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UNIVERSITY OF CALIFORNIA,
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Impacts of electric highways for heavy-duty trucks

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Civil and Environmental Engineering

by

Mariana Teixeira Sebastiani

Dissertation Committee:
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2020

To my father, Luiz Eduardo, my mother, Marcia, my brother, Henrique,
and my grandmother, Neida.

To Diogo and Luigi, amor.

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ABSTRACT OF THE DISSERTATION

Impacts of electric highways for heavy-duty trucks

By

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Doctor of Philosophy in Civil and Environmental Engineering

University of California, Irvine, 2020

Professor Stephen Ritchie, Chair

The incorporation of alternative fuel vehicles has been essential in reducing emissions in the transportation sector. Particularly to heavy-duty trucks, zero-emission technologies are becoming more attractive. However, batteries and fuel cells still face a long way until they became a viable solution in terms of price, autonomy, weight, and infrastructure. An interim solution is the use of an overhead catenary system, also known as eHighway. The pilot project demonstrated the feasibility of the eHighway system; however, the literature exploring this type of technology is lacking. This dissertation aims to cover this literature gap and propose a new framework to comprehensively explore the aspects of an eHighway implementation in terms of optimal placement, effects on the well-to-wheel (WTW) emissions, and impacts on the power grid. This methodology was applied to a California model using data from the California Statewide Freight Forecasting Model.

First, we defined the optimal eHighway placement to maximize vehicle miles traveled in the system or minimize emissions around disadvantage communities in four different scenarios for the years of 2020 and 2040. This process shows that most

eHighways would be located along the I-5 or close to ports to maximize vehicle miles traveled or in Central Valley to maximize the benefit for disadvantage communities.

Second, we estimated the WTW emissions for heavy-duty trucks according to the truck's fuel type for each of the scenarios with adoption rates from 25% to 100%. The total emissions in terms of CO₂ and NO_x were compared to a scenario without eHighway. All the eHighway scenarios for 2020 and 2040 reduced the total WTW heavy-duty truck emissions. The best-case scenario for 2020, with 500 miles of total eHighway length and adoption rate of 100%, reached a reduction of almost 8% in CO₂ emission and over 20% of NO_x. The same scenario showed a reduction of 16% in CO₂ and 20% of NO_x for the year 2040.

Finally, we analyzed the impacts of the eHighway energy demand on the state's power grid. We showed that some of the systems would require up to 1 MWh of daily energy from some power substations. However, due to the unavailability of public data on California's power grid, we could not draw conclusions in terms of the ability of these substations to handle such demands.

These results show the applicability of the proposed methodology for the deployment and impacts of the eHighway system. Furthermore, although there are other aspects to be considered before large-scale implementation of the eHighway system (e.g., costs), the results presented in this study support the deployment of an eHighway system in California to support the urgent need for making road freight transport more sustainable.

CHAPTER 1. INTRODUCTION

1.1 The impacts of transportation in the environment

As the world develops, a concern of many governments is the impact that high levels of air pollutant emissions, such as diesel particulate matters (PM), nitrogen oxides (NO_x), carbon dioxide (CO₂), have on the environment and the health of the population. This issue can be a more prominent problem to the communities adjacent to high demand freight corridors. According to the United States Environmental Protection Agency (EPA) [1], the transportation sector is the leading source of greenhouse gases (GHG) emissions in the United States, with 28% of total emissions. For 2017 in California, the transportation sector is also the number one source of GHG emissions; however it accounts for over 40% of the total and, within this sector, heavy-duty trucks are responsible for 20.9% of this type of emission [2], as seen in Figure 1. Furthermore, all GHG emissions in the transportation sector only account for tailpipe emissions, excluding the ones emitted during fuel production.

The South Coast Air Quality Management District (SCAQMD), a Southern California air pollution agency, analyzed the emissions in terms of NO_x and stated that within the on-road mobile sources – which accounts for 56% of total sources – heavy-duty trucks are the largest segment, emitting 147 tons of NO_x each year [3].

With an expected 2.4% average annual growth of heavy-duty trucks [4], the California government is making efforts to incentivize the use of alternative fuel vehicles through more than 30 laws and incentives programs [5]. One specific project, the California Sustainable Freight Action Plan [6], is pursuing an improvement in freight efficiency and the transition to zero-emission technologies in the state.

In 2006, California adopted a state law, the Assembly Bill 32 (Global Warming Solutions Act), establishing a program to reduce environmental emissions over the years. After a 2% increase in California's total GHG emission from 1990 to 2015, the initial target

proposed in the law was to return to the 1990 level of emission by 2020 [7]. In 2017, another state law was established (Assembly Bill 398) extending the GHG reduction program to reach at least 40% below the 1990 level of emissions by 2030 and 80% reduction from 1990 level by 2050 [8], [9].

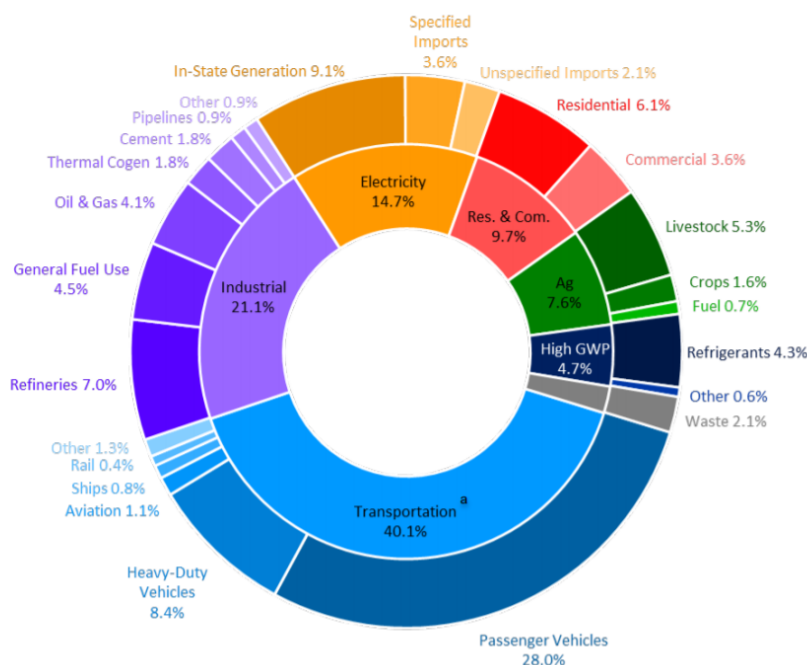


Figure 1. Greenhouse gases emissions for California in 2017 by sector and sub-sector [2]. The inner ring shows the broad sectors. The outer ring breaks out the broad sector into sub-sectors.

The California Air Resources Board (CARB) is a state agency responsible for protecting the population from the harmful effects of air pollution by creating innovative solutions, programs, and actions to fight climate change and reduce GHG emissions in California. CARB estimates that around U\$53 billion will be spent over the next ten years to address emissions on the transportation sector [10].

1.2 Alternative fuel technologies

The leader on freight destination in the United States, the state of California has the fifth busiest airport in the country by total cargo (the Los Angeles International Airport – LAX), the fourth busiest land port (Otay Mesa Land Port of Entry), and three of the five busiest ports (Port of Los Angeles, Port of Long Beach, and Port of Oakland). The Port

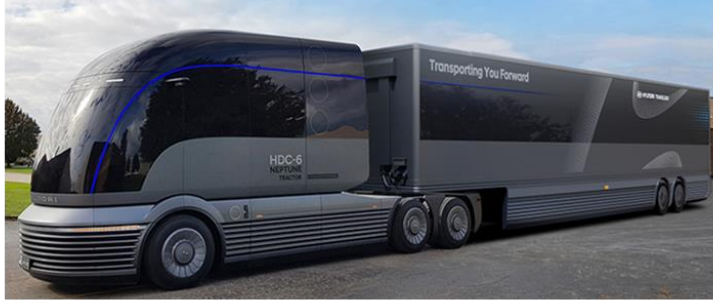
of Los Angeles and the Port of Long Beach together comprise the San Pedro Bay Ports (SPBP) complex. This complex is an essential part of the state's and nation's economies, being the fifth busiest port on the world [11].

Because of this large truck movement in California and the need to achieve the state climate goals, solutions that improve the efficiency of alternative fuel vehicles and their performance become an essential research goal. Alternative fuel vehicles are motor vehicles that operate on a dedicated, flexible fuel or dual fuel, different from conventional petroleum fuels, such as petrol or diesel. There are more than a dozen types of alternative fuel in production or under development such as biodiesel, compressed natural gas (CNG), liquified natural gas (LNG), propane, electricity, hydrogen, blends of 85% or more of methanol, ethanol, among others [12].

Among the zero-emission truck technologies, the two leading fuel options are hydrogen fuel cells and electricity [13]. Fuel cells powered by hydrogen have become an attractive technology where the hydrogen powers an electric motor, and the only emission out of the tailpipe is water. Because of its potential benefits to the environment, some companies, such as Hyundai., Nikola, Cummings, and Toyota [14], [15] are starting to develop prototypes of hydrogen fuel cell trucks (not yet in the market) and plan to have a larger fleet in approximate five years (Figure 2).

Likewise, full electric trucks also have an electric motor (powered by electricity) that creates a zero-tailpipe emission vehicle and are also sparked the interest of truck manufacturers, such as Tesla [16], Daimler Trucks [17], Mercedes-Benz [18], among others Figure 3. The race here is to develop a battery with a large range (minimizing the need for refueling infrastructure) but light at the same time.

Both of these technologies are promising and popular. However, there are still challenges that need to be overcome for wide-scale development and market injection, for example, the high initial costs (which will be solved with higher volumes) and insufficient driving range. There are two ways to cope with the insufficient driving range: development of a strong fueling infrastructure or extending the driving range itself.



(a)



(b)



(c)

Figure 2. Example of hydrogen fuel cell trucks. (a) HDC-6 Neptune by Hyundai, (b) Nikola ONE by Nikola Motor Company, and (c) Hydrogen truck by Cummins Inc. None of these trucks are currently available in the market but are planned to be sold in the near future.



(a)



(b)



(c)

Figure 3. Example of battery-electric trucks. (a) eActros by Mercedes-Benz, (b) Tesla Semi by Tesla Inc., and (c) eCascadia by Daimler AG. None of these trucks are currently available in the market but are planned to be sold as soon as 2021.

For infrastructure development, there is a dilemma. While those developing the infrastructure are waiting for fleet growth to make it a viable business, companies that will use such infrastructures are waiting for enough fueling locations for minimal daily operations to be implemented before growing their fleet of electric trucks. Governmental or truck manufacturer's initial investment may be necessary to solve this issue [19].

Extending the driving range can be obtained by increasing the capacity of the electric batteries or hydrogen tanks carried by trucks, hence reducing their dependency on the fueling infrastructure [16], [20], [21]. However, here the problem falls into the size and weight of the batteries/tanks. The major issue of having a large and heavy battery in a truck is the significant reduction in the payload of the vehicles, resulting in a financial loss to the transport carriers. Moreover, the increase in truck weight will also increase the required torque, which will consume more energy from such batteries (somewhat of a vicious cycle) [22]. Boltze (2019) gives an estimated of how heavy a battery for a full-electric heavy-duty truck using current technology would need to be. For example, assuming the energy consumption of the truck is 2.37 kWh/mile, a 40-ton truck traveling around 500 miles with one charge would need approximately 1,700 kWh. To guarantee enough energy for this trip, a lithium-ion battery with an energy density of 90.7 Wh/pound would weigh about 9.37 tons [23]. In California, the maximum gross weight for an entire vehicle is 80,000 pounds (40 tons) [24]. That means the battery alone would account for about a quarter of the entire truck. Another issue is related to the emissions embodied in the production of the battery. For larger and heavier batteries, the environmental implications during the production are greater compared to the small and traditional batteries for electric vehicles [25].

Even with the technology progress on new batteries, the need for charging stations will continue to exist, and investing in this infrastructure can be costly [26]. Overall the investments in both technologies have grown considerably in the last few years; however, their performance and feasibility for heavy-duty trucks remain unclear [27], [28].

1.3 Electric road system

Given that there is also a trend of incentives toward the use of renewable sources for power generation, it makes sense to explore other solutions that use electricity for freight transportation. Besides using on-board storage truck technologies, as mentioned before, there is another group of vehicles that are powered by external energy supply. In this case, the trucks are charged during their ride using an electric road system (ERS) [29].

ERS is a technology in which the electric power is transferred from the road to the electric vehicle while the vehicle is moving. The ERS consists of five main subsystems [19], [30]:

1. Energy supply: is the power transmission process that delivers energy over long distances to the grid that will power the ERS substations.
2. Road: involves the pavement, barriers for safety and noise protection, and other auxiliary components such as road signs.
3. Power transfer: consists of three components: road power transfer (road equipment that detects the vehicle has attached to the system and initiates the power transfer), vehicle power transfer (controls the power safely received by the vehicle), and the control component (monitors the energy handover and system operation).
4. Road operation: is the energy management of the overall system, handling and controlling access to the ERS lanes of the road based on vehicle identification (optional).
5. Vehicle: converts the receiving power into the vehicle propulsion or stores the energy into the battery. It also provides user information, vehicle positioning, and supports fleet management.

Due to this almost direct path from energy production to vehicle propulsion, the ERS systems can be more efficient (less energy loss) than other zero-emission options, as shown in Figure 4, using data presented by Siemens based on Germany's infrastructure. These data show that from 100 kWh energy production, an ERS vehicle

outputs a range of 60 km with an overall efficiency of 77%, where only 4 kWh are lost when the energy reaches the vehicle. The battery-electric trucks have a similar pathway where the energy goes from the source directly to the grid and then to the truck's battery; however, it only outputs a range of 48 km with an overall efficiency of 62%. This lower efficiency comes from the energy losses when charging the battery by transforming electrical into chemical energy. Finally, for both the hydrogen and natural gas trucks, the energy pathway is more complicated, ending up in various energy losses during each step of the process. In the end, the two technologies present efficiency of only 29% for hydrogen and 20% for natural gas, with a range of 24 km and 17 km, respectively. Figure 4 also presents the use of energy in terms of cost per kilometer in cents of Euro, where ERS has the lowest cost at 19 cents/km, followed by 20 cents/km for the battery trucks, 55 cents/km for hydrogen truck, and 70 cents/km for natural gas trucks [31].

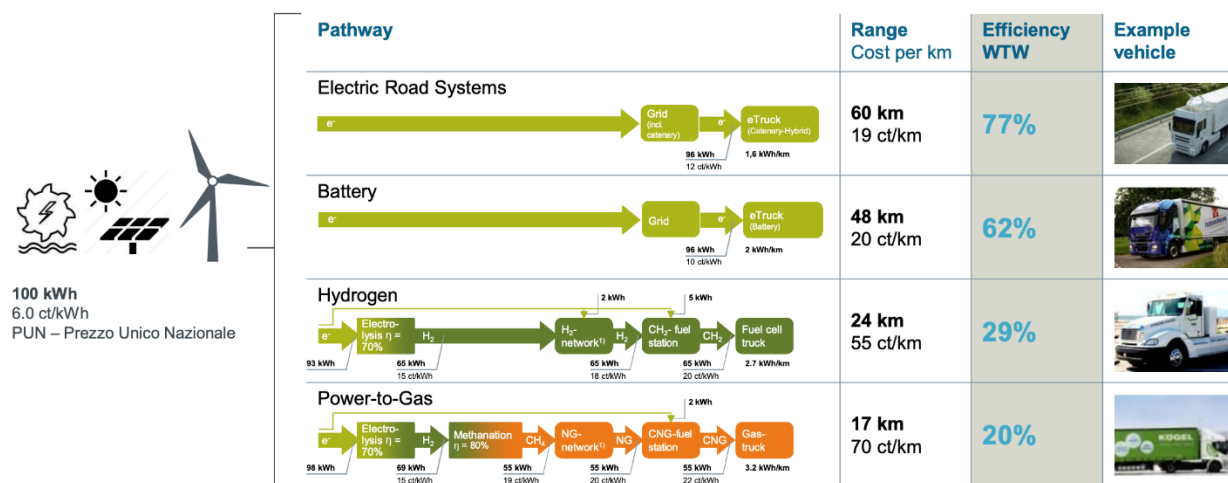


Figure 4. Alternative fuel vehicles efficiency comparison [31]. The data were based on Germany's infrastructure and compared the range, cost per kilometer, and well-to-wheel (WTW) efficiency for ERS, battery-powered, hydrogen, and power-to-gas trucks.

Currently, there are three types of ERS: ground-based contact line (also known as conductive rails), inductive power supply (a wireless solution), and overhead contact line. Figure 5 illustrates these three types of ERS [30]:

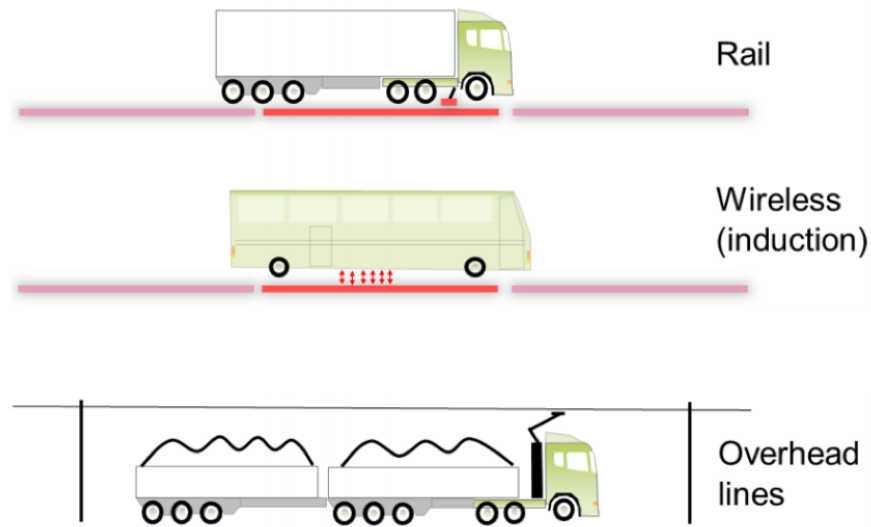


Figure 5. Three electric road system concepts. (Top) the rail system with conductive rails on the road, (middle) induction solution with wireless power transmission, and (bottom) overhead lines with catenary and pantograph system.

The conductive rails system uses an electric rail on the road to power and recharges the truck through a power receiver pick-up arm installed under the vehicle. The arm detects rail's location and, once the vehicle is above it, the arm goes to a lowered position. It stays that way while there is a rail underneath the truck. When overtaking or changing roads, the arm is automatically raised. The rail that is connected to the power grid also enables the vehicle's batteries (when available) to be recharged [30]. In April 2018, Sweden opened the first public demonstration of this kind of technology. The 2 kilometers (1.24 miles) test track was installed along public road 893 between the Arlanda Cargo Terminal and the Rosersberg logistics area outside Stockholm. A consortium comprising several companies from Sweden is managing the project, aiming to generate knowledge, experience, and real data that could lead to an expansion of the system in other locations [32].

For the inductive power supply solution, the system uses a magnetic field coupling between two conducting coils (a transmitting coil installed in the road and a receiving coil installed beneath the vehicle) to transfer the power from the road to the vehicle. Even though this technology seems more current, the first research was conducted by UC

Berkeley in the 1990s [33]. However, due to limited technology at the time, the vehicle range output was low compared to a large amount of energy used, resulting in low efficiency. This study was followed by a shuttle service charged wirelessly in the Utah State University in 2016. After a couple of years of testing, the fully electric 20-passenger bus achieved an efficiency greater than 90% from the power grid to the battery [34]. There have also been several other projects in Europe (France, Italy, Germany, Spain), one in South Korea, and one in Israel [35]–[38]. All of them were able to achieve efficiency over 80% from the power grid to the battery; however, most of them are designed only for buses or passenger cars. The only exception is the Bombardier's PRIMOVE in Germany that performed tests with a hybrid electric truck on a test track. The truck was found to be able to be inductively supplied with approximately 183 kW, with 89% energy power transfer efficiency [39].

The overhead contact line uses a conductive line (also known as catenary) to transfer power to receiver devices installed on the top of the vehicles. This technology is similar to that used for many years in some trains and trolleybuses. An important element of the system is an intelligent pantograph on the trucks that enables it to connect and disconnect from the catenary at high speeds. Since this system is height dependent, it aims to serve only similar size vehicles, in particular trucks, unlike the first two concepts that could also serve passenger vehicles at the same time. On the other hand, the overhead system does not demand a larger constructional intervention in the road surface, that would equate in more expensive initial costs and longer installation process (that could not be feasible in situations with no alternative route) [40].

With that in mind, Siemens developed the eHighway, an overhead catenary system that allows electric and hybrid heavy-duty trucks to power an electric motor and recharges their batteries as they drive. The trucks are equipped with a pantograph that automatically connects and disconnects from the catenary wires. The eHighway can be installed by upgrading existing roads, without the need to develop new costly routes. And when equipped, the road remains fully accessible to all the road users. The overhead catenary is a robust technology with comprehensive experience from the railway, tram, and trolleybus operation.

