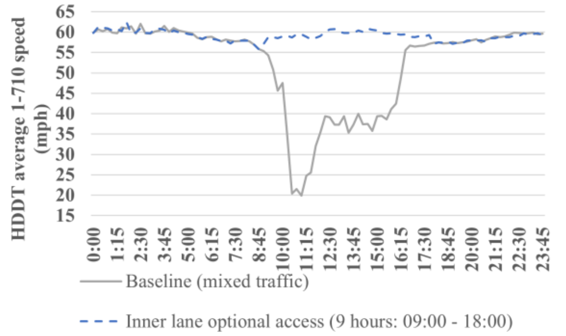
Figure 4.7 I-710 SB speed variations after I deployed CACC HDDTs and a share of passenger vehicles (10% - 50%) with a reserved lane



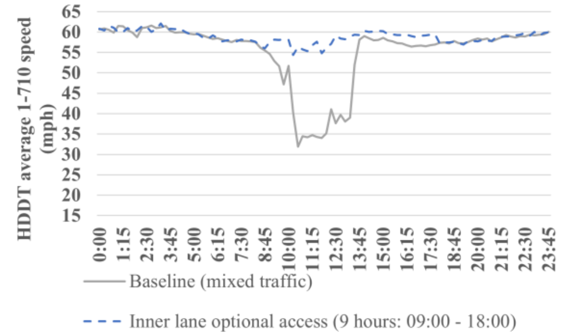
Panel A: I-710 SB average speeds (10% CACC LDVs)



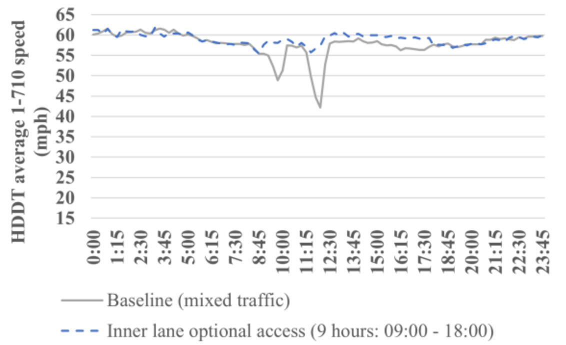
Panel B: I-710 SB average speeds (20% CACC LDVs)



Panel C: I-710 SB average speeds (30% CACC LDVs)



Panel D: I-710 SB average speeds (40% CACC LDVs)



Panel E: I-710 SB average speeds (50% CACC LDVs)

Figure 4.8 I-710 SB HDDT speed variations after I deployed CACC HDDTs and a share of passenger vehicles (10% - 50%) with a reserved lane

4.5 Conclusions

In Chapter 4, I calibrated a regional microscopic simulation to model 24 hours of Southern California traffic on freeways connecting the San Pedro Bay Ports to the Inland Empire. This area is a key economic artery, including I-710, the main route connecting the San Pedro Bay Ports to off-dock rail yards and inland warehouses. Traffic congestion originated from slow-moving trucks, with forecasts for 2035 projecting a 145% increase in drayage traffic. This is bound to degrade traffic conditions despite the small share of HDDTs compared to the 6.5 million simulated vehicles, particularly on I-710. In Chapter 2, I found a 64% HDDT speed decrease on the freeway and arterial network surrounding the SPBP. My analysis here aimed to assess the speed improvements associated with implementing lane management strategies for deploying CACC-enabled vehicles.

I found that vehicle connectivity alone only makes marginal performance improvements when deployed under mixed traffic conditions; other Southern California simulation studies reported ~2 -6% speed improvements in overall traffic after deploying CACC-enabled vehicles under mixed traffic conditions (Ramezani et al., 2018a). However, metropolitan planning organizations, such as SANDAG in its 2021 Regional Plan, have proposed implementing managed lanes and active demand management for the deployment of CVs (SANDAG, 2019). I considered three 2035 scenarios, including a baseline scenario where I deployed CACC-enabled vehicles under mixed traffic conditions. Two scenarios reserved the first lane (left-most lane) for CACC-enabled vehicles under restricted and optional access. I tested lane management scenarios when HDDTs were CACC-enabled and when HDDTs and 10% of LDVs were CACC-enabled. Likewise, my testing periods were selected based on HDDT peak traffic periods (9:00 – 18:00).

My results suggest that while reserving the first lane (left-most lane) for CACC-enabled vehicles with optional access only provides marginal speed improvements on overall traffic (~1% improvement compared to Scenario A, where I deployed CVs under mixed traffic conditions), restricting CACC-enabled vehicles to the first lane decreases the average speed of all vehicles. I-710 average speed for the best-case scenario, where I reserved the first lane for CACC-enabled vehicles with optional access during the hours of highest HDDT traffic, showed significant improvements during the implementation period, for both the average speed of all vehicles and for port HDDTs, bringing the average speed from as low as 45 mph to 60 mph and the speed of HDDTs from as low as 20 mph to up to 60 mph. In addition, I found that implementing lane management strategies during the busiest nine hours for HDDT traffic (9:00 – 18:00) yielded the best results bringing speed over 50 mph during the implementation period on selected segments. However, I found that the impact of CACC passenger vehicles is bounded by the share of slow-moving trucks on the road.