The remaining of this work will focus on these eHighway systems, looking at optimal placement, potential emission reductions, and impacts on the power grid.

1.4 Research objectives

The discussion on the previous section explored concerns about the impact the transportation sector, in particular heavy-duty trucks, on the environment. It also discussed how advances in alternative fuel technologies could lead to significant improvement in emission production. Among the new technologies, the electric road system (ERS) is gaining ground as it presents benefits in terms of efficiency and is not limited by charging time, charging infrastructure availability, and driving range restriction that battery-electric trucks have.

Gustavsson et al. (2019) state that between the three main ERS concepts, the overhead line concept is currently the most mature technology, with few system prototype demonstrations ongoing in an operational environment around the world [30]. However, the literature in this technology is still limited, and we have no knowledge of a specific study conducted on the best placement for deploying an overhead catenary system and its effects on the power grid and emissions. Therefore, the main objective of this study is to cover this literature gap, evaluating different aspects of deploying an eHighway system in California. More specifically, it will address the following questions:

- Where is the optimal placement and length to deploy an eHighway system in California? Here, we assume different scenarios (target years), multiple main objectives of the project (reduction of local emission in disadvantage communities or maximum emission reduction statewide), and eHighway characteristics (minimum section length and total eHighway mileage deployed). We aim to identify which roads are more suitable and present the most beneficial for an eHighway implementation in the state.
- Is there an emission reduction once the eHighway is deployed? Considering a well-to-wheel (WTW) analysis is crucial to measure all the emissions related to electric trucks, from energy production to energy consumption. Therefore, for each of the

scenarios studied, we estimate total emissions per pollutants locally (where the system is deployed) and statewide. We also present an analysis looking at the effects of a range of adoption rates.

- What are the impacts on the power grid with the implementation of the eHighway? Can the current grid handle the extra electric energy demand? We present an energy model for the eHighway system to estimate the energy consumption of all the vehicles in the network. With this model, we can calculate how much energy is being pulled from California's power grid at specific power stations. We then evaluate if the current system would be able to support the new load created with the deployment of the eHighway system.

1.5 Outline of the dissertation

To answer the questions mentioned above, we developed and shared a methodology to optimize and evaluate the implementation of eHighway systems in California.

Specifically, in CHAPTER 2, we define the concept of the eHighway system, explaining how it works and describing its main characteristics. Currently, four different countries have tested or are in the process of inaugurating pilot projects of eHighway systems. Each demonstration is described in this chapter, stating their status, initial results, and next steps. As it is still a relatively new technology, the research is limited. However, studies are indicating the potential of the eHighway system and discussing their main technical and design features. We review these studies and present state of the art for eHighway systems.

CHAPTER 3 includes a comprehensive overview of the California Statewide Freight Forecasting Model that provides an analysis of freight movements at the statewide level. We present the methodology used in this study to aggregate, filter, and order the quarter-million road segments found in the model. We explore the volume and vehicle miles traveled in the processed model and use these data throughout the remaining of this study from the eHighway road selection, emissions estimation, and the power grid impact analysis.

In CHAPTER 4, we proposed an optimized way for selecting the roads that are suitable to deploy the eHighway system using multiple target years (2020 and 2040), objectives (reduction of local emission in disadvantage communities or maximum emission reduction statewide), and eHighway characteristics (minimum section length and total eHighway mileage deployed). We presented and discussed the selected eHighways location and length for a total of eight proposed scenarios, the total vehicle mile traveled covered in each of them, and the proportion of each of the fifteen commodities in the eHighway network.

In CHAPTER 5, a well-to-wheel emission analysis is introduced and applied to estimate the CO₂ and NO_x emissions for each scenario presented in the previous chapter. The heavy-duty trucks are divided into eHighway trucks and non-eHighway trucks (based on current and forecasted California's fleet mix) and, for each group, the well-to-pump and pump-to-wheel emissions are calculated. We discussed the main findings of this analysis, presenting the total emissions for heavy-duty trucks in the model for each scenario and comparing them to a base scenario where no eHighway was implemented. More specific analysis of the scenarios with eHighways closed to the disadvantage communities was also presented to estimate local pollution in those areas.

In CHAPTER 6, we give an overview of the characteristics of the California electric grid and power sources and introduce a methodology to calculate the additional loads in California's substations to supply the energy necessary to power the eHighway system. We show that the eHighway system may demand over 1 MWh of energy in one day from a single station. We also discuss how this methodology could be applied to understand if the current grid can support the eHighway implementation.

CHAPTER 7 reviews the main contributions of this work and discusses directions for future research.

CHAPTER 2. ELECTRIC HIGHWAY

2.1 The eHighway by Siemens

In 2012, the first overhead wire system project was presented by Siemens, which included a completed solution with trucks and electric infrastructure. The system named “eHighway” (standing for electric highway) is the solution that reached the furthest in terms of development and feasibility compared to other ERS solutions [41]. According to an interview conducted by Moller (2017) with Siemens, the company considered different concepts that electrified the vehicle, and the overhead wire turned out to be the most promising system [42].

The eHighway is a system that combines characteristics of resource-efficient railways with the flexibility of road transport. It is an electrified corridor that uses overhead wires to get power into the electric motor and the truck’s battery simultaneously. In contrast to the conventional hybrid electric trucks, the eHighway trucks can charge in transit when encountering an electrified road, operating then in a pure electric way. First, a sensor embedded in the truck checks whether the electric lane is equipped with contact lines (Figure 6a). If so, the truck raises its pantograph, connecting it to the lines. The overhead lines are continuously supplied with electric energy by substations (Figure 6b). The energy transfers directly to the electric motor and charges the battery in parallel for off-line sections (Figure 6c). When overtaking another vehicle or at the end of an electrified section, the pantograph lowers itself to a safe position [43] detached from the overhead lines.

Also, whenever the truck is not connected to the catenary, it can use the energy stored in the battery or its conventional diesel (or other alternative fuel) engine to power itself. Another feature of this technology is the possibility of using the regenerative braking system, in which unused braking energy is fed into the onboard energy storage or back into the grid to be used by other connected trucks [44]. It is also worth mentioning that parallel developments in battery-electric trucks that could be seen as a competing

technology would increase the overall efficiency of this system on non-electrified sections [45].

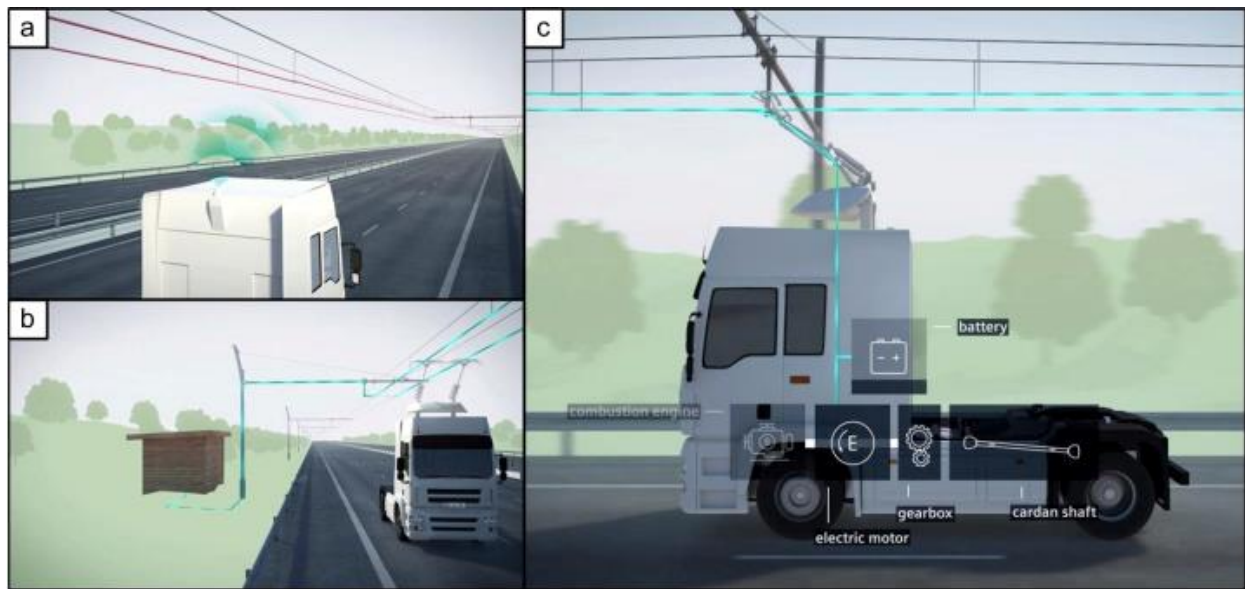


Figure 6. eHighway functionalities. (a) contact line detection, where the truck sensors find the electrified lines. (b) substation that provides energy from the grid to the overhead lines (c) power flow, with energy going from the overhead lines to the electric motor and the battery in parallel [43].

Boltze (2019) states that in the current situation, after driving for a given distance on a catenary section, it is assumed that the truck could drive at least the same distance on its storage battery [23]. Therefore, the system can be adaptable to different situations, such as bridges, interchanges, tunnels, and low clearances – avoiding infrastructure difficulties. Other traffic operations such as changing lane, overtaking other vehicles, or performing an evasive maneuver are also executable by detaching from the overhead lines. After implementing the eHighway system, the road – including the electrified lane – remains fully accessible to all the road users.

In this study, our focus is the eHighway application of heavy-duty trucks (long or short haul) on a freeway network. However, this system can also be applied to shuttle transportation for short distances (inside a port, for example) or in an electrified mining transport, connecting pits and mine to storage locations.

There are no concessions on truck availability (no decrease in axle weight rating and load capacity) and performance (trucks can reach up to the maximum highway

speed). The eHighway offers flexibility in terms of vehicle type (different axle sizes), different sources of on-board electricity (battery or fuel cell), different sizes of combustion engine (for hybrid trucks), and non-electrical energy sources (when they are not connected to the catenary system) [43], [46].

The eHighway presents the following core features [43], [45], [47]:

- 1) Vehicle: various truck types or manufactures can be enabled to utilize the eHighway system. Some modification and adaptations, although, are needed:
 - a) Active pantograph: this intelligent pantograph, installed on the roof of the truck, can connect and disconnect the vehicle to the lines ensuring a steady connection at all speeds and regardless of the road conditions. It is generally composed of a lower arm, an upper arm, a pantograph head, and connections between them, as illustrated in Figure 7. The pantograph transfers the energy from the overhead lines to the electric motor on the truck. There is a sensor that automatically adjusts the position, compensating any lateral movements from the truck. It also compensates for any vertical movements of the vehicle due to potential height variations or bumps in the road.



Figure 7. The eHighway pantograph. It is used to transfer the energy from the overhead lines to the electric motor on the truck [47].

- b) Drive system: the eHighway system can be adapted to different configurations – parallel-hybrid, serial-hybrid, or full-electric. This drive mode ensures the system

flexibility by covering the first and last mile or any other non-electrified part of each journey.

- c) Energy storage: the system is also designed to take advantage of the regenerative braking, allowing unused braking energy to be stored in their internal batteries or fed back into the grid.
- 2) Power Supply: the electrical infrastructure system is based on mature rail electrification technology and consists of:
 - a) Substation: installed along the way, they provide a constant power supply to the system. They are designed as containers, prefabricated at the factory, and placed near the eHighway roadway. They are connected to the medium-voltage power grid, and the voltage at the catenary is around 670 V DC.
 - b) Contact line: a specially designed two-pole contact-tine system ensures a secure energy supply to the trucks at speeds of up to 90km/h (55mph). The line is suspended by cantilever arms that are attached to tall poles (Figure 8). The pillars are mounted along the road at a distance of 160 ft to 200 ft to each other. They can be adapted to curves, bridges, or freeways entries and exits.



Figure 8. The eHighway contact line. A specially designed two-pole contact-tine system ensures a secure energy supply to the trucks [48].

- 3) Driveway: is the existing roads. However, some additional requirements are needed to guarantee safety, such as crash protection for the poles and substations, and a traffic management system control to supervise any abnormality.

- 4) Operation: the eHighway also requires an operation and control center (OCC), like any rail electrification system. From the OCC, maintenances can be programmed and monitored for a specific area or the overall system. The OCC can also be used for measuring and billing the energy consumption of each truck.

According to a Siemens report [47], in general, the eHighway has been able to achieve an efficiency of around 80-90%, depending on the size and materials of the power cable, vehicle's speed, etc.

Although it is a promising technology, there are some disadvantages to the overhead line systems. Unlike the two other ERS concepts (conductive rail and wireless induction), the catenary cannot be used by passenger cars since the height distance between the lines and the pantograph requires a vehicle with a minimum height. The various cables and poles can make this system aesthetically unattractive and somewhat old-fashioned. They are also a possible safety hazard that needs to be regulated, such as substation security and the wire's height, so that only vehicles have access to them – not humans or animals [30].

2.2 Pilot projects

Similarly to the United States, and in particular to California, Europe has been setting heavy goals to become less dependent on fossil fuels and fighting towards alternative fuel heavy-duty vehicles to reduce overall emissions. In Germany, for example, the government set a climate protection plan to guarantee a 45% reduction in GHG emissions by 2030 compared to 1990 levels, reaching zero emissions by 2050 [30].

In line with these worldwide actions, Siemens has partnered with governments to begin testing the eHighway technology in some countries using pilot projects. These pilot projects are intended to bring experience and knowledge about the system in a real highway, revealing potential issues, difficulties, and other aspects that were not encountered during the typical test phase. The information gathered will help to conclude if the system is suitable for future commercial use and worthy of further expansion. They

are also a way to present the new technology for potential investors and to the general public.

This section reviews the demonstrations that have been undertaken, finalized, or are still ongoing worldwide. The first pilot project was implemented in Sweden in 2016, followed by an American project in California in 2017. Germany has also implemented an eHighway in 2019 with two others to be inaugurated soon. Finally, Italy announced in 2018 the inauguration of a new project.

2.2.1. PILOT PROJECT IN SWEDEN

In June 2016, the world's first eHighway system on a public road was inaugurated in Sweden. The overhead catenary system was constructed on a 2 kilometer stretch of the E16 highway north of Stockholm. The contract was awarded by the Swedish Transport Administration to the County Council of Gävleborg and was set to last two years. The project had the collaboration with the truck manufacturer Scania – that provided 2 Euro 6-certified hybrid diesel trucks that were adapted to operate under the catenary. Figure 9 shows the 8-ton truck on the eHighway trial project. It has a lithium-ion battery of 5kWh that gives a driving range up to 3 kilometers when not connected to the eHighway [49], [50].



Figure 9. Euro 6 hybrid diesel truck driving on the eHighway in Sweden [50].

After the two years, Siemens was expected to release a report with the results and finding for the project. However, to our knowledge, there is no official report about this specific trial. Even though there is no study on this particular eHighway system (neither from the company nor a third-party research group), there was extensive media coverage since its inauguration as it was the first eHighway to open in the world.

2.2.2. PILOT PROJECT IN THE UNITED STATES

Siemens and the South Coast Air Quality Management District (SCAQMD) inaugurated a pilot project of the United States' first eHighway in July 2017. This demonstration was developed to evaluate the feasibility of the technology and test various technical components. The catenary system was built on a one-mile bi-directional stretch of Alameda Street in the city of Carson, CA, which is a major truck route that serves the ports of Long Beach and Los Angeles (Figure 10). The project also focused on installing a power supply substation and testing three different configurations trucks, all of them equipped with a pantograph [43], [51].



Figure 10. Alameda Street eHighway pilot project. (Top left) shows the three trucks adapted to run on the eHighway system, (top right) shows one of the trucks driving along with the system next to regular traffic, (bottom left) shows an aerial view of the catenary system, and (bottom right) highlights the pantograph engaged with the catenary [51].

For this demonstration, three different truck configurations were tested: a serial hybrid with CNG range extender, a full electric configuration with batteries, and a parallel hybrid with a diesel combustion engine. The first two configurations were integrated into a Navistar truck and operated by Transpower. The last one was integrated into a MACK truck and operated by Volvo.

While the project execution was underway, they encountered some undocumented utilities, that required a new design, permits, approvals, and other additional constructions. These difficulties delayed the project in one year and shortened the testing run from twelve months (initially intended) to six months (from July 2017 to December 2017). This reduction was necessary because the operation license could not be extended [43].

On the 2018 final report for Alameda Street [43], Siemens concluded that, despite these issues, the viability of the eHighway implementation, with the class 8 trucks operating without any tailpipe emissions and proving to be a suitable option for a zero-emission road freight transports.

This US\$ 13.5 million project was funded by the SCAQMD (US\$ 2.5 million), China Shipping (US\$4 million), California Energy Commission (US\$ 3 million), Port of Long Beach (US\$ 2 million), L.A. Metro (US\$ 2 million), and Siemens.

Siemens reported that they intended to collect data and evaluate the benefits of the eHighway in the U.S.[47], however, to our knowledge, no results have been published yet regarding the collected data (only the technical report [43]).

2.2.3. PILOT PROJECT IN GERMANY

In Germany, the Federal Ministry of Environment, Nature Conservation, and Nuclear Safety are financing three field tests on public roads. Those project's main goals are to test possible complications during the construction and operation phase, as well as to collect data that could be relevant for a potential expansion of the system. Although the actual value varies from source to source, the Ministry of Environment is spending around 50 million euros (approximately 55.2 million dollars in 2020 conversion) on the three

projects, plus other investment costs coming from Siemens for the pantograph, the truck manufacture Scania, Entega AG as the electricity supplier, and several other transport partners [23], [52].

The ELISA (ELEktrifizierter, INnovativer Schwerverkehr auf Autobahnen that translates to electrified, innovative heavy vehicle traffic on motorways) was the first demonstration to be inaugurated in May 2019. This project, led by the Road Authority Hessen Mobil, is located between the cities of Darmstadt and Frankfurt on motorway A5 (Figure 11).



Figure 11. The ELISA pilot project in Germany. (Left) Map showing the location of the ELISA test track between Frankfurt Airport and Darmstadt, and (right) picture of the implemented catenary system.

The highlighted highway has four lanes in each direction, with an average of 135,000 vehicles per day, in which 10% are heavy-duty trucks. The catenary system is 5 kilometers long (3.11 miles), with 229 poles and two substations. Unlike the pilot project in California, the ELISA implemented the catenary on the rightmost lane in both directions. Five companies transporting different goods were selected to test one vehicle each on the eHighway system. Two of them are already using the test track since its inauguration as the remaining three are scheduled to deliver the trucks by February and June 2020. All of the companies are using (or will be using) heavy-duty trucks and are taking a

minimum of three daily trips. In addition to the companies, some truck manufacturers will be using the test track as a research field for their trucks c.

The ELISA project will be open until 2022 when the German government will do a final evaluation of the system performance. One of the main questions to be evaluated is concerning the emissions reductions and local levels of noise and air pollution when operating eHighway trucks in a real environment. Another important issue to be analyzed are the impacts on the traffic flow, such as driving behavior, lane choice, and flow speed.

Other road operations are concerning the visibility of the traffic signs (the overhead lines can occlude them) and the potential impact on traffic safety. For some of these questions, a preliminary survey was conducted (although the number of people taking the survey was not published), and the results showed that 96% of car drivers are not changing their driving behavior because of the catenaries, even though they are feeling somewhat insecure on those special lanes. Around 87% of the car drivers had no problem with reading the traffic signs; however, 4% stated that they felt strongly disturbed by the overhead lines. Another test using loop detectors on the road showed that there is none or very limited influence on the lane choice because of the eHighway infrastructure. Other results are being analyzed and are expected to be released by the end of this phase in 2022 [23].

The next steps on the research project include demonstrating the system prototype in an operation environment (from 1 to 5 years), the completed system quality certification, and operation of the final system [23].

Two other eHighway projects in Germany are currently under construction. The FESH (Feldversuch eHighway Schleswig-Holstein translated as Field Test eHighway Schleswig-Holstein) being installed on the motorway A1 near the city of Lübeck in the state of Schleswig-Holstein, which is a 10 kilometers test track that is planned to open between 2020 and 2022 [53]. And the eWayBW, which will equip 6 kilometers of the federal road B462 near the city of Kuppenheim in the state of Baden-Württemberg with overhead lines. This project, unlike the other two, is being implemented on a main road (instead of a highway), which will bring some different construction components that will

serve as a pilot for other types of applications. Once the planning and construction phase is completed, the operation phase starts and is programmed to last from 3 to 4 years [54]. The map in Figure 12 shows the location of the three current eHighway systems being tested/implemented in Germany.

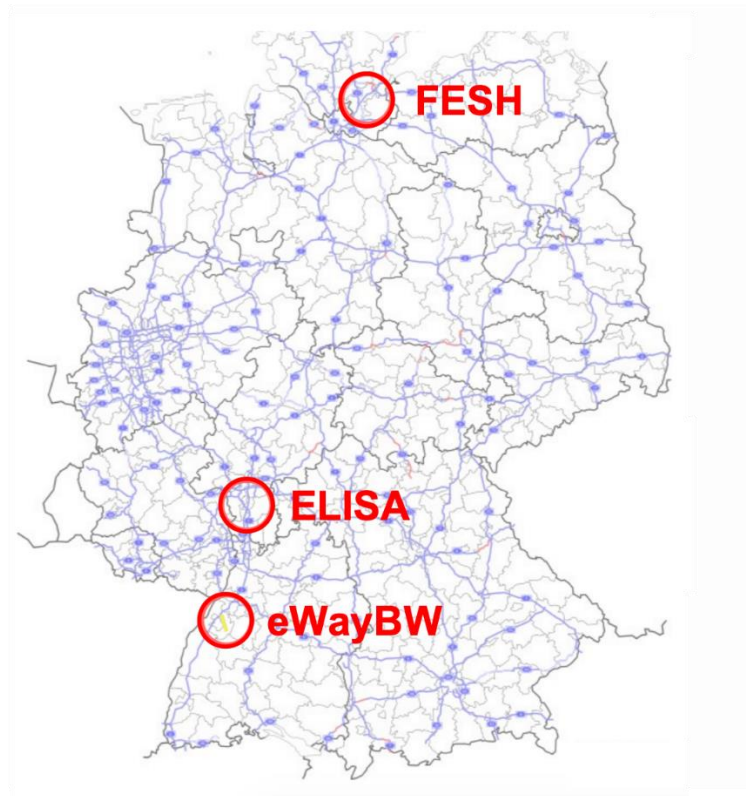


Figure 12. Map with the three pilot projects in Germany [55]. ELISA is already deployed, and under testing, FESH will be inaugurated between 2020 and 2022, and eWayBW does not yet have an inauguration date defined.

2.2.4. PILOT PROJECT IN ITALY

Following the example of the other trials, in September 2018, Italy announced the construction of a new eHighway in the country. The A35 Brebemi autostrada (in the northern part of the country) connects Brescia, Bergamo, and Milan, three main cities in Lombardy's region. The project united national and local politicians, with representatives from Scania, Siemens, and some local partners. The trucks, supplied by Scania, are the same hybrid models used in the Sweden and Germany pilot projects that were launched in 2016.

In the first part of the demonstration, the catenary technology will be installed in a 6 kilometers stretch of the A35 Brebemi between the commune of Romano di Lombardia and the city of Calcio in the province of Bergamo. The final stage of this project involves electrifying 62.1 kilometers of the highway and install solar panels along the road to power the eHighway. Since the whole system will be electrified with renewable energy (solar energy), the ultimate goal is to become the first “zero impact” eHighway in Europe [56], [57].

Since its announcement in late 2018, there has been no published reports or any updates on the progress of this project

2.3 eHighway cost analysis

An essential part of implementing any new transportation system is analyzing the overall economic feasibility. Some of the already implemented pilot projects have released the total amount spent on the eHighway construction, but there is still some discrepant between those values among the different sources. The United States project estimated the costs to be around 5.7 million dollars per mile before its construction [58]. However, due to several issues encountered during the construction, the actual amount was approximately 13.5 million dollars for the one-mile bi-directional eHighway [43]. The ELISA demonstration in Germany costs around 2.43 million euros (or 2.72 million dollars using the average conversion for 2019) per mile plus other investments in truck manufacturing [23]. This substantial price difference between projects (even before the added costs during construction in the United States) may be justified by the reduction in cost when building longer stretches of eHighway as the one in Germany, proving that larger-scale projects offer potential to reduce infrastructure costs.

Due to the lack of information available, a detailed cost analysis is not feasible and is out of the scope of this dissertation. However, these results can give a rough estimation of the total costs of an eHighway implementation. A more comprehensive analysis that includes the direct costs (feed lines, substations, poles, catenaries, guard rails, etc.) and

the indirect costs (vehicle and infrastructure maintenance, fuel costs, etc.) needs to be conducted before the deployment of an eHighway system.

2.4 Literature review on eHighway

Since this is a relatively new technology, limited research has been done in this field, especially considering the potential impacts on the electric grid, emissions, and traffic flow. However, this section will provide a synthesis of the initial research covering the overhead catenary system. Moreover, the articles and reports on this subject are mainly limited to the specific aspects of the eHighway, such as design and technical analysis, infrastructure characteristics, or details of any particular road.

Arkeman et al. (2016) [59] rings a detailed report about the technical details on the eHighway system, covering some initial results when the technology was in the testing phase inside Siemens. However, the study did not present deepening on the impacts of the eHighway system, such as grid effects, emission, or energy consumption. In the same line, a research conducted by Siemens, the Technical University of Dresden, and the Federal German Highway Research Institute (2016) [60] tested different safety issues and other technical adjustments on the infrastructure and vehicles performance, such energy supply and grid connection. This work recommended moving the positioning of the poles and wires, reducing the masking effects on traffic signs, as well as altering the type, combination, and location of road barriers minimizing the effects of a crash.

Several Master's degree theses considered the electric road system (ERS), including the eHighway, as an option for reducing emissions. Singh (2016) conducted a study at the Royal Institute of Technology in Sweden, evaluating three different ERS technologies from an environmental and economic perspective [61]. The results indicated that the overhead catenary system has a low investment cost compared to the other technologies, however because of its restriction to specific heavy-duty vehicles, the emissions do not have an impact as pronounced as the other systems. The study also concludes that the overhead road technology could be implemented on specific road

sections (versus electrifying the entire road) where there is an intense demand for heavy-duty trucks, minimizing costs when compared to other systems.

The same institution published another work in 2017 [42] assessing available ERS and comparing them in selected categories, such as construction measures, efficiency, cost, safety, maintenance, and vehicle. The data collection relied on the literature review and interviews with experts on each technology. However, because of data availability and many uncertainties, most of the comparisons did not achieve any conclusion. The eHighway had the best performance compared to the other ERS concepts on the efficiency aspect. The results were qualitative, with limited data to support their claims.

Jelica (2017) presents in this master's thesis a case study using an hourly traffic pattern model for a 323 kilometers long route in Sweden, investigating the energy use and CO₂ emissions with an ERS (although it is not specified which type of ERS would be used) [19]. Some assumptions had to be made to achieve the results, but the model showed that with the current traffic levels in that route, the implementation of ERS would electrify 4% of the annual traffic volume in Sweden and reduce the CO₂ emissions by 5.3%. Finally, the study also shows that if the ERS is implemented in 2 or 3 highways at the same size as the case study, the technology will achieve the environmental goals set by the Swedish government in the transportation system for the years of 2030 and 2045.

Another master thesis finalized in 2018 in the Purdue University [40] analyzed the market adoption and the criteria pollutants and greenhouse gas emissions of the ERS. The study includes a survey of the general population in Los Angeles, California, to determine the driver's intentions of driving on electrified roads and purchasing electric vehicles. The level of adoption was then identified through the results from the survey and divided into three groups: early adopters (corresponding of 48.5%), mid-adopters (27.67%), and late adopters (23.83%). The emissions for light-duty vehicles were estimated using available California's data for those adoption levels. The results showed that ERS has the potential to provide emission reductions of 4 to 24%. Even though the results seemed promising, the scope of the project did not include the use of heavy-duty trucks.

The last master study on eHighway was conducted at the University of California, Irvine, and proposed analyzing the changes in congestion and emissions after the creation of electrified truck lanes on I-710 [62]. For different scenarios of eHighway trucks' demand, the results showed a significant reduction in the emission. However, the research did not account for the WTP emissions, which can have a great impact on emissions depending on the electric power used to electrify the trucks. The study also indicated that congestion was reduced after building the catenary lines, but is considered the eHighway as an exclusive lane implemented on the right lane of the road, which is not how the system was proposed to be implemented by Siemens.

There are two other reports about ERS [30], [63] that provide a thorough system description, highlighting the several ongoing studies and demonstration projects of this technology around the world. Both studies present the advantages and disadvantages of each ERS concept, including the overhead catenary system. The main goal of them is to provide a state-of-the-art description and report the findings and updates for interested readers; however, there are no novel results presented in these studies.

Another technical report outlined the state-of-the-art strategies for zero-emission trucks, and the eHighway is cited as a promising one [64]. The study provides an estimation of the eHighway's truck energy consumption and the energy cost per kilometer. It also projects the maintenance, fuel, and production costs of different types of trucks, approximating the values for the European market. However, at the time this report was written, 2013, the eHighway technology was not fully studied and implemented, therefore most of the data presented were based on estimation and outdated.

In another research, the overhead catenary system implementation is considered in two roadways, the I-710 and SR-60, both in California, United States. It presents forecasted demand and electricity consumptions for 2020 and 2030 in three scenarios: the "in line with current adoption" based on anticipated market growth, the "aggressive adoption" based on aggressive new incentives and regulations, and the "in-between" that fall somewhere between the first two adoptions. The results were estimated based on the

annual average daily traffic (AADT) for 2009 to 2011. Once again, the study was conducted with scarce real information about the eHighway system [65].

The South Coast Air Quality Management District (SCAQMD) presented the eHighway, through the 2018 Clean Fuel Program [66], as one of their strategies to encourage clean fuels and advanced mobile source technologies. Other papers also cite the eHighway as a viable solution for zero-emission transportation road and rapidly discussed future projections of electrified freight roads [67]–[69]; however, they did not present new data or novel information on the eHighway system.

Boltze (2019) published a paper that was entirely focused on Germany's eHighway pilot project ELISA. It described the system, the research program for the field test, and its main characteristics, such as road location, infrastructure construction, and test vehicles. Yet, since the demonstration started in 2019 and the work is still in progress, the paper was a progress report, discussing the approaches to make this transport sector more sustainable, but no data from the system is presented [23].

Siemens has published a few reports about the eHighway development, planned projects, and the construction of the demonstration [41], [44], [45], [47]. The focus of those reports was in terms of design, applied technology, specific system characteristics, and expected outcomes. However, they fall short on reporting real results and collected data on the pilot projects.

Because this is a relatively recent technology, with a new market and first pilot project implementation completed just a few years ago, this gap in the literature can be justified. However, more comprehensive research, covering all the impacts and effects related to the deploying of an eHighway system, is needed, and this study aims to provide that.

2.5 Conclusions

This chapter brought a comprehensive description of the eHighway, detailed information on its operation, and the main features of the system. It showed the design concept and discussed the potential challenges with the technology as well as its main

benefits. The six past, current, and future eHighway pilot projects are also discussed. We provided the timeline of these projects, discussing their characteristics, successes and failures, and what is planned for the years to come. A rough cost estimation based on the pilot projects was also presented.

We also gave an overview of the current literature on the overhead catenary systems, going into the main outcomes (or lack of it) from the papers and technical reports published by Siemens, governmental agencies, and research groups. We highlighted the lack of real data being used for some of the studies and limited conclusions drawn by others. It is clear from this review that, even though many new eHighway systems are being implemented, and millions of dollars are being invested in this technology, little has been shown regarding the technology benefits in real applications and the impacts of this technology in the system as a whole, including energy generation and distribution, impacts on the power grid, effects on total emissions, and changes in traffic flow.

CHAPTER 3. CALIFORNIA STATEWIDE FREIGHT FORECASTING MODEL

After the Assembly Bill 32 adoption in 2006 [7], other regulations were proposed to reduce emissions in California. Those new environmental policies made it crucial for the state to have a tool that would analyze different economic, social, and environmental policies associated with goods movement. Therefore, the California Department of Transportation (Caltrans) saw necessary the development of the California Statewide Freight Forecasting Model (CSFFM) [11].

3.1 CSFFM description

The CSFFM was developed by the Institute of Transportation Studies at the University of California, Irvine, and is a policy-sensitive model for forecasting commodity flows and multi-modal vehicle flows within California [11]. It was designed using the Citilabs CUBE software platform and would address socioeconomic conditions, freight-related land-use policies, environmental policies, and multimodal infrastructure investments. State agencies such as Caltrans, the California Air Resources Board, the California Energy Commission, and regional agencies such as Metropolitan Planning Organizations and Regional Transportation Planning Agencies, could take advantage of this model for various purposes, such as statewide analysis of demo-economic changes, major upgrade of transportation facilities, or sub-area analysis of congestion and capacity upgrades [11].

The model is based on a variation of the traditional four-step model (regression, logit share model, mode route choice, and vehicle flow distribution). However, it consists of five core modules that will address socioeconomic conditions, land use, and environmental policies related to freight, and multimodal infrastructure investments:

- Commodity module: produce production and attraction and distribution of commodities;
- Mode-split module: establish, for each origin-destination pair, its mode share;

- Transshipment module: designate commodity flows at the transport logistics nodes;
- Seasonality and payload factor module: provide seasonal and annual flows by truck classes and commodity groups;
- Network module: comprise of route choice and traffic assignment.

The flow modeling is based on 97 freight analysis zones (FAZs) in California, defined at county and sub-county levels (Figure 13). There are 38 import/export gateways (19 land ports across the Mexican border, 8 airports, and 11 seaports), and 31 transport logistic nodes (13 airports and 18 rail terminals including five virtual rail terminals) [70].

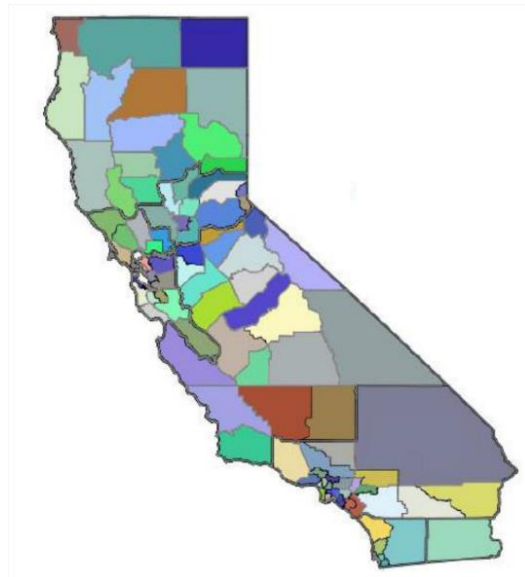


Figure 13. Freight analysis zones in California. The flow modeling in the CSFFM is based on these 97 freight analysis zones [70].

The CSFFM truck classification was designed based on the aggregation of axle configuration-based truck classes associated with the Federal Highway Administration (FHWA) vehicle classification scheme. The trucks are then classified into five categories, according to Table 1:

Figure 14 shows the daily truck volumes across the state of California for each class of the trucks (class 5 was omitted on the CSFFM).

Table 1. CSFFM Truck Classification.

Class	Definition	Corresponding FHWA vehicle classification
Class 1	2-axle 6 tire single unit trucks	Class 5
Class 2	3-axle single unit trucks	Classes 6 & 7
Class 3	Trucks pulling single trailers	Classes 8, 9 & 10
Class 4	Trucks pulling multiple trailers	Classes 11, 12 & 13
Class 5	Others	Unclassified trucks

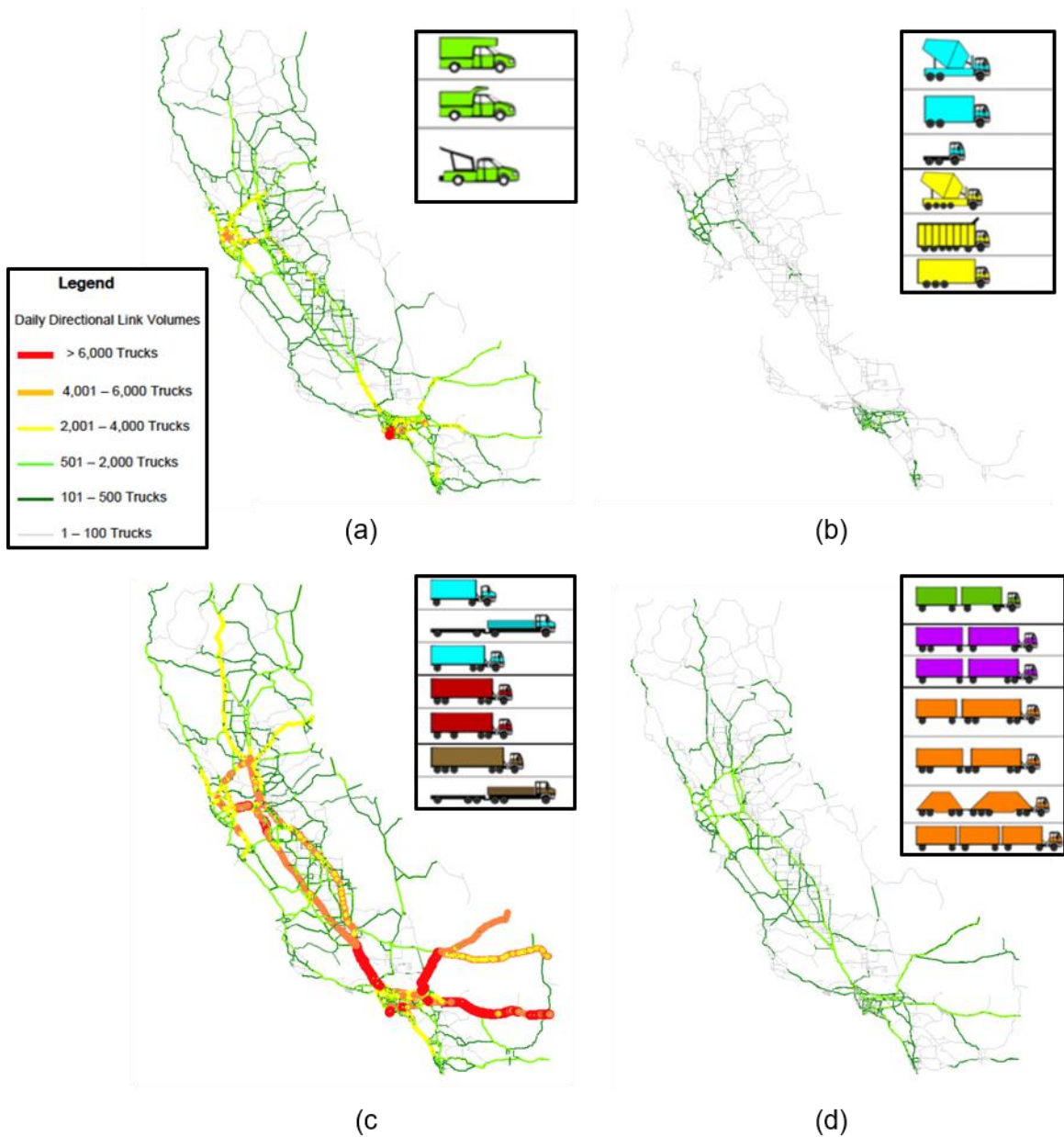


Figure 14. Daily truck volume for each CSFFM truck classification [11], [71]. Volume for CSFFM for trucks in the (a) class 1, (b) class 2, (c) class 3, and (d) class 4.

Most of the truck volumes are attributed to truck classes 1 and 3. On the one hand, class 1 trucks that are frequently used for short-distance deliveries present their volumes closer to metropolitan areas. On the other hand, class 3 trucks that are typically used for long haul freight movement, are spread out throughout major interstate corridors in the state. Class 4 trucks have just about the same location as class 3; however, their volumes are significantly lower. Class 2 trucks are typically associated with commodities such as gravel and fuel; therefore, their movements are located in specific areas. All the eHighway pilot projects to date have used only trucks in class 3, as these are the most likely to benefit from an eHighway system [11]. Therefore, for the remaining of this study, we will focus on trucks in this class only, removing any truck in the other classes from the analysis.

The CSFFM used public and private data sources and was calibrated and validated using available truck count data in California for the years 2007 and 2010. Lastly, this model also provides forecast results for the year 2020 and 2040. Numbers related to employment, population, livestock sales, harvested acreage, diesel fuel prices, and manufactured gross domestic product were forecasted based on estimated input data corresponding to these forecast years for all domestic zones in the model [11].

Defining the commodity groups (CGs) is an essential task for a commodity-based freight forecasting model because the level of disaggregation for the model and data depends directly on the definition of the commodity groups used in the model. The process of aggregating those CGs on the CSFFM took into consideration related industry, trip length distribution, dominant node, and weight of commodities (ktons of shipment). The model includes fifteen commodity groups (CGs), according to Table 2. The total vehicle miles traveled (VMT) for each commodity in the CSFFM are presented for both target years of 2020 and 2040.

Table 2. Commodity groups in CSFFM and their vehicle miles traveled (VMT) for 2020 and 2040.