While typically, the speed benefits of connected vehicles are small, combining lane management strategies to support the deployment of CACC-enabled vehicles could maximize their contribution to traffic performance and safety.

One limitation of this study is the lack of quantification of safety benefits. More in-depth analyses of increasing percentages of CACC-enabled passenger vehicles on the benefits of combining managed lanes with CACC for SPBP trucks and an in-depth assessment of their impact on traffic safety are left for future work.

CHAPTER 5 CONCLUSIONS

In this dissertation, I analyzed how electrification, connectivity, and active lane management could affect the system-wide performance, regional environmental quality, health, and environmental justice impacts of drayage trucks operations in a subset of the Los Angeles Air Basin. Although I relied heavily on microscopic traffic simulation for my analyses, I also used tools to estimate vehicle emissions, calculate the concentration of various air pollutants, and estimate health impacts.

In Chapter 2, my analysis was centered on the I-710 freeway. I analyzed an arterial and freeway network linking the San Pedro Bay Ports with downtown Los Angeles. The main objective of this analysis was to explore the impact on traffic and road infrastructure demand of replacing conventional diesel heavy-duty port trucks (dTs), with CACC-connected dTs, electric trucks (eTs; 1,000 hp heavy-duty electric/hydrogen-electric trucks), and CACC-connected eTs (eCATs) during an accident-free day (24 hours). To the best of my knowledge, this is the largest analysis of the interactions between heavy-duty truck technologies and road infrastructure in a realistic setting. While the electric trucks I simulated in Chapter 2 are not yet available (the Tesla Semi is now expected for 2023), my results suggest that heavy-duty truck technology improvements could be a substitute for road infrastructure. Particularly, around controversial freight corridors such as I-710, which has taken a disproportionate toll on disadvantaged communities due to the economic activity that it supports, and for decades has been the focus of planning efforts that have been ultimately abandoned due to environmental justice concerns.

In Chapter 3, I built and calibrated a regional freeway network and used an integrated methodology to assess the health, environmental, and environmental justice implications of drayage operations in 2012 and in 2035. My analysis incorporated a regional microscopic simulation model, which I built and calibrated to simulate 24 of accident-free traffic while accounting for projected cargo growth at the SPBP, regional population changes, and regulatory and technological changes. I found that while truck technology improvements and increasingly stringent emission standards are expected to drastically decrease emission rates of diesel HDDTs, replacing the fleet of HDDTs with ZE HDDTs in 2035 would still result in ~$1.3 billion in avoided mortality in 2035 alone compared to ~$5.5 billion in 2012, a reduction in asthma attacks of about 2,142 cases compared to 15,468 cases in 2012, and at least $220 million in climate costs. Moreover, 68% of mortality benefits and 78% of asthma benefits would accrue to disadvantaged communities in my study area, as identified by the designation based on the most recent version of CalEnviroScreen. These findings highlight that while diesel HDDT would continue to seriously harm vulnerable segments of the population, replacing them with ZE-HDDTS would substantially contribute to Environmental Justice in the region. Overall, my results justify implementing a scrappage program for non-ZE-HDDTs and replacing them with ZE-HDDTs by 2035.

In Chapter 4, I explored how active lane management could be combined with vehicle connectivity to absorb the projected growth in drayage traffic by 2035. My methodology used the regional freeway network presented in Chapter 3, and 2035 travel demand data adjusted to represent the projected 145% cargo growth handled by the SPBP. This demand increase is bound to significantly degrade traffic conditions, as also illustrated by Chapter 2 results. I found that while vehicle connectivity alone only provides marginal performance improvements, as reported by the literature (Ramezani et al., 2018a), combining lane management strategies to support the deployment of CACC-enabled vehicles could maximize their contribution to traffic performance and traffic safety.

My results are only as good as my underlying assumptions, the many sub-models in my simulation software, and the data they require (especially OD demand data for 2035). Additional limitations include the uncertainty about the technical characteristics of the technologies I considered, being unable to restrict the number of vehicles in a CACC string, that my simulation is accident-free, and that my simulations do not reflect that electric trucks can almost instantly generate high torque. Additionally, my simulations leave out arterial traffic and truck idling at the SPBP gate and nearby railyards for the regional model, thus, underestimating the magnitude of environmental and health benefits. Finally, another limitation stems from the uncertainty of my emissions and air quality results as these cannot be easily compared against existing inventories due to differences in methods and underlying assumptions.

Future work could explore the traffic impacts of higher levels of automation both for drayage trucks and other types of vehicles as a function of their penetration level and investigate the impact of electric/hydrogen-electric and connected trucks on traffic safety. The effect of traffic impacts due to accidents or mechanical breakdowns would also likely impact environmental and health impacts. Additionally, refining and updating a TCO analysis for drayage trucks serving the SPBP; explicitly accounting for cost and technological uncertainty in the decision of both CARB and drayage truck operators to switch to ZE HDDTs; and analyzing the costs of upgrading the electric grid in support of ZE HDDTs is left for future work.

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