Commodity group	VMT	% of total VMT	VMT	% of total VMT
	[2020]	[2020]	[2040]	[2040]
CG-1: Agriculture products	3,359,342	10.6	3,549,850	9.5
CG-2: Wood, printed products	2,081,188	6.6	2,066,430	5.5
CG-3: Crude petroleum	42,123	0.1	42,226	0.1
CG-4: Fuel and oil products	1,063,994	3.4	1,243,636	3.3
CG-5: Gravel/ sand and non-metallic minerals	5,898,526	18.6	8,310,164	22.3
CG-6: Coal / metallic minerals	0	0	0	0
CG-7: Food, beverage, tobacco products	3,497,050	11	3,958,744	10.6
CG-8: Manufactured products	3,437,808	10.8	3,874,599	10.4
CG-9: Chemical/ pharmaceutical products	1,539,135	4.9	1,610,619	4.3
CG-10: Nonmetal mineral products	4,120,895	13	4,306,023	11.6
CG-11: Metal manufactured products	1,952,994	6.2	2,611,416	7
CG-12: Waste material	3,205,814	10.1	4,000,894	10.7
CG-13: Electronics	523,157	1.7	573,467	1.5
CG-14: Transportation equipment	702,821	2.2	835,253	2.2
CG-15: Logs and lumber	262,286	0.8	255,554	0.7
Total	31,687,133	100	37,238,875	100

3.2 Road aggregation, sorting, and filtering

The CSFFM is composed of about a quarter-million segments of road that include attributes such as identification, length of the segment, daily volume for each truck class and commodity, road name, and county where it is located. Some of these attributes are filled in for all roads (e.g., identification, length, and daily volumes) and others only for highways (e.g., road name). One challenge to using the CSFFM for the eHighway analysis was to aggregate, filter, and order the segments that belong to the same highway. Here, the aggregation process collects the segments belonging to the same highway and label them accordingly. Sorting enumerates each of the segments belonging to a highway such that the correct segment sequence is obtained. And finally, filtering that removes urban roads, on-ramp, off-ramp and major/minor arterials that are not part of the freeway; it is not expected to deploy the eHighway systems into any of these types of segments and removing them reduces unnecessary noise when analyzing the model for the eHighway implementation (see Figure 15). These steps are going to be described

in detail in this section, and the Python code used for this process is available in APPENDIX A.

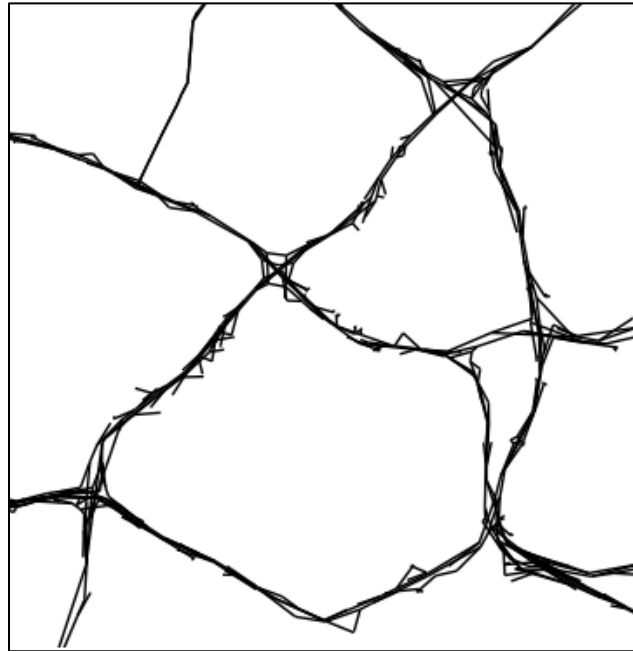


Figure 15. Sample of a small area in the CSFFM. Many of the segments of the model are on-ramp, off-ramp, and major/minor arterials that are not part of the freeway and should not be used for eHighway deployment; therefore, the model needs filtering before it can be further used in this project.

The whole process starts by loading the shapefile output from Citilabs CUBE software with the CSFFM data using the GeoPandas, an open-source package that enables geospatial processing data in Python. Coordinates are loaded using the California Albers projection EPSG 3310.

Segments without valid data in their name attribute (CT_ROUTE attribute in the CSFFM) or county attribute are filtered out. In the CSFFM, CT_ROUTE holds road names, which is only filled in for highways (not for urban roads), so these can be eliminated. Moreover, only segments within California have data in the county attribute. Since this work is limited to California, segments outside of the state are removed. Segments that are set to restricted use (another attribute in the model) are also removed. And, finally, counties with misspelled names are fixed to match the actual county name (these misspellings were found manually by looking for names that did not match any of California's counties, for all cases, it was clear which was the correct county). The

remaining segments are ready for aggregation, which is performed by grouping all the segments with identical name (CT_ROUTE) attribute.

Segments in each road are now grouped; however, even though we have the geographic location of the links, finding which links belong to each direction and sorting the links in the road, are still a challenge. This step is necessary because when deploying an eHighway, it is likely to span multiple segments (as these are short, on average just a mile long), and therefore, knowing which segments come after the other in a specific road is paramount for the eHighway analysis. Here, we propose using the principal component analysis to solve this problem.

Principal Component Analysis (PCA) is one of the oldest techniques for multivariate statistical analysis. Although PCA has been used for a variety of applications, such as clustering, outlier detection, and regression analysis, the main application of PCA is for dimensionality reduction.

PCA looks for a linearly independent basis, called Principal Components (PCs), which can represent the data without any loss of information. Moreover, this new set of axes (basis) is ranked according to the variance in the data along with them. That means, more important dimensions, those with more data variance, occur first. Using the new ranked basis, one can select the N first dimensions, with N smaller than the dimension of the original data, to reduce the data dimensionality with minimal information loss. Figure 16 shows an example of the two PCs for a 2-dimension data sample.

Even though PCA can be used for powerful statistical analysis, the mathematical definition of PCA is simple. First, a covariance matrix is calculated for all the points in the data (assuming the data is normalized). Second, the eigenvalues and eigenvectors for the given data are calculated. Third, the eigenvectors are ranked according to the decreasing order of their eigenvalues. Fourth, choose the N first eigenvectors (N is the desired dimensionality of the output data) as the basis of the new data. And lastly, transform the original data into the axis formed with the eigenvectors. This whole process can be performed using the PCA module in Python's scientific library, SciPy.

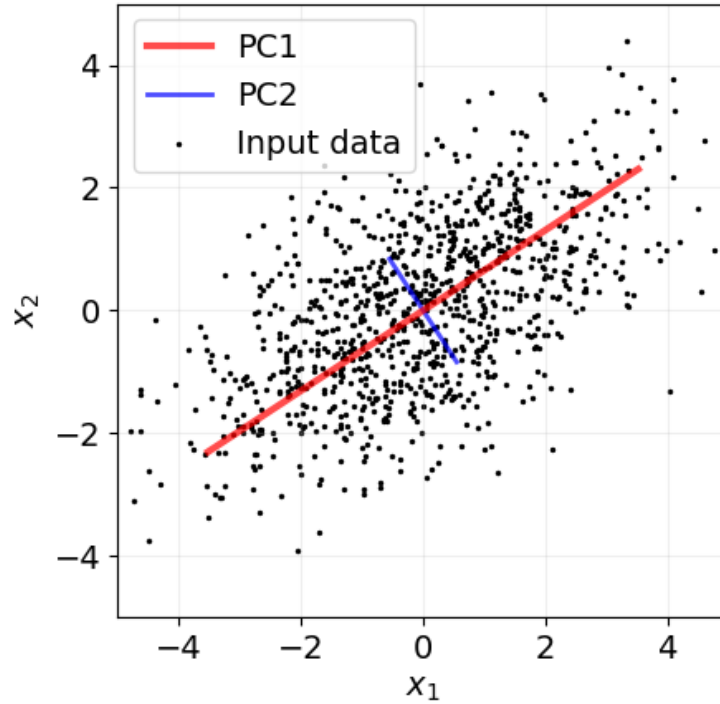


Figure 16. PCA applied to a 2-dimension dataset. Each dot is one sample in the dataset; the red and blue lines represent the direction of the first and second principal components, respectively. The length of the lines is proportional to how much variance that component explains.

Even though there are no references to our knowledge of PCAs used for this type of problem, we can use its concept to sort the segments belonging to each freeway based on their coordinates data. The segment sorting is performed by following the steps presented below, and a simplified, hypothetical stretch of road is used to represent this process in Figure 17. These steps are applied to each of the roads aggregated using the method mentioned above.

- Step 1: Apply the PCA to the latitude, longitude pairs of all nodes (beginnings and ends of each road link) in a road; this will return two PCs. The first principal component (PC1) is the vector in the direction of most variance in the data, which we will use as the main direction of the road being analyzed. The PC1 vector for the hypothetical road (of just one direction) is presented in Figure 17a.
- Step 2: Project each of the latitude, longitude pairs onto the PC1. This step will give a 1-dimension representation of the points in the direction of the largest variance PC1. In Figure 17b, the beginning and endpoints are projected onto the

vector. This 1-dimension projection allows us to sort the segments based on their initial node value in the projection. That means the smaller the projection of the initial node of a segment, the earlier it comes on that road (assuming all segments are going in the direction of increasing projection value).

- Step 3: Find the direction. Links going up (increasing projection value from beginning to the end of the link) on the dimension of PC1 are going in the same direction, those going down (decreasing value) are going in the opposite direction. We can estimate if the road is going South/North or East/West by looking at the latitude/longitude rate of change of PC1. Figure 17c shows a two-direction road. For each direction, we have the beginning and endpoints that are projected onto the same PC vector.

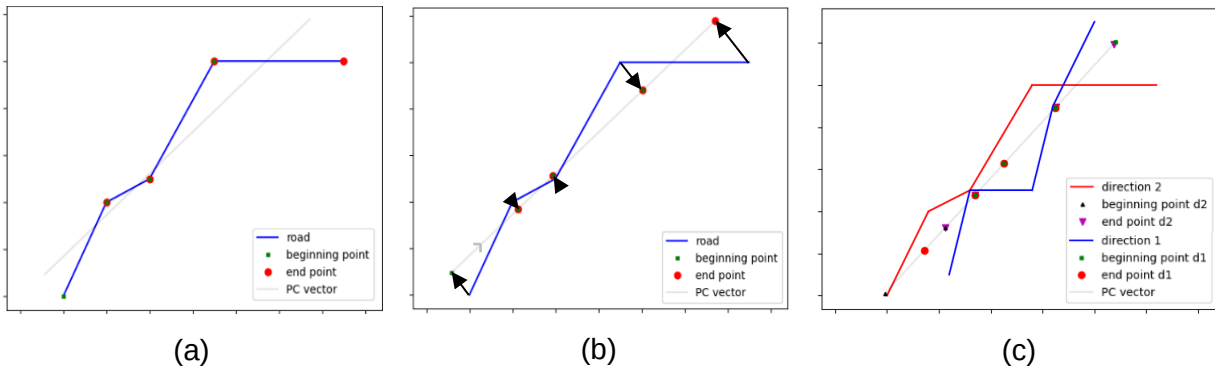


Figure 17. Principal Component Analysis process. (a) Apply the PCA to all the nodes on the road. (b) Project points to the PC1. (c) find the direction.

The last step to prepare the model is filtering. Here, we aim to remove on-ramp, off-ramp, and major/minor arterials road segments that are not part of the freeway. On-ramp and off-ramp sections always end and start, respectively, within another segment. After sorting the segments of a road using the PCA process, the off-ramp segments are removed by eliminating segments that do not have their initial node connected to the final node of the previous segment. Likewise, for on-ramp sections, segments that do not have their final node connected to the initial node of a segment in the main road were eliminated. For other parallel segments (that both started and ended parallel/along the main road), the path with higher VMT was kept.

This filtering process was performed interactively, as multiple parallel roads could exist, and removing all in one algorithm pass was too challenging. This process was executed as many times as necessary until no further segments were eliminated.

After the application of the steps presented here for aggregation, sorting, and filtering of the CSFFM we obtain a simplified model only containing the roads of interest in a format possible for eHighway implementation (we will call this model the filtered model, or just CSFFM in next chapters for simplicity). This filtered model keeps all the road segments that have high class 3, heavy-duty truck volume, and are important for eHighway implementation. Most of the removed segments are from urban areas, and on- and off-ramps. Figure 18 shows the segments of the original CSFFM and the filtered model. On a large scale (Figure 18, left), we can mostly see the removal of urban roads, and little difference is observable on the highways. However, zoom in to the highways it is possible to notice the effects of the applied filtering. All these steps to aggregate, sort, and filter the CSFFM can be found in the Python scripts in APPENDIX A.

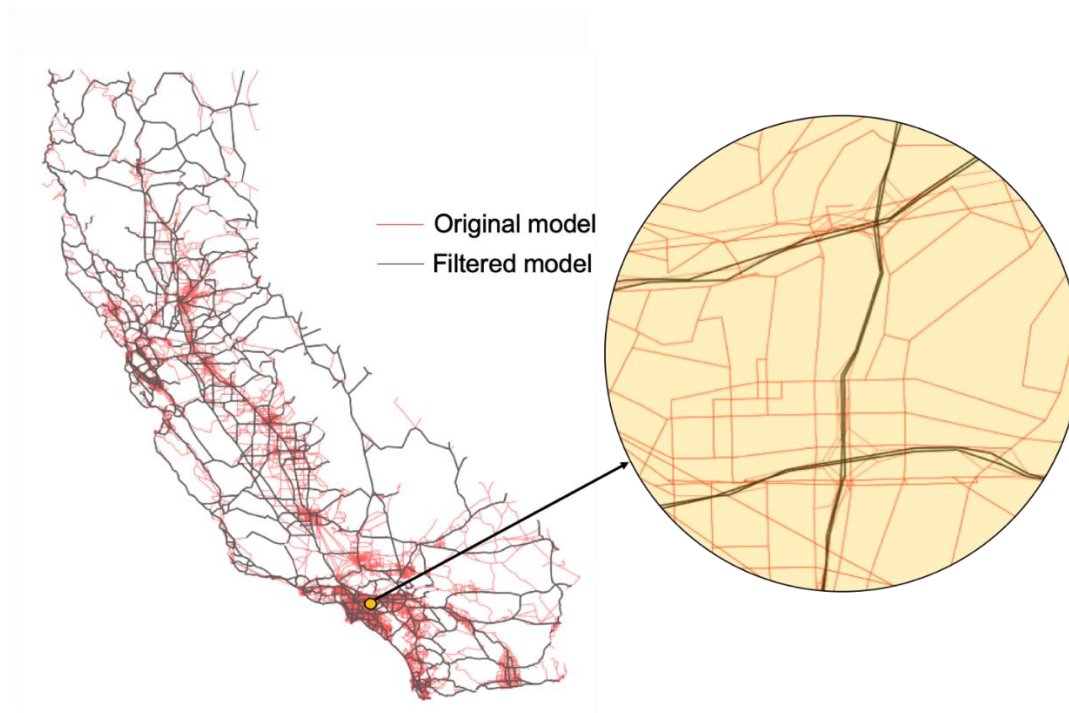


Figure 18. Segments of the original CSFFM and the filtered model. (Left) shows the whole map of California with the original model (in red) and the filtered model (black). In this scale, the removal of most of the urban roads can be observed. (Right) presents a zoom in of a small area of the map, showing the removal of many on- and off-ramp segments as well as segments parallel to the main roads.

3.3 Filtered model

After applying the methodology presented in section 3.2 to CSFFM, the new model is ready to start investigating the effects of eHighway implementation. In this chapter, we will show the details of the filtered model for both years of interest, 2020, and 2040.

The 2020 model includes a total of almost 32 million miles traveled per day over 27,000 miles of roads. Figure 19 shows the daily volume distribution across the roads in the state. There is a large distribution in road length (top right of Figure 19), but the average truck volume is more uniform (bottom right of Figure 19). The map shows, however, that high daily volume is concentrated in few roads and specific locations. This is a key observation for the implementation of the eHighway such that shorter stretches of eHighway could be used by more trucks and have larger impacts on emissions.

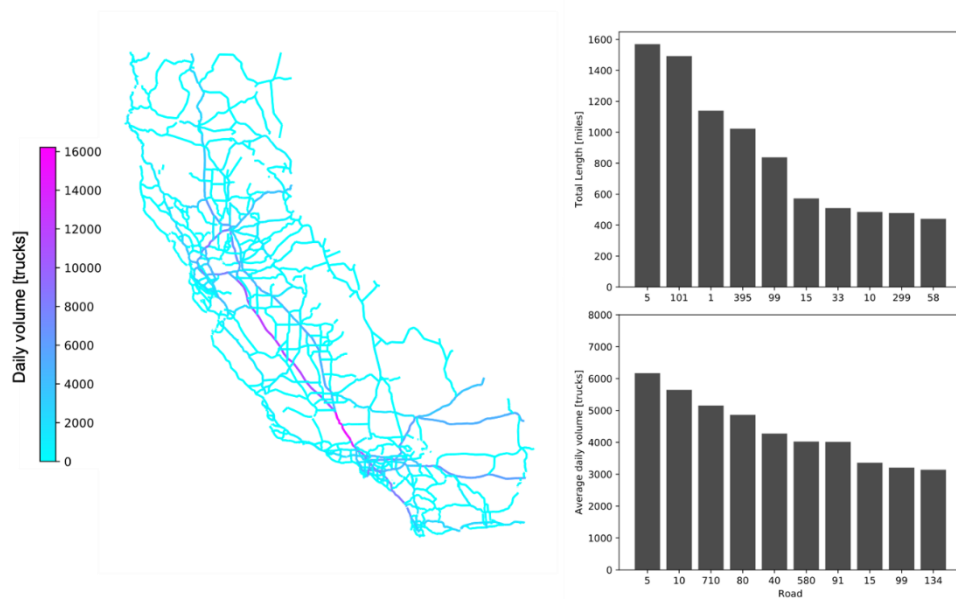


Figure 19. Daily truck volume in the filtered model for the year 2020. (Left) shows the CSFFM after the filter process with segments' color encoding truck daily volume. (Top right) presents the length in miles of the top 10 longest roads. (Bottom right) shows the average truck daily volume across the top 10 busiest roads in the model.

The forecast model for 2040 uses the same infrastructure as the 2020 model, with no additional roads or changes in the current system (as seen comparing the top right of Figure 19 and Figure 20); however, the VMT increased by 15% going to 37 million miles

traveled. We see slight changes in the order of the top 10 average daily volume for the two years; however, all of them are increasing in volume from 2020 to 2040. However, the general pattern of truck volumes across the state looks similar for both target years.

Looking at the change of daily volume from 2020 to 2040, as shown in Figure 21, we observe that the increase in daily volume is low and uniform for most of the state. However, some specific roads see a sharper increase in volumes, in particular the already busy I-5. Interestingly, there are daily volume decreases for punctual road stretches. These changes should be taken into account when selecting the location of eHighway implementation. These considerations will be further discussed in the next chapters.

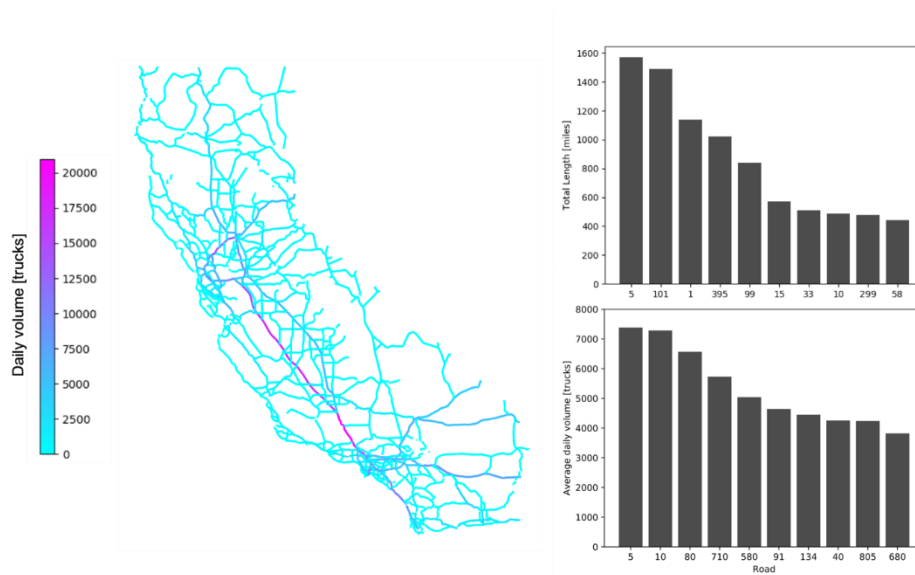


Figure 20. Daily truck volume in the filtered model for the year 2040. (Left) shows the CSFFM after the filter process with segments' color encoding truck daily volume. (Top right) presents the length in miles of the top 10 longest roads, which is identical to the one for the year 2020. (Bottom right) shows the average truck daily volume across the top 10 busiest roads in the model.

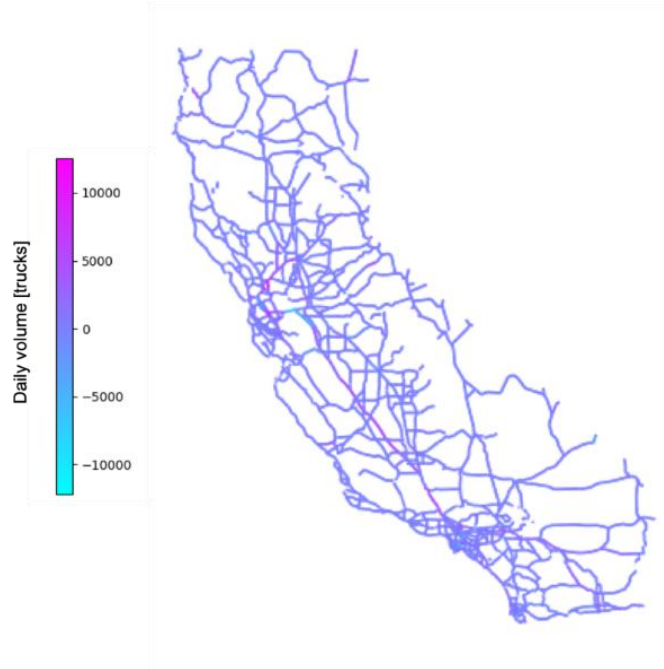


Figure 21. Change in daily truck volume from 2020 to 2040. It shows a non-uniform change in daily volume between the two target years, with segments' color encoding the change in truck daily volume.

3.4 Conclusions

In this chapter, we introduced and detailed the California Statewide Freight Forecasting Model. We showed how it is constructed and divided, including the different classes and commodities presented in the model.

We discuss how the original model includes many segments for urban areas and smaller roads, that have limited truck traffic needed to be filtered out for further analysis. We then discussed how to aggregate, filter, and order the roads in the model such that we can explore the implementation of the eHighway system and understand the impacts it will have on emissions in the state.

We compare the new, filtered model for both target years, 2020 and 2040, and discussed how the pattern of truck volumes across the state (with shorter stretches having high heavy-duty truck volumes) creates an excellent opportunity the implementation of the eHighway system. Finally, we show that the changes in volume from 2020 to 2040 are mostly low and uniform across the state, but punctual increase and decrease in the

truck volume are seen and should be taken into account when selecting the eHighway location.

CHAPTER 4. EHIGHWAY ROAD SELECTION

4.1 Choosing the eHighway location

There are two ways to implement an eHighway. The first option would be building a new road with all the system's features already integrated. Another option would be starting from an already existing road and incorporating the necessary infrastructure of the eHighway. Since the second option is cheaper and independent of infrastructure and environmental analysis, we are making the road selection based on the current roads in California.

Aiming to have the most effective placement and the largest reduction of emissions, the optimal location should be determined by taking into account some important aspects. For example, Stamati and Bauer (2013) suggested that the deployment should be based on the daily traffic of the road (the number of vehicles per kilometer) [72]. Likewise, Limb et al. (2016) cited the vehicles miles traveled per mile of roadway should be considered as a determining factor [25]. Therefore, one of the metrics that will be used in this study to determine the eHighway road selection is the road VMT (vehicle miles traveled). This scenario selects road stretches with the higher heavy-duty truck VMTs based on the data from the filtered California Statewide Freight Forecasting Model (CSFFM), maximizing the total use of the system. As explained in CHAPTER 3, the filtered CSFFM includes only trucks in class 3, as these are the most likely to benefit from an eHighway system.

Another factor that could affect the decision for the eHighway location and is an important consideration in California is related to local emissions levels. Selecting roads that are closer to disadvantage communities in terms of pollution is a way to improve and maintain a clean and healthful environment – this is called environmental justice (EJ). Identifying the corridors that show most benefits in terms of air quality not only would help

those communities, but they are also likely to be more conducive to governmental incentivization.

After exploring the location, another aspect that needs to be considered is the length of each of the eHighway – here we are considering the possibility of deploying multiple eHighway systems across the state, and two parameters need to be defined. The first one is the minimum length of one eHighway stretch. There is an overhead cost of implementing the eHighway system (installing substations, setting up infrastructure, connecting to the main grid, etc.), and building an eHighway that is very short is an unlikely scenario. The second is the total number of miles of all the eHighways added together.

An algorithm was developed using the filtered model presented in CHAPTER 3 and is detailed in the following subchapters to define which sections of roads would make the most effective eHighway placement. This algorithm will be applied to optimize two variables: total vehicle miles traveled in the eHighway, and the sum of the environmental justice score across the communities the system is deployed. At the end of this chapter, the eHighway location and length for different scenarios will be presented. These selected eHighway systems will be used in the next chapters to estimate emissions and analyze the effects on California's power grid.

4.2 Selection based on VMT

The vehicle miles traveled (VMT) is a measure of the amount of travel in a road over a given time. It is calculated by multiplying the length of a road by its vehicle volume. This metric can be obtained in the CSFFM for every road in California. VMT is directly correlated with the emission levels, which makes it an ideal optimization metric to maximize the impacts of the eHighway on the environment.

In this section, we present an algorithm that searches through all the road segments in the CSFFM and looks for the optimal location to implement the eHighway systems. The only input variables are the total length of all the eHighways added and the minimum length of each of these eHighways. Ideally, the total length input variable would

be in terms of project cost (e.g., the total cost to be spent implementing the eHighway). However, as discussed in section 2.3, this information is still unknown. Therefore, to run this analysis in California, these variables were chosen to simulate the impacts of the implementation of medium size projects. The eHighway systems here are much larger than the ones used in the pilot studies; however, they still cover a very small percentage of the highways in the state. In future studies, the eHighway costs would be a constraint or new objective to be optimized during this process.

After defining the minimum length (l) for deploying an eHighway, we divide each road (r) in the state into sections (s), moving one mile at a time and overlapping them for $(l - 1)$ miles:

$$\begin{aligned} s_0 &= \text{mile } 0 \text{ to mile } l, \\ s_1 &= \text{mile } 1 \text{ to mile } l + 1, \\ &\dots \\ s_{l_r-l} &= \text{mile } (l_r - l) \text{ to mile } l_r \end{aligned}$$

Note that segments in the CSFFM do not have equal length, and sections are approximated to the closest full segment. We then calculate the total VMT for each section as the sum of the VMTs within the miles of that section in each road (r):

$$VMT_{r,s_i} = \sum_{m=s_i} VMT_{r,m}$$

where, VMT_{r,s_i} is the total VMT within the section s_i in road r and $VMT_{r,m}$ is the VMT of mile m at road r .

All the sections are then ordered from the highest to the lowest VMT. This step is followed by an interactive process that picks the section with the highest VMT and deploys an eHighway at that location (remember, each section has the length of a minimal allowed eHighway). If the newly deployed eHighway overlaps or is too close to another eHighway, these eHighways are merged into one. Here, too closed is defined a distance from the end of an eHighway to the beginning of the next being less than the minimal length (l)

allowed. The total eHighway mileage is then updated with the newly deployed system, following the pseudo-algorithm:

Define *minimum_ehighway_length*

Define *total_ehighway_mileage*

For each section **in** ordered sections **until** *ehighway_deployed* $\geq$ *total_ehighway_mileage*

Get section road, length and starting point

If the road **has** ehighway deployed, **then**

If the distance from section to ehighway $<$ *minimum_ehighway_length*

or section and ehighway overlap, **then**

Merge sections

Make sections ehighway

Else

Deploy ehighway in the section

Update *ehighway_deployed*

This algorithm outputs the road, starting mile, and length of each eHighway that maximizes the VMT in the network. The selection process considers the eHighway implementation to be done in both directions for each selected road. The Python script correspondent to this algorithm can be found in APPENDIX B.

4.3 Scenarios based on environmental justice

The Department of Energy of the United States defines environmental justice as the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income concerning the development, implementation, and enforcement of environmental laws, regulations, and policies. In other words, the population health should not suffer because of the environment they live or work [73]. The concept of environmental justice began in the 1980s due to the realization that a disproportionate number of polluting industries, power plants, and waste disposal areas were located near

low-income or minority communities. Because of this disproportionality, a movement started ensuring a fair distribution of environmental burdens among all people regardless of their background.

Unfortunately, some locations are more affected by pollution than others, and those areas are called disadvantaged communities. The Office of Environmental Health Hazard Assessment (OEHHA) released environmental health information identifying the disadvantaged communities in terms of pollution [74], [75]. The data is divided by census tract zones, as presented in Figure 22. For each tract, an overall *CalEnviroScreen* score is calculated based on the pollution burden (exposures and environmental effects) and population characteristics (sensitive population and socioeconomic factors).



Figure 22. Census tract zone division exemplified in the Long Beach Port area [75].

Seven exposure indicators were presented in the report as criteria to estimate the exposure of certain pollutants and five indicators for the environmental effect, which are the adverse environmental conditions caused by pollutants. On the population characteristics side, we have the socioeconomic factors and the indicators for sensitive population – which are the populations with biological traits that result in increased vulnerability to pollutants. Figure 23 shows all the indicators used for estimating the overall score.

Figure 24 shows the map of California divided by the zone tracts, highlighting the disadvantaged communities (with higher scores). For selecting roads based on

environmental justice, the goal is to decide on roads that are closest to the communities with a higher *CalEnviroScreen* score. In that way, the pollution caused by transportation would be reduced in these regions since eHighway trucks have no tailpipe emissions.

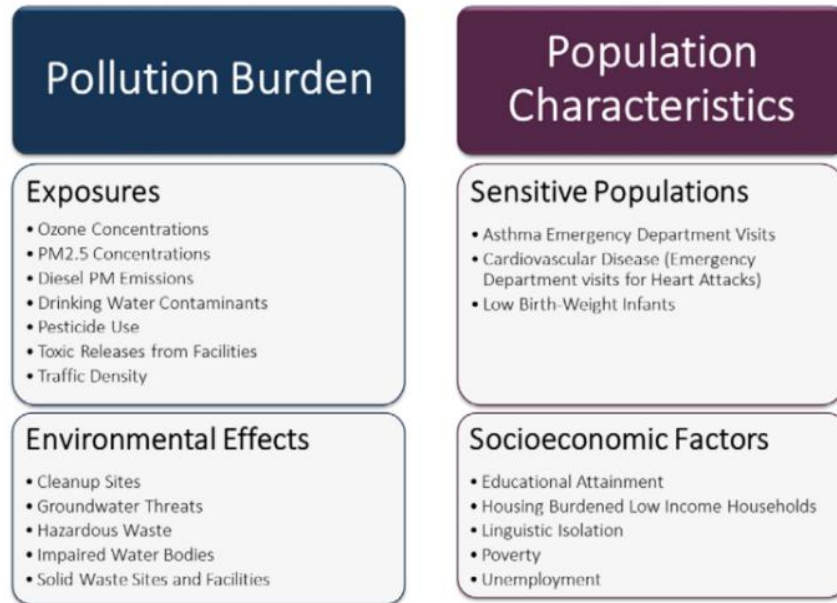


Figure 23. Indicator and component scoring for the *CalEnviroScreen* [75].

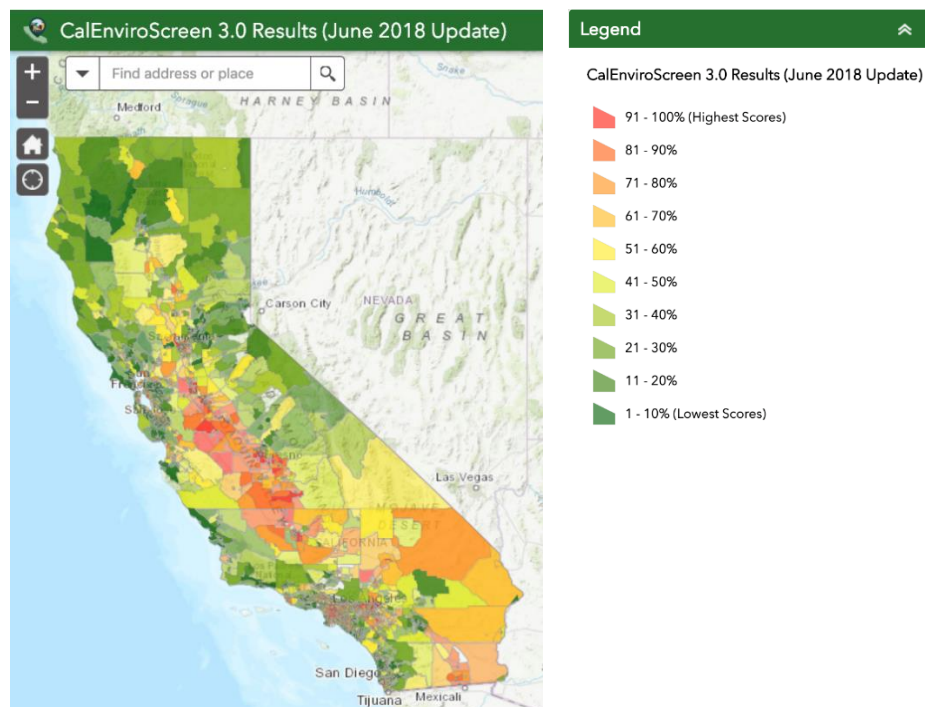


Figure 24. *CalEnviroScreen* map of disadvantaged communities [74].

The algorithm follows the same strategy as used to maximize VMT. However, instead of VMT, we aim to maximize the *CalEnviroScreen* score. For each segment from the CSFFM, we find which tract zone it belongs to and associates the segment with the *CalEnviroScreen* score for that zone. If a segment passes through two or more tract zones, then we use the average of the *CalEnviroScreen* score for those zones.

To select the eHighway locations and lengths, we re-divide the roads into sections as shown in the VMT maximization process (in section 4.2), and the minimum length of an eHighway segment and the total eHighway mileage are defined. An environmental justice (EJ) score for the section is assigned based on the maximum score across all the segments (i) in the section. We repeat this process for all sections (s) in all roads (r), where i is the segment in section (s):

$$EJ_{r,s_i} = \max_{m=s_i} [EJ_{r,m}]$$

where, EJ_{r,s_i} is the environmental justice score for the section s_i in road r and $EJ_{r,m}$ is the environmental justice score for mile m in road r .

All sections can now be ordered from the highest to the lowest EJ. The same interactive process explained before to maximize the VMT (the pseudo-algorithm in section 4.1) is applied to maximize the EJ. This process outputs the road, starting mile, and length of each eHighway that maximizes the EJ in the network. The selection process considers the eHighway implementation to be done in both directions for each selected road. The Python script correspondent to this algorithm can be found in APPENDIX B.

4.4 Scenarios results for 2020

In this section, we explore the results for different scenarios that were obtained using data from the 2020 model using the algorithms presented in sections 4.1 and 4.2. The scenarios were picked to maximize two metrics (road VMT and EJ) and different minimum and total eHighway lengths, with four scenarios evaluated:

- Scenario 1: maximizes VTM with a minimum eHighway length of 20 miles and a total eHighway length of 500 miles

- Scenario 2: maximizes VTM with a minimum eHighway length of 10 miles and a total eHighway length of 500 miles
- Scenario 3: maximizes VTM with a minimum eHighway length of 10 miles and a total eHighway length of 100 miles
- Scenario 4: maximizes EJ with a minimum eHighway length of 20 miles and a total eHighway length of 500 miles

The outputs for each of these scenarios are presented and discussed in the subsequent sections.

Even though we do not have a detailed cost analysis for the eHighway system, we can look at the costs per mile from the pilot projects to estimate an upper bound of the cost of the scenarios proposed here. For the 100-mile scenario, the total cost would be from 235 to 570 million dollars, and the 500-mile scenarios total cost would be from 1.18 to 2.85 billion dollars. These are upper-bound estimates, as larger-scale projects would likely have a more significant drop in cost per mile, and these scenarios are orders of magnitude larger than the pilot projects deployed to date.

4.4.1. SCENARIO 1

In this case, the selection was based on the number of vehicles miles traveling on the roads. The minimum eHighway length was set to 20 miles, and the total eHighway mileage was limited to 500 miles. The algorithm presented in section 4.2 was applied, and Figure 25 shows the eHighway locations on the California map. It also brings a list of all the selected roads, including the starting mile and length of the segment.

Here, we have two long stretches (137 miles stretch in the I-10 and 121 miles in the I-5); however, only eight roads were selected (with nine different eHighway systems deployed). As expected, a scenario based on VMT would have most of the road segments around Los Angeles County, where there is a heavier truck movement. The I-5 is a major interstate that crosses California from south to north, and in this scenario, two different segments of the road were selected: a larger one in Southern California and a 27-miles stretch close to Sacramento. An extensive part of the I-80, a transcontinental interstate

highway in the United States, was also selected covering the northern part of the state, close to San Francisco and the Bay Area, other areas with high truck traffic.

In total, the eHighway network covers 3.03 million VMT, or 9.6% of the total VMT in the model, by deploying only 500 eHighway miles, or 1.8% of the total number of miles in the model. This result comes to shows that selecting the correct locations for the eHighway deployment is paramount and that the algorithm proposed is successful in doing so.

Road	Starting mile	Length (mile)
5	55	121
5	495	27
10	11	137
710	0	24
91	3	58
15	123	29
80	0	62
210	22	25
101	0	20



Figure 25. Output for scenario 1 based on VMT with a minimum of 20 miles and a total of 500 miles for 2020. (Left) shows the road, starting mile, and length for each of the eHighway systems deployed, and (right) shows the location of the eHighway on California's road map.

4.4.2. SCENARIO 2

One of the benefits of the eHighway system is that it can be deployed onto short sections of the road. Here, we explore a similar scenario as presented in section 4.4.1; however, shorter systems can be deployed, with a minimum length of 10 miles (half of the ones presented earlier).

For this scenario, Figure 26 presents the location of the eHighways across the state with a list of the roads of deployment, their starting miles, and eHighway length.

Road	Starting mile	Length (mile)
5	57	113
5	500	21
5	183	11
710	0	18
10	16	47
10	89	17
10	134	13
91	8	48
15	129	22
15	100	17
15	166	13
101	0	14
80	0	60
580	31	17
99	17	15
210	24	21
215	16	13
880	31	11
134	0	10



Figure 26. Output for scenario 2 based on VMT with a minimum of 10 miles and a total of 500 miles for 2020. (Left) shows the road, starting mile, and length for each of the eHighway systems deployed, and (right) shows the location of the eHighway on California's road map.

This scenario resulted in the eHighway system being deployed in more roads but with shorter stretches, with a total of 19 individual eHighways (compare to 9 in the previous scenario). From the 19 systems, 12 are shorter than the 20 miles limit for the previous scenario. In general, the same areas of Figure 25 with high VMT were covered. Even though the total mileage is the same as in the previous case, the construction burden of deployment the system in so many roads could increase the costs substantially

(although a comprehensive cost analysis is still necessary to understand these results better, however, that is outside the scope of this project).

In total, these eHighways covers 3.08 million VMT, or 9.7% of the total VMT in the model, by deploying only 500 eHighway miles, or 1.8% of the total number of miles in the model (compare to the previous scenario with 3.03 million VMT covered or 9.6% of the total VMT). Even though it is a small change in total VMT coverage (compared to the previous scenario), the change in emissions could be more impactful, which will be analyzed in the coming chapter.

4.4.3. SCENARIO 3

Here, we explore a simpler deployment structure, with only 100 miles of an overhead catenary in total (and a minimum length of 10 miles). Based on the pilot demonstrations around the world, one can consider the eHighway as an expensive technology. Therefore, this scenario is suggested as a suitable alternative in case of cost constraints and perhaps more appropriate for earlier stages of the technology injection. For this scenario, Figure 27 shows the location of the eHighways across the state with a list of the roads of deployment, their starting miles, and eHighway length.

The output of this scenario only includes the busiest roads in the model, the I-5, I-10, and I-710, as observed in Figure 19. In particular, the I-710 would be a strong candidate for the eHighway system as it starts inside the San Pedro Bay Ports complex and, therefore, has a significant number of trucks making multiples trips per day.

One hundred miles of eHighway equates to only 0.37% of the total number of miles in the model; however, the selected 100 miles cover 2.6% of the total VMT (or 0.82 million).

Road	Starting mile	Length (mile)
5	116	49
5	87	14
710	0	13
10	26	31



Figure 27. Output for scenario 3 based on VMT with a minimum of 10 miles and a total of 100 miles for 2020. (Left) shows the road, starting mile, and length for each of the eHighway systems deployed, and (right) shows the location of the eHighway on California's road map.

4.4.4. SCENARIO 4

This last case utilizes the EJ metric to make the eHighway road selection, as shown in section 4.3. Even though the same parameters as scenario 1 were used, the outcome from the deployment based on EJ is expected to be different since it is prioritizing locations where the local pollutions levels are higher. In Figure 28, the roads were plotted on top of the map of the *CalEnviroScreen* scores, where selected roads are highly overlapping with disadvantaged communities, validating the road selection by the proposed method. Figure 28 also shows the road, starting mile, and length of each of the eHighways deployed.

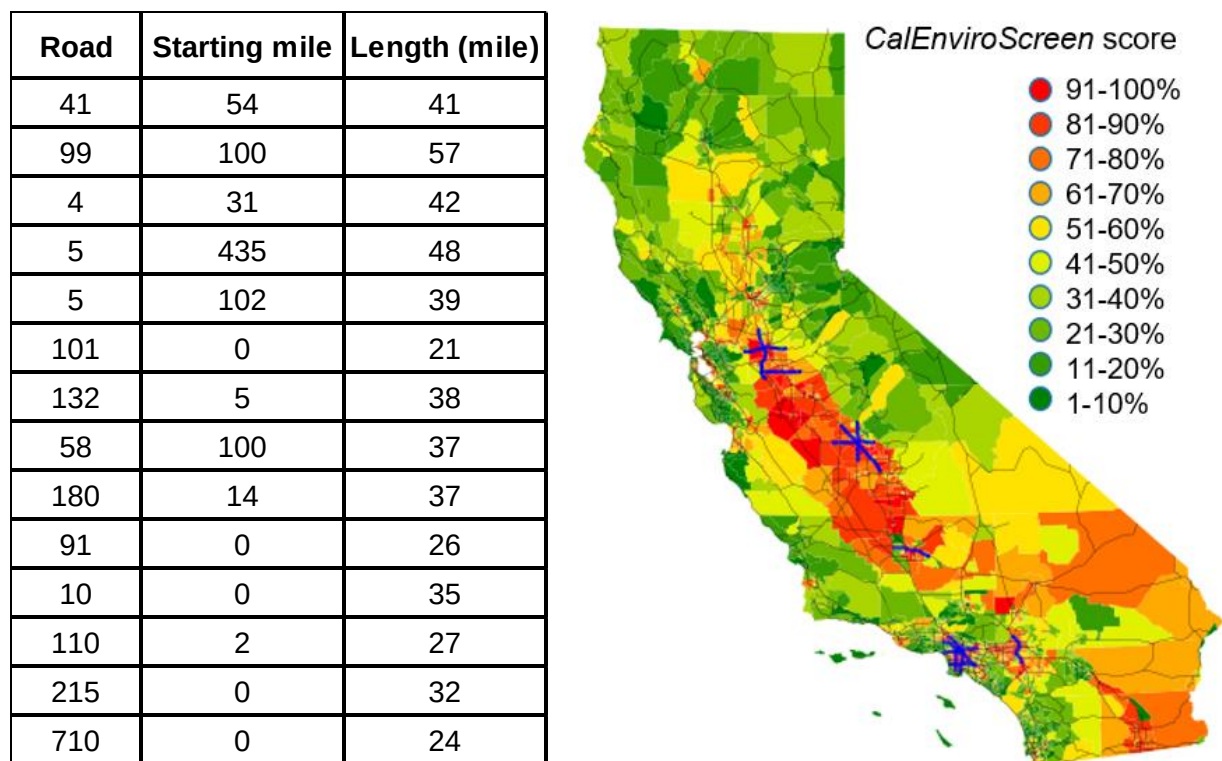


Figure 28. Output for scenario 4 based on EJ with a minimum of 20 miles and a total of 500 miles for 2020. (Left) shows the road, starting mile, and length for each of the eHighway systems deployed, and (right) shows the location of the eHighway on top of the environmental justice score map.

Not only different roads were selected, as expected, but there are 13 different roads, with 14 eHighway systems deployed (compare to 9 in the scenario 1 with the same parameters but optimizing for VMT). Another interesting feature is that the maximum segment length is 57 miles on California State Route 99. Highway 99 covers a lot of the Central Valley, a location that concentrates several disadvantage communities.

However, by optimizing for EJ, we see that the VMT coverage by the eHighway network is reduced. With 500 miles of eHighway (1.8 % of the total number of miles in the model), only 3.8% of the total VMT is covered (compare to 9.6% in scenario 1 and 9.7% in scenario 2). Here, the emission reduction is expected to be more prominent for disadvantaged communities but not as notable for the state as a whole. One could think that this is still a high VMT coverage for a “random” choice of roads (1.8% roads chosen to 3.8% of VMT covered); however, likely, one of the reasons for the high EJ score in these regions is exactly due to the high traffic. Another option is that regions with higher

industry concentration, and therefore higher emissions, are also going to have higher traffic of heavy-duty trucks.

4.5 Scenarios results for 2040

Even though it is interesting to look at the impacts of the eHighway system in a current traffic situation, it makes sense to look at forecasts and focus the implementation to be beneficial for decades to come.

The same four scenarios are now being generated using the data from 2040. As discussed in CHAPTER 3, from 2020 to 2040, the heavy-duty truck's VMT on the California roads has increased by 18%. As this increase is not uniform across all the roads, different results can be expected. The four scenarios for 2040 are named as follows:

- Scenario 5: maximizes VTM with a minimum eHighway length of 20 miles and a total eHighway length of 500 miles.
- Scenario 6: maximizes VTM with a minimum eHighway length of 10 miles and a total eHighway length of 500 miles.
- Scenario 7: maximizes VTM with a minimum eHighway length of 10 miles and a total eHighway length of 100 miles.
- Scenario 8: maximizes EJ with a minimum eHighway length of 20 miles and a total eHighway length of 500 miles.

4.5.1. SCENARIO 5

Using data for the 2040 projection, Figure 29 shows the location of the eHighways across the state as well as a list of the roads of deployment, their starting miles, and eHighway length for this scenario. Some of the locations remained the same as for the 2020 case (i.e., I-10, I-710, SR 91, I-15, I-80, I-210), but there were also some new locations selected due to the VMT difference in the 20-year apart models.

Road	Starting mile	Length (mile)
5	56	121
10	12	138
710	0	24
91	4	54
80	0	68
210	20	29
15	125	23
580	27	27
805	1	20



Figure 29. Output for scenario 5 based on VMT with a minimum of 20 miles and a total of 500 miles for 2040. (Left) shows the road, starting mile, and length for each of the eHighway systems deployed, and (right) shows the location of the eHighway on California's road map.

In total, the eHighway network, with nine separate eHighway systems deployed over nine different roads, covers 3.85 million VMT, or 10.3% of the total VMT in the model, by deploying only 500 eHighway miles, or 1.8% of the total number of miles in the model.

4.5.2. SCENARIO 6

In this scenario, the minimum eHighway length is reduced to only 10 miles, and Figure 30 shows the location of the eHighways across the state as well as a list of the roads of deployment, their starting miles, and eHighway length. Most of the eHighway selections are similar to that in scenario 2 (the counterpart for this scenario using data for the 2020 model which had one extra eHighway on the I-5 and I-10, but no eHighway on the I-134). This consistency of location selections across the model shows that it is possible to implement a system with high benefit across decades.

Road	Starting mile	Length (mile)
5	59	108
5	502	16
5	183	11
710	0	17
10	18	88
10	124	20
91	8	45
80	0	60
210	23	21
580	31	17
134	0	11
15	134	15
15	102	14
880	31	11
101	0	12
99	18	14
215	18	11
805	9	11



Figure 30. Output for scenario 6 based on VMT with a minimum of 10 miles and a total of 500 miles for 2040. (Left) shows the road, starting mile, and length for each of the eHighway systems deployed, and (right) shows the location of the eHighway on California's road map.

There are 18 eHighways in the selected network over 14 different roads. This network covers 3.93 million VMT, or 10.5% of the total VMT in the model, with 500 miles of eHighway.

4.5.3. SCENARIO 7

In this scenario, we look again at a smaller network implementation with only 100 miles in total and a minimum length of 10 miles. This network has virtually identical road selection when comparing to the output from scenario 3 (same parameters but using the data for the year of 2020). This result shows once again that, if the correct locations are select for the eHighway deployment, it can be highly effective across decades (relying on

the quality of the CSFFM forecasting). Figure 31 shows the location of the eHighways across the state with a list of the roads of deployment, their starting miles, and eHighway length.

Road	Starting mile	Length (mile)
5	116	47
5	88	12
710	0	13
10	27	31



Figure 31. Output for scenario 7 based on VMT with a minimum of 10 miles and a total of 100 miles for 2040. (Left) shows the road, starting mile, and length for each of the eHighway systems deployed, and (right) shows the location of the eHighway on California's road map.

This network covers 0.96 million VMT, which is about 2.6% of the total VMT of the model by using only 100 miles of eHighway.

4.5.4. SCENARIO 8

Finally, the last scenario uses the data for the year of 2040 and aims to maximize EJ by placing eHighway in regions with higher local emissions. The total eHighway miles are set to 500, and the minimum eHighway length is 20. For this scenario, Figure 32 shows the location of the eHighways across the state with a list of the roads of deployment, their starting miles, and eHighway length.

Road	Starting mile	Length (mile)
41	54	41
99	100	57
4	31	42
5	435	48
5	102	39
101	0	21
132	5	38
58	100	37
180	14	37
91	0	26
10	0	35
110	2	27
215	0	32
710	0	24

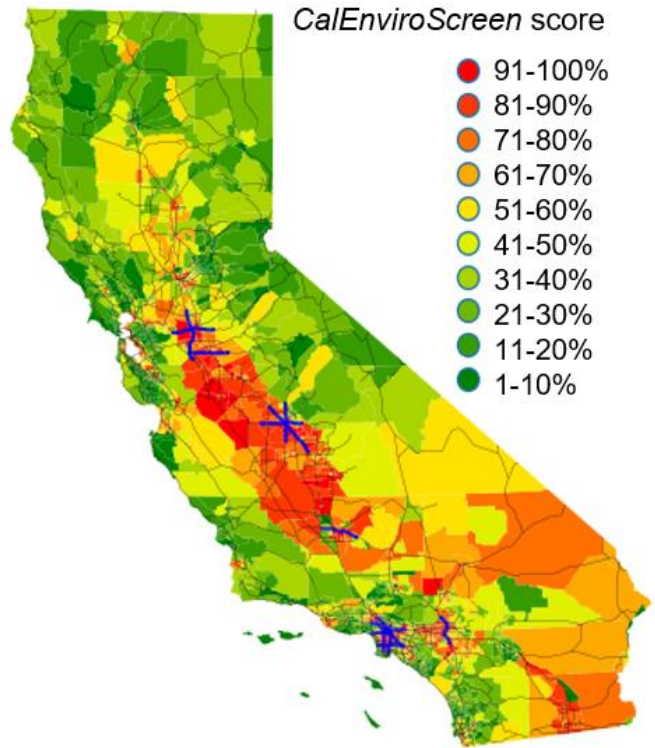


Figure 32. Output for scenario 8 based on EJ with a minimum of 20 miles and a total of 500 miles for 2040. (Left) shows the road, starting mile, and length for each of the eHighway systems deployed, and (right) shows the location of the eHighway on top of the environmental justice score map.

One important point for this scenario is that we do not have data forecasting EJ scores for 2040. Here, we are using the same information as in scenario 4. As the EJ optimization algorithm does not depend on the VMT of the roads, and the EJ scores have not changed, the roads selected are the same as in scenario 8. However, the total VMT covered by the eHighway network does change, which is now 1.36 million miles (3.6%) of the total VMT in the model, compared to 1.20 million for the 2020 model.

4.6 Commodities distribution

As mentioned in CHAPTER 3, the CSFFM classifies all the heavy-duty trucks in the model by fifteen different commodity groups and estimates the VMT for each one of them, as previously presented in Table 2. This division is based on the cargo industry that each truck carries and can help to identify the most prominent commodity in each road in

the model. This information can help focus incentive programs targeting specific industries that could give (and get) the most benefit from the eHighway system.

Therefore, in this section, we are analyzing the total VMT per scenario broke down by each one of the fifteen commodities. Table 3 depicts the VMT percentage of each commodity group in the scenario of interest – remembering that scenarios 1 to 4 represent the target year of 2020 and scenarios 5 to 8 the year of 2040.

Table 3. Vehicle miles traveled (VMT) percentage by commodity group.

Commodity group	VMT distribution							
	2020				2040			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8
	VMT-20-500	VMT-10-500	VMT-10-100	EJ-20-500	VMT-20-500	VMT-10-500	VMT-10-100	EJ-20-500
CG-1: Agriculture products	8.2%	9.0%	9.9%	14.7%	6.6%	7.9%	9.2%	13.7%
CG-2: Wood, printed products	3.9%	3.6%	3.6%	4.8%	3.7%	3.6%	3.2%	4.3%
CG-3: Crude petroleum	0.1%	0.1%	0.0%	0.3%	0.0%	0.1%	0.0%	0.2%
CG-4: Fuel and oil products	4.1%	4.4%	6.2%	4.5%	4.0%	4.1%	5.1%	4.2%
CG-5: Gravel/sand and non-metallic minerals	17.2%	17.4%	12.2%	15.9%	23.5%	22.5%	17.1%	20.2%
CG-6: Coal/metallic minerals	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
CG-7: Food, beverage, tobacco products	12.1%	11.5%	12.5%	11.3%	11.3%	11.4%	12.5%	11.6%
CG-8: Manufactured products	15.4%	15.2%	16.8%	13.5%	13.7%	13.6%	15.3%	13.3%
CG-9: Chemical/ pharmaceutical products	4.6%	4.6%	4.5%	4.4%	4.1%	4.1%	3.9%	4.0%
CG-10: Nonmetal mineral products	12.5%	11.8%	9.9%	11.0%	10.7%	10.5%	9.2%	9.7%
CG-11: Metal manufactured products	6.8%	6.8%	7.7%	5.9%	9.2%	8.6%	8.5%	5.8%
CG-12: Waste material	9.6%	10.5%	11.9%	9.6%	8.2%	8.9%	11.5%	9.2%
CG-13: Electronics	2.2%	2.0%	1.8%	1.3%	1.8%	1.7%	1.6%	1.1%
CG-14: Transportation equipment	3.0%	3.0%	2.7%	2.2%	3.1%	2.9%	2.7%	2.0%
CG-15: Logs	0.3%	0.3%	0.1%	0.8%	0.1%	0.2%	0.1%	0.6%
TOTAL VMT	3,031,171	3,082,723	823,508	1,199,443	3,852,739	3,925,989	961,817	1,357,193

At first glance, some commodities stand out in general, such as gravel/sand and non-metallic minerals (CG-5), food, beverage, tobacco products (CG-7), manufactures products (CG-8), and nonmetal mineral products (CG-10). Particularly for scenarios based on EJ (scenarios 4 and 8) have a much higher proportion of trucks in the agriculture products commodity (CG-1). These results are expected as some of the eHighway is located in more predominantly rural areas in California. On the other hand, the scenarios with only 100 miles and optimized for VMT coverage (scenarios 3 and 7) have higher proportions of waste material (CG-12) and manufactured products (CG-8), which are expected closer to ports and urban areas where these eHighway networks are placed.

4.7 Conclusions

This chapter was mainly focused on obtaining the best location for deploying an overhead catenary system in California. First, we proposed an algorithm that can be used

to select the optimal eHighway location based on the CSFFM data and two parameters: total eHighway length and minimum eHighway length. We proposed four different scenarios that explored different optimization metrics (road VMT and environmental justice) and a selected range of parameters for total eHighway length and minimum eHighway length. We applied the proposed algorithm, with each of these scenarios, on the CSFFM for two target years 2020 and 2040. We presented the road selection (including location and length) and showed the total VMT coverage for each of them. These selections will then be used to estimate the emissions produced in each scenario and evaluate the overall benefits of the system.

Lastly, we presented a commodities distribution analysis in which can help understand which industries should be focused on maximized eHighway usage.

As of right now, there is no sufficient available data to determine the costs of implementing the eHighway; therefore, the road selection did not consider the costs. However, we explore different total eHighway length and minimum eHighway length to cover the different implementation strategies that could have budget limitations. For future studies, other scenarios could be designed to guarantee an optimal location in terms of reducing emissions and minimizing construction costs.

CHAPTER 5. EMISSIONS ANALYSIS

In California, the transportation sector remains for the last few decades as the largest source of greenhouse gases (GHG) emissions, accounting for over 40% of overall emissions in the state. Due to this significant percentage, an alternative technology is desired, and the potential emission reduction of an eHighway system seems a suitable option. Therefore, in this chapter, we are analyzing the well-to-wheel (WTW) emissions produced by heavy-duty trucks for each one of the eight scenarios presented in section 4, comparing them with a base scenario where no eHighway is implemented.

5.1 Well-to-wheel analysis

The WTW analysis investigates the energy use and emissions necessary to produce the fuels used for transportation as well as the efficiency of fuels associated with vehicle technology. The first researches that used the WTW analysis approach are dated in the 1980s, and they were motivated primarily by the beginning of battery-powered electric vehicles. Even though electric vehicles have no tailpipe emission, the emissions from generating and distributing electricity can offset partially or completely these benefits. Therefore, the pursuit of reductions in emissions in the transportation sector, as well as the introduction of new fuels, demand a WTW analysis [76].

For transportation technologies, especially internal combustion engines, emissions occur either in the fuel production phase or in the fuel usage phase. Therefore, the WTW process consists of two stages: the well-to-pump (WTP) or fuel cycle stage, and the pump-to-wheel (PTW) or vehicle efficiency stage [77].

The WTP accounts for all the energy and emissions associated with fuel production, including feedstock extraction (mining the energy source), distribution, transportation, storage, and fueling. The PTW considers the operation energy and emissions associated with vehicle technology; in other words, it is the energy used to move the vehicle and the emissions associated with it. The whole WTW process, including the WTP and PTW stages, is illustrated in Figure 33.

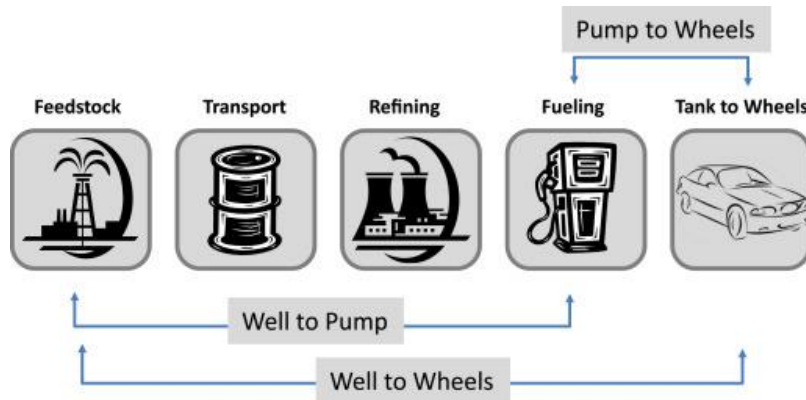


Figure 33. Well-to-wheel emission analysis. The well-to-pump stage includes feedstock, transport, refining, and ends at the fueling stations. The pump-to-wheel stage starts at the fueling station and ends on the vehicle [77].

This analysis will be made in terms of two important pollutants: carbon dioxide (CO_2) and nitrogen oxide (NO_x). CO_2 is the main GHG, and it is composed of one carbon and two oxygen atoms. It occurs naturally in Earth's atmosphere, but it is also a result of the complete burning of fuel molecules during the combustion process [78]. The emission from this pollutant is the leading cause of climate change, and it has been increasing for the last several years [79]. The NO_x is a collective term used to refer to NO (nitric oxide) and NO_2 (nitrogen dioxide). It is a poisonous and highly reactive gas that, combined with hydrocarbons and sunlight, can increase the levels of ozone in the Earth, contributing to the formation of smog and acid rain. NO_x is formed through the reaction of nitrogen and oxygen during the engine combustion processes. Therefore, areas with high vehicle traffic are more prominent locations of NO_x emission, contributing even more to air pollution [78].

There are other important pollutants to be considered to analyze the emission effects of deploying an eHighway system, such as particulate matter (PM), the volatile organic compound (VOC), sulfur dioxide (SO_2), etc. However, some of the models we are using in this study do not estimate these pollutants, and this would limit the WTW analysis. Therefore, at this time, we are only considering emissions in terms of CO_2 and NO_x .

5.2 Emission analysis methodology

To calculate the WTW emissions, the trucks in the model were split into two categories: the eHighway trucks, which are the vehicles that can connect to the catenary system, and the non-eHighway trucks, which account for any other truck in the model that is not an eHighway truck.

The fleet of non-eHighway trucks contains vehicles of different fuel types. To determine the fleet mix, including the fuel types available, we followed the vehicle proportions found in the CARB's Vision model. This model will be further described in Section 5.3, highlighting its features and applications. The fleet mixes used for 2020 and 2040 models are presented in Table 4.

Table 4. Heavy-duty truck's fleet mix for 2020 and 2040.

Fuel type	2020	2040
Diesel	99.43%	86.30%
Compressed Natural Gas	0.54%	12.06%
Electricity	0.03%	1.47%
Hydrogen	0.00%	0.16%

In the target year of 2020, the fleet mix is virtually composed exclusively by diesel trucks. By 2040, it is expected the compressed natural gas trucks and electric trucks will have started to take part in the market.

With the fleet mix, we can start estimating the WTP and the PTW emissions, which were performed separately. The WTP analysis was conducted using the GREET model database, which will be further detailed in Section 5.2. The same CARB's Vision model used to obtain the fleet mix was used to estimate the PTW emissions, which utilizes the EMFAC database for vehicle emission's characteristics (more details can be found in Section 5.3). The WTW emissions rate per mile for non-eHighway trucks was then achieved by summing the PTW and the WTP emissions. Finally, the VMT of non-eHighway trucks was multiplied by this WTW emission rate to obtain the total emission of each one of the pollutants for non-eHighway heavy-duty trucks.

For the eHighway trucks fleet, we are assuming they are hybrid electric trucks that, once connected to the catenaries, work as a full-electric truck. However, when they are not connected, they are powered by other types of fuel, according to the same fleet mix presented in Table 4 (all these hybrid combinations or full electric trucks have been tested and validated in the eHighway pilot studies in the U.S. and Europe). Therefore, the emissions caused when they are not connected to the eHighway system are calculated in the same manner as non-eHighway trucks. However, when they are connected to the catenary system (and working as full electric), they do not produce any PTW emissions. The WTP emissions produced by the generation of additional electricity demanded by the system need to be taken into consideration. These emissions are estimated using the statewide HiGRID model (which is further explained in Section 5.4), where the difference in total emission for electricity generation in the state between a baseline scenario (without eHighways) and those with eHighway, result in the additional CO₂ and NO_x emissions needed to operate the system.

The last step of the WTW methodology analysis is to establish the total emissions produced by heavy-duty trucks in California for each target year. This step can be accomplished by combining the WTW emissions from non-eHighway trucks to the eHighway ones for each scenario. This methodology can be seen in Figure 34, and the Python code to reproduce it can be found in APPENDIX C.

To implement this WTW emissions estimation methodology, we are breaking down the emission sources into three categories:

- The WTP stage that will be used to estimate fuel production emissions for non eHighway trucks;
- The PTW stage that will be used to estimate tailpipe emission for non eHighway trucks;
- The electricity generation emissions for the electric eHighway trucks.

These three categories are discussed in the following sections, which describe the data and the data sources used to estimate the emissions in each of them, and present the results obtained using the methodology proposed.

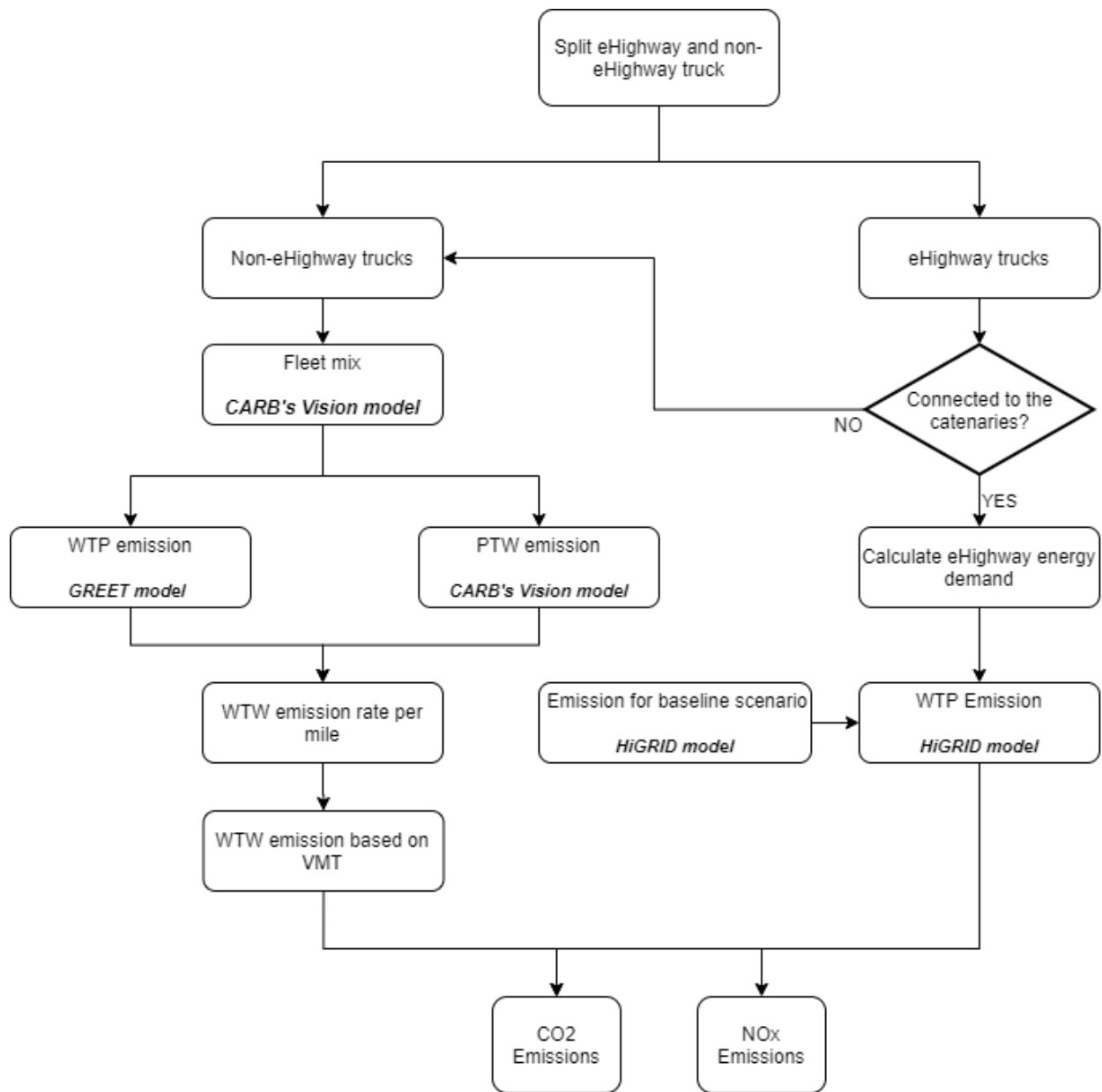


Figure 34. Block diagram for the well-to-wheel emission analysis methodology. Trucks are split into non-eHighway and eHighway. For non-eHighway trucks, the emissions are estimated by calculating the well-to-pump and pump-to-wheel emissions separately and combining them later based on the VMT of those trucks. For the eHighway trucks, once they are connected to the catenaries, the emissions related to energy generation are estimated and their only source of emissions. When they are not connected to the catenaries, their emissions are estimated by the same process as the non-eHighway trucks.

5.3 Well to pump emission analysis and the GREET model

To estimate the well to pump (WTP) emissions, we are using the analysis tool GREET (Greenhouse gases, regulated emissions, and energy use in transportation). The GREET is a life cycle assessment model that calculates per-mile energy use and emission rates for various combinations of vehicle technologies and fuels. It was developed by the Argonne National Laboratory, sponsored by the US Department of Energy, and evaluates the impacts of fuel cycles and total energy cycles [80].

The GREET model includes, for a specific target year, detailed simulations for all the activities within the fuel cycle, resulting in the energy contribution by fuel type (e.g., fossil fuel, coal fuel, natural gas fuel, etc.) in Joules/mile and the emissions by pollutant in grams/mile [81]. It includes emissions from the six criteria pollutants (VOC, CO, NO_x, SO_x, PM₁₀, PM_{2.5}) and three traditional greenhouse gases (CO₂, CH₄, and N₂O).

The model uses referenced or assumed values for emission factors and energy use. The data source for those estimations is based on open literature, engineering analysis simulation tools, stakeholders' inputs, vehicle simulation models, emission test results, national agencies models, such as MOVES from the United States Environmental and Protection Agency [82] and EMFAC from the California Air Resources Board [83]. The GREET applies the Monte Carlo simulation method to address uncertainties in the input parameters and deliver results in the form of a statistical distribution [81] [84].

Since the development of GREET 1.0 (which was a fuel-cycle model only) in 1999, the model has evolved, and it is updated annually with new fuel pathways and vehicle configurations. GREET offers two free platforms: a Microsoft Excel calculation tool (a multidimensional spreadsheet) and the GREET.net software (fully graphical toolbox) [85].

According to the GREET latest version (2019) database, the WTP emissions rate of CO₂ and NO_x for heavy-duty trucks for 2020 can be seen in Table 5.

Table 5. CO₂ and NO_x well-to-pump emission rate for heavy-duty trucks in 2020.

Fuel type	CO₂ emission rate	NO_x emission rate
Diesel	244.01 g/mile	0.38 g/mile
Compressed Natural Gas	187.40 g/mile	0.85 g/mile
Electricity	1551.16 g/mile	0.77 g/mile
Hydrogen	1290.73 g/mile	0.38 g/mile

Even though the WTP CO₂ emissions for electric and hydrogen vehicles are much higher than diesel and natural gas trucks, the former fuel types are still beneficial considering their lack of tailpipe emission. It is important to notice that CO₂ and NO_x are not necessarily proportional, e.g., hydrogen trucks have significantly higher CO₂ emission per mile than compressed natural gas, however lower NO_x emission.

To estimate the 2020 overall WTP emissions for non eHighway trucks, we obtain a CO₂ and NO_x emission rate for the fleet, this is calculated as a weighted average of the emissions by each fuel type, with the weights defined as their proportion in the mix (presented in Table 4). This estimation results in a WTP emission rate of 244.08 grams/mile for CO₂ and 0.38 grams/mile for NO_x.

For the 2040 target year in the GREET model, the WTP emissions rate of CO₂ and NO_x for heavy-duty trucks are presented in Table 6.

Table 6. CO₂ and NO_x well-to-pump emission rate for heavy-duty trucks in 2040.

Fuel type	CO₂ emission rate	NO_x emission rate
Diesel	230.92 g/mile	0.34 g/mile
Compressed Natural Gas	181.83 g/mile	0.84 g/mile
Electricity	1408.31 g/mile	0.7 g/mile
Hydrogen	1273.2 g/mile	0.37 g/mile

After 20 years, due to technology development and more efficient energy generation, it is expected a decrease in emissions rate for both pollutants analyzed – which can be seen comparing the 2020 and 2040 emissions. Again, to estimate the overall WTP emissions for non-eHighway trucks for 2040, the fleet mix for the same year (Table 4) is used to calculate the average emission rate. The WTP CO₂ emission is 244.06 grams/mile, and the NO_x emission is 0.41 grams/mile.

Following the proposed methodology, we can now work on estimating PTW emission for the same vehicles to calculate their total emission contribution.

5.4 Pump to wheel emission analysis and the CARB's Vision Model

The CARB's Vision Model is used in this study to approximate the fleet mix of heavy-duty trucks in California, as presented in Section 5.1. It is also used to estimate the pump to wheel (PTW) emissions for non eHighway trucks.

Based on the Argonne National Laboratory (ANL) Vision model – which only estimated on-road vehicle GHG emissions using national average emission factors – the California Air Resources Board (CARB) designed in 2012 a new Vision model that includes specific data from California. It is used to analyze the impacts of transportation technologies, fuels, and energy patterns, as well as to make projections that meet the kinds of deadlines and goals that California faces [86].

The latest model (Vision 2.1) uses inventory data from the EMFAC model, forecasts data up to 2050, and outputs results in terms of greenhouse gas emissions, criteria pollutant emissions, and energy mix [87]. The inventory model Emission FACTors (also known as EMFAC model) was also developed by the CARB, and calculates statewide tailpipe emissions (PTW) from on-road motor vehicles, including light-duty and heavy-duty trucks, operating on highways, freeways, and local roads in California [83], [88].

The modeling process is based on three main steps: defining the emission factors, determining the vehicle activity data, and multiplying both values to estimate the emissions rate. Those rates are expressed in mass of pollutant emitted per mile traveled per vehicle per day. The EMFAC database provides the emissions by region, calendar year, season, vehicle category, model year, speed, and fuel type. In this research, we are using annual statewide emissions for heavy-duty trucks of aggregate model years and speed for the target years of 2020 and 2040 [83]. Table 7 presents the CO₂ and NO_x PTW emissions for the year 2020 and Table 8 for the year 2040.

Table 7. CO₂ and NO_x pump-to-wheel emission rate for heavy-duty trucks in 2020.

Fuel type	CO ₂ emission rate	NO _x emission rate
Diesel	1528.31g/mile	3.81 g/mile
Compressed Natural Gas	3439.77 g/mile	3.77 g/mile
Electricity	0 g/mile	0 g/mile
Hydrogen	0 g/mile	0 g/mile

Table 8. CO₂ and NO_x pump-to-wheel emission rate for heavy-duty trucks in 2040.

Fuel type	CO ₂ emission rate	NO _x emission rate
Diesel	1120.86 g/mile	0.40 g/mile
Compressed Natural Gas	1108.06 g/mile	0.17 g/mile
Electricity	0 g/mile	0 g/mile
Hydrogen	0 g/mile	0 g/mile

As expected, electric and hydrogen-powered trucks do not have any PTW emissions. Compressed natural gas has higher CO₂ emission than diesel in the year 2020; however, with technological developments, it is expected to have a significant drop by 2040, leveling up with diesel.

Using the fleet mix presented in Table 4 as weights, we can calculate a weighted average to the PTW emissions as an emission rate per mile for the non-eHighway trucks. This rate is 1538.28 grams/mile of CO₂ and 3.82 grams/mile of NO_x for 2020. For 2040, the rates are 1100.96 and 0.37 grams/mile for CO₂ and NO_x, respectively.

5.5 Electric emissions analysis and the HiGRID model

Based on the pilot projects around the world, we used full electric and hybrid trucks as part of the eHighway system. For hybrid trucks, we are assuming that once they are connected to the catenaries, they work fully electric. For all trucks in the eHighway system, including those full electric, the energy from the catenary system goes directly to their electric motor without using energy from (or transferring to) the battery storage. The energy used to charge these fully electric trucks are, however, accounted for in the general energy demand prediction of the HiGRID model that will be further discussed in this section. Once trucks are disconnected from the system and drive in other non

eHighway roads, they work utilizing other types of fuel, according to the same fleet mix presented in Table 4, and their emission is calculated similarly to those vehicles, as presented in the previous chapters. Therefore, this section only accounts for the electric emissions of the eHighway trucks while they are connected to the catenary system.

Even though those trucks act as full electric once connected to the catenaries, generating zero emissions from vehicle operation, they are still producing emissions through the production and distribution of their electric demand. These emissions change according to the location the energy is generated since they are dependent on the energy generation mix. For example, Figure 35 shows a map with the different annual WTW emissions for a typical electrical passenger car by the state in terms of pounds of CO₂ equivalent [89].

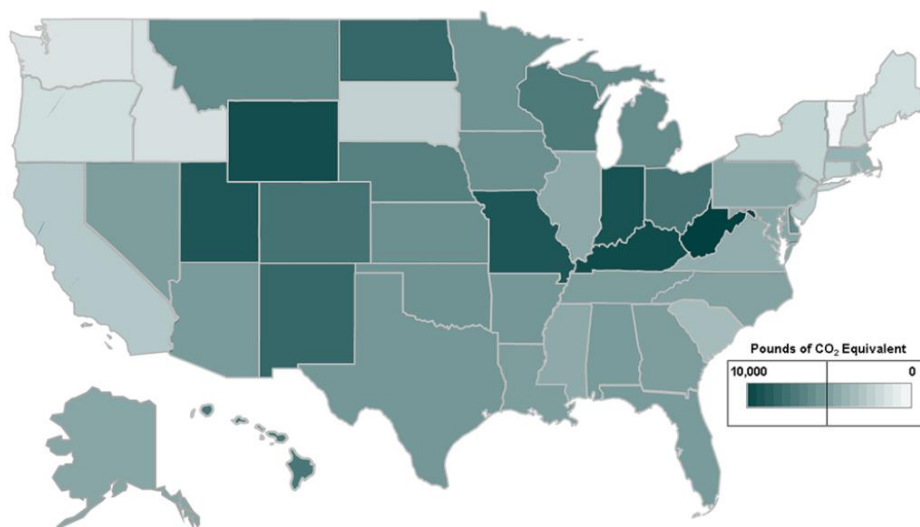


Figure 35. Annual well-to-wheel emissions from a typical electrical vehicle by state. States with darker colors indicate a higher rate of well-to-wheel emissions in pounds of CO₂ equivalent [89].

The top 3 states with the least emissions (less than 1,200 pounds of CO₂ equivalent annually) are Vermont, Washington, and Idaho. California sets on the eleventh position producing 2,706 pounds of CO₂ equivalent for a typical electric vehicle. West Virginia has the highest number on the country, with 9,451 pounds of CO₂ equivalent. For comparison purposes, the national average for an electric vehicle is 4,815 pounds of CO₂, while a gasoline vehicle emits 11,435 pounds of CO₂ per year.

As can be seen in Figure 35, the same vehicle configuration can have different WTW emissions depending on the location of energy production. Therefore, to assess an accurate evaluation of the energy and environmental impacts of deploying an eHighway system in California, we are using the California based model, the Holistic Grid Resource Integration, and Deployment (HiGRID) model.

The HiGRID was developed by the Advanced Power and Energy Program (APEP) at the University of California, Irvine. It is a temporal energy modeling tool, adaptable for electric vehicle implementations, which meets the scope of this study. It analyzes the emissions of statewide systems on an hourly timescale, integrating the baseload (non-renewables), dispatchable, and intermittent (non-dispatchable) renewable generation [90]. The main objective of this platform is to determine the effects of injecting renewable resources into the electric grid, in terms of economic and technical performance. It can also intelligently advise agencies on how the use of renewable power generation can help achieve new climate policies, as well as identifying potential obstacles encounter during this deployment [90].

To estimate the eHighway grid emissions, the HiGRID uses as input the annual energy consumption of all eHighway trucks per hour per day. To calculate the energy consumption, we are using the VMT data extracted from the filtered CSFFM and multiplying by the truck's energy consumption. Moultaq, Lutsey, and Hall (2017) [91] estimate that electric overhead catenary trucks in the United States will consume in average 5.3 MJ/km (about 2.369 kWh/mile) in 2020, improving each year reaching 3.7 MJ/km (about 1.654 kWh/mile) in 2040.

Combining both information, we now have the energy consumption of all trucks per day. However, the HiGRID uses an hourly timescale and, therefore, we are using data from the Truck Activity Monitoring System (TAMS) – a truck counting system, to estimate volume distribution patterns through the day and across the state, which uses inductive loop detector sites to collect continuous real-time detailed truck data.

TAMS was developed by the University of California, Irvine, Institute of Transportation Studies [92] as a potential system for identifying truck and trailer

configurations to understand truck activity patterns and behavior better. TAMS has more than 90 data collection sites in California that transmit the data nightly to a database available online through a web interface. The TAMS interface provides current and historical data for each site, such as daily volume by vehicle class and hourly volume by month (specified by weekdays and weekends).

The information collected using TAMS in 2016 and 2017 will be used to estimate annual VMT per hour for each month simulated in the model. For each road on the network, we identified the closest TAMS site and assumed the traffic flow on those roads have the same hourly travel pattern as the data collected on that site. Figure 36 shows each road and its designated TAMS site (based on their color). Three different sites were selected to exemplify how the daily vehicle distribution per hour for each month and the average for one year of data separated by weekdays and weekends.

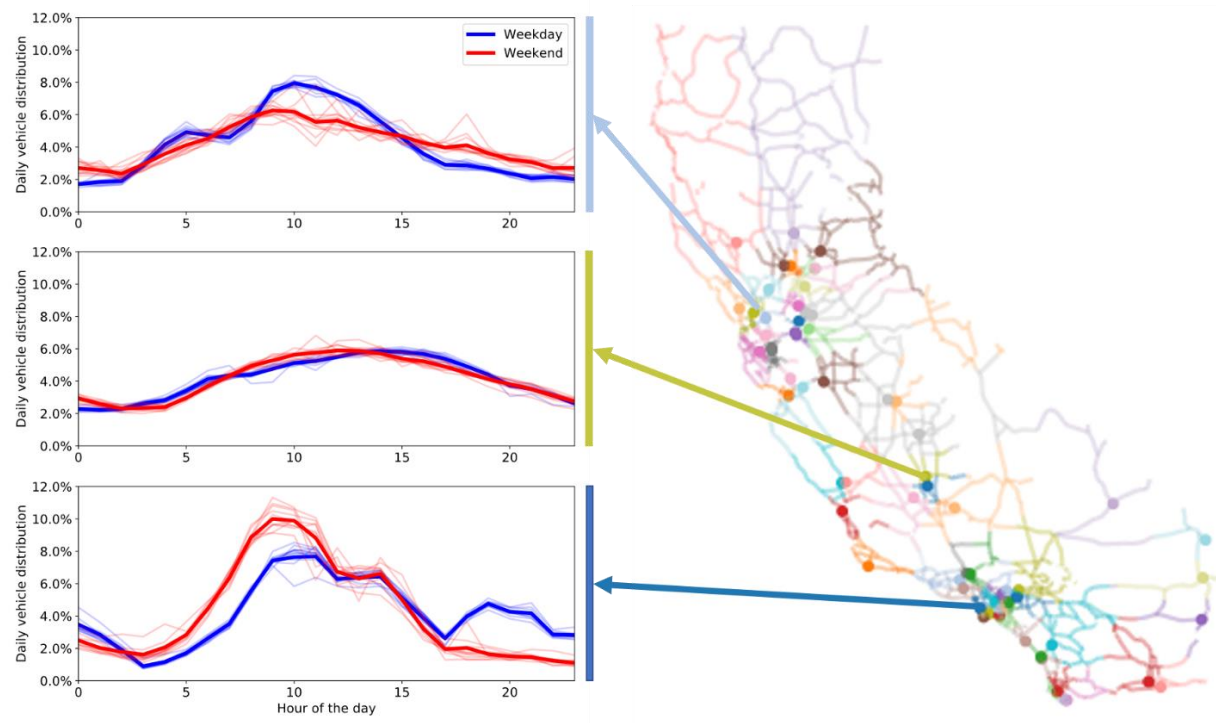


Figure 36. Road to TAMS sites association to estimate daily vehicle distribution. (Right) shows all the roads in the model color-coded to their associated (closest) TAMS site (circles). (Left) shows three examples of daily vehicle distribution patterns per hour of the day. In blue, the weekday pattern for each month (thin lines) and their average across one year (thick line). In red, the same for weekends.

The daily vehicle distribution pattern varies significantly across the sites. This is an important consideration for two reasons: 1 – different than full electric trucks that can be charged overnight, the eHighway system may demand more energy during the day time and rush hours; 2 – as we are considering the injection of renewable energy sources, different energy demand patterns may influence the source of energy used (for example, during the day, more solar energy may be available than overnight) and, therefore, the emissions from energy generation. These factors are taken into account when calculating energy emission using the HiGRID model. The final step to achieve the VMT per hour is to distribute the daily VMT to the hours of the day based on the truck rate obtained from the TAMS data.

This process was applied to all the scenarios presented (for both 2020 and 2040), assuming different eHighway adoption rates (25%, 50%, 75%, and 100%), which allows us to calculate the energy per hour consumed by the whole eHighway system. Figure 37 presents an example of energy consumption per hour in January for scenario 1 (based on VMT with a minimum of 20 miles and a total of 500 miles of 2020) with an adoption rate of 50%.

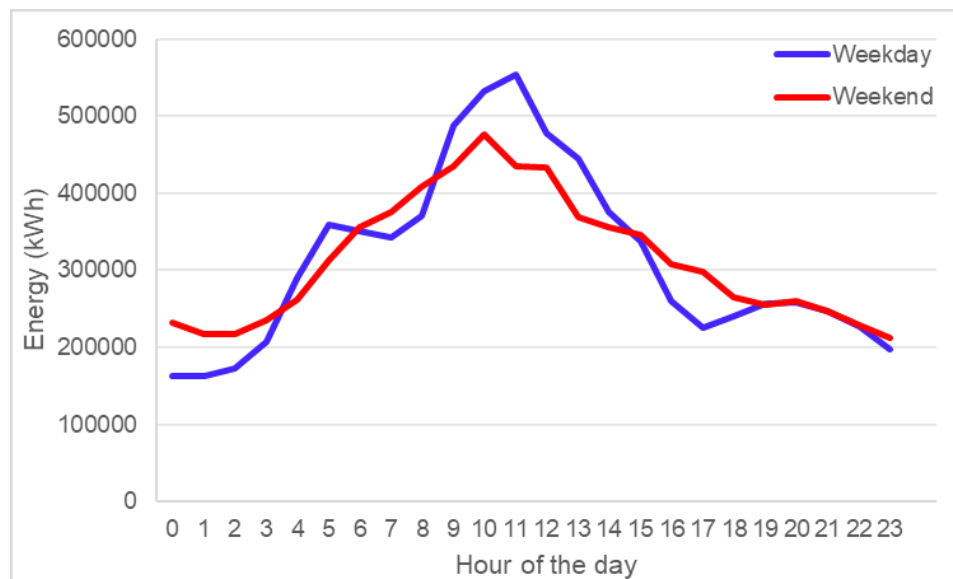


Figure 37. Example of energy consumption per hour in January for scenario 1. Scenario 1 is based on VMT with a minimum of 20 miles and a total of 500 miles and a 50% adoption rate. Energy is calculated using the VMT from the model, the daily vehicle distribution from the TAMS sites, and the estimated vehicle energy consumption for the eHighways in the year of 2020. In red is the average for the weekdays and in blue for the weekends.

Once the energy consumption is estimated for all the scenarios, the HiGRID model estimates the CO₂ and NO_x emissions of the electric grid in California for each specific scenario. The additional emissions (due to the energy generated for the eHighway system) are calculated by comparing the results from the HiGRID model for each scenario to a baseline scenario where no eHighway is implemented. Any extra emission, for both CO₂ and NO_x, is then attributed to the eHighway system.

Now that we have all the data necessary to implement the methodology presented in Figure 34, we can proceed to estimate the emission impact of deploying the different eHighway scenarios in California.

5.6 Emission results for 2020

In this section, we present the emission results, in terms of CO₂ and NO_x, for scenarios 1 to 4 related to the year 2020 and comparing them with a “base” scenario where the eHighway was not implemented. For each scenario, we assumed different adoption rates of eHighway trucks: 25% of trucks being eHighway trucks, 50%, 75%, and 100%, which represents an extreme adoption and the best-case scenario for implementing an eHighway system.

The annual CO₂ total emissions for each scenario are presented in Table 9 with the change to the base scenario in million-metric tons per year (MMT/year) and the percentage change to the base scenario. The total emissions account for the WTW emissions for all heavy-duty trucks on the network in each scenario. The list is presented from the most pollutant scenario to the least one.

Both scenarios based on VMT with a 100% adoption rate and total mileage of 500 miles obtained the highest reduction of total emissions to the base scenario (~8% or ~1.8 MMT/year). Even disregarding such a radical adoption rate, the same scenarios are still polluting less compared to the others. However, since the difference between them is virtually zero, the choice of picking one over the other should take into consideration other aspects, such as costs, construction burdens, specific location characteristics, etc.

Table 9. Annual CO₂ well-to-wheel emissions for heavy-duty trucks per scenario for 2020. The table presents the total emissions in million-metric tons (MMT) per year for each scenario with different adoption rates. It also shows the difference in emissions between each scenario with the base scenario (with no eHighway implemented), and the percentage change to the base scenario. The scenario name is defined as [type of optimization, VMT for vehicle miles traveled, and EJ for environmental justice]-[minimum eHighway length]-[total eHighway length]. For example, VMT-10-100 was defined to maximize vehicle miles traveled covered by the network with minimum eHighway length of 10 miles and a total eHighway length of 100 miles.

CO ₂					
Scenario		Adoption rate	Total Emission (MMT/year)	Change to base (MMT/year)	Change to base (%)
Base	no eHighway	-	22.455	0.000	0.00%
Scenario 3	VMT-10-100	25%	22.384	-0.071	-0.31%
Scenario 4	EJ -20-500	25%	22.300	-0.155	-0.69%
Scenario 3	VMT-10-100	50%	22.223	-0.232	-1.03%
Scenario 3	VMT-10-100	75%	22.133	-0.322	-1.44%
Scenario 4	EJ -20-500	50%	22.066	-0.389	-1.73%
Scenario 1	VMT-20-500	25%	22.058	-0.397	-1.77%
Scenario 2	VMT-10-500	25%	22.056	-0.399	-1.78%
Scenario 3	VMT-10-100	100%	21.985	-0.470	-2.09%
Scenario 4	EJ -20-500	75%	21.861	-0.594	-2.65%
Scenario 4	EJ -20-500	100%	21.679	-0.777	-3.46%
Scenario 1	VMT-20-500	50%	21.554	-0.902	-4.02%
Scenario 2	VMT-10-500	50%	21.529	-0.926	-4.12%
Scenario 1	VMT-20-500	75%	21.111	-1.344	-5.99%
Scenario 2	VMT-10-500	75%	21.090	-1.365	-6.08%
Scenario 1	VMT-20-500	100%	20.666	-1.789	-7.97%
Scenario 2	VMT-10-500	100%	20.661	-1.794	-7.99%

This reduction in CO₂ can offset some of the infrastructure costs of implementing the eHighway system by looking at carbon auction prices or the social-economic impacts (e.g., health care costs, property destruction, food price increase, among others) of CO₂ pollution [93]. The Environmental Defense Fund published the prices of a recent Quebec-California carbon auction for 2020 with future allowances cleared at 18 dollars per metric ton of CO₂ [94]. With this rate, the scenario with most emission reduction (scenario 2) with 100% adoption rate, generates a total savings in CO₂ of over 32 million dollars a year. For social-economic impacts, the current carbon cost estimate is 50 dollars per metric ton

of CO₂ [95], which results in savings of almost 90 million dollars per year. At this rate, the initial cost of the eHighway implementation would be fully offset in as soon as 13 years.

It is also worth mentioning that even though we got an almost 8% reduction in CO₂ emissions, the scenarios with 500 miles of eHighway cover only 1.8% of the total number of miles in the model. The scenario with 100 miles of eHighway and 100% of adoption rate got a CO₂ emission reduction of 2.09%; however, this scenario only covers 0.37% of the total number of miles in the model.

Even the scenarios with limited total eHighway length of 100 miles presented a reduction in emissions compared to the base scenario without eHighway. As expected, their total benefit was smaller than those with a total eHighway length of 500 since their VMT coverage was significantly smaller. However, even though the 500-mile scenarios have five times the total eHighway length of the 100-mile scenarios, the pollution reduction of the best 500-mile scenario is only 3.8 times larger than the best 100-mile scenario. That means, in proportion to the eHighway mileage deployed, the 100-mile scenario had better performance. Therefore, they are still strong candidates for cost-constrained projects or earlier phases of a larger project.

As expected, the scenarios based on EJ, even the ones with high adoption rates, did not perform as well as the scenarios based on VMT with the same total eHighway length on a statewide level. However, we are also projecting that emission reduction will have a greater effect locally, close to the disadvantage communities. Further analysis of the local impact of the scenarios based on EJ is presented in Section 5.7.

Similar to the CO₂ discussion above, we analyzed the emissions in terms of NO_x. Table 10 presents the total emission changes for all the scenarios.

The scenarios based on VMT with 500 of total eHighway mileage presented the best results. All the scenarios ranked the same as for CO₂ when ordered by the change to base. Another important aspect to be noticed is that NO_x emissions presented a higher reduction percentage compared to CO₂, which means that this pollutant will have a bigger impact on the deployment of the eHighway system. This fact is due to the high NO_x

emissions during the PTW stage of the non-eHighway trucks, which is completely removed for the catenary-connected trucks.

This reduction in NO_x emissions can be particularly impactful for areas with high traffic and, therefore, with low environmental justice scores, as the NO_x has a great contribution to local air pollution. These aspects of local pollution will be further explored in subsequent sections.

Table 10. Annual NO_x well-to-wheel emissions for heavy-duty trucks per scenario for 2020. The table presents the total emissions in thousand metric tons (kMT) per year for each scenario with different adoption rates. It also shows the difference in emissions between each scenario with the base scenario (with no eHighway implemented), and the percentage change to the base scenario. The scenario name is defined as [type of optimization, VMT for vehicle miles traveled, and EJ for environmental justice]-[minimum eHighway length]-[total eHighway length]. For example, VMT-10-100 was defined to maximize vehicle miles traveled covered by the network with minimum eHighway length of 10 miles and a total eHighway length of 100 miles.

NO _x					
Scenario		Adoption rate	Total Emission (kMT/year)	Change to base (kMT/year)	Change to base (%)
Base	no eHighway	-	52.916	0.000	0.00%
Scenario 3	VMT-10-100	25%	52.172	-0.745	-1.41%
Scenario 4	EJ -20-500	25%	51.725	-1.191	-2.25%
Scenario 3	VMT-10-100	50%	51.429	-1.487	-2.81%
Scenario 3	VMT-10-100	75%	50.686	-2.230	-4.21%
Scenario 4	EJ -20-500	50%	50.535	-2.381	-4.50%
Scenario 1	VMT-20-500	25%	50.280	-2.636	-4.98%
Scenario 2	VMT-10-500	25%	50.254	-2.663	-5.03%
Scenario 3	VMT-10-100	100%	49.942	-2.975	-5.62%
Scenario 4	EJ -20-500	75%	49.344	-3.572	-6.75%
Scenario 4	EJ -20-500	100%	48.154	-4.762	-9.00%
Scenario 1	VMT-20-500	50%	47.644	-5.272	-9.96%
Scenario 2	VMT-10-500	50%	47.591	-5.325	-10.06%
Scenario 1	VMT-20-500	75%	45.009	-7.907	-14.94%
Scenario 2	VMT-10-500	75%	44.928	-7.988	-15.10%
Scenario 1	VMT-20-500	100%	42.375	-10.541	-19.92%
Scenario 2	VMT-10-500	100%	42.267	-10.649	-20.12%

For both CO₂ and NO_x pollutants, we broke down the emission from heavy-duty trucks by their stages (i.e., WTP and PTW). The scenarios are presented in Figure 38

and Figure 39 in order of higher to lower (left to right) total emissions. Here, non-eHighway WTP incorporates both non-eHighway trucks as well as eHighway trucks when not connected to the catenary system. All scenarios can be compared to the base scenario, which, even though it has no eHighway emissions contribution, both of its WTP and PTW emissions are still higher than all the other scenarios for both pollutants.

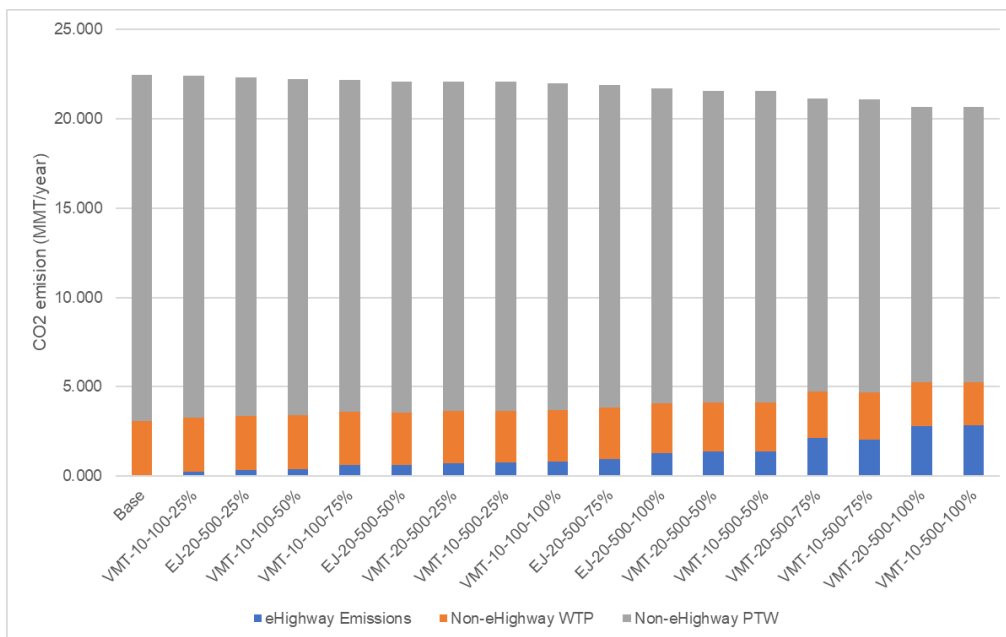


Figure 38. Annual CO₂ emissions divided by well-to-wheel stages for 2020 scenarios. In gray are the pump-to-wheel emissions that include both non-eHighway trucks as well as eHighway trucks when not connected to the catenary system (when in the catenary system, there are not pump-to-wheel emissions for eHighway trucks). In orange, the well-to-pump emissions for non-eHighway trucks. In blue, the emissions from generating additional electric energy to power the eHighway system.

As previously mentioned, NO_x is mainly emitted in the WTP stage of the non-eHighway trucks, and the amount produced for the energy generated to power the eHighway system is almost negligible, as seen in Figure 39.

The figures also illustrate that the majority of the emissions caused by the heavy-duty trucks are a result of their tailpipe emissions (also known as WTP), which supports the investments on electric vehicles as a potential technology to reduce air pollution since their WTP emissions are zero.

Moreover, for all the scenarios evaluated, using VMT or EJ metrics, there was a reduction in total CO₂ and NO_x emissions. This result shows the benefit, in terms of

emissions, of implementing the eHighway system, as the reduction in PTW emissions overcomes the additional eHighway emissions (due to energy generation to run the system). These benefits escalate as the adoption rate increases, showing that the eHighway can achieve the main goal of this technology, which is to reduce total emissions of heavy-duty trucks.

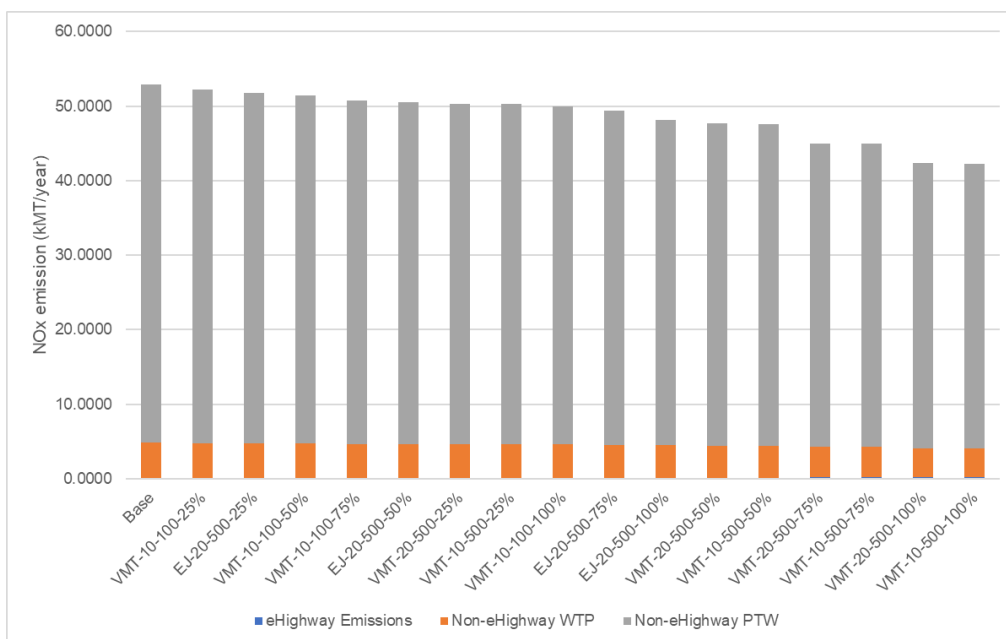


Figure 39. Annual NO_x emissions divided by well-to-wheel stages for 2020 scenarios. In gray are the pump-to-wheel emissions that include both non-eHighway trucks as well as eHighway trucks when not connected to the catenary system (when in the catenary system, there are not pump-to-wheel emissions for eHighway trucks). In orange, the well-to-pump emissions for non-eHighway trucks. In blue, the emissions from generating additional electric energy to power the eHighway system.

As presented in CHAPTER 1, heavy-duty trucks are responsible for 8.4% of the total emissions in California (only accounting for tailpipe). That means the best-case scenario (100% adoption of scenario 2 based on VMT with 500 miles of eHighway deployed and a minimum length of 10 miles) has the potential to reduce as much as 0.8% of the total emission in the state.

5.7 Emission results for 2040

Similar to the results in Section 5.5, here, the total emissions of CO₂ and NO_x are presented for scenarios 5 to 8 related to the year 2040. We are comparing those results

with the scenarios with no eHighway (base) for different adoption rates (25%, 50%, 75%, and 100%) using the 2040 CSFFM forecast.

Table 11 presents the results in terms of annual WTW CO₂ emissions for all the heavy-duty trucks in the model. The eHighway scenarios specify the total emissions (in MMT/year) and they are compared to the base scenario (with no eHighway). Again, the list is presented from the most pollutant scenario to the least one.

Table 11. Annual CO₂ well-to-wheel emissions for heavy-duty trucks per scenario for 2040. The table presents the total emissions in thousand metric tons (kMT) per year for each scenario with different adoption rates. It also shows the difference in emissions between each scenario with the base scenario (with no eHighway implemented), and the percentage change to the base scenario. The scenario name is defined as [type of optimization, VMT for vehicle miles traveled, and EJ for environmental justice]-[minimum eHighway length]-[total eHighway length]. For example, VMT-10-100 was defined to maximize vehicle miles traveled covered by the network with minimum eHighway length of 10 miles and a total eHighway length of 100 miles.

CO₂					
Scenario		Adoption rate	Total Emission (MMT/year)	Change to base (MMT/year)	Change to base (%)
Base	no eHighway	-	20.207	0.000	0.00%
Scenario 7	VMT-10-100	25%	19.991	-0.216	-1.07%
Scenario 8	EJ -20-500	25%	19.910	-0.298	-1.47%
Scenario 7	VMT-10-100	50%	19.773	-0.434	-2.15%
Scenario 8	EJ -20-500	50%	19.600	-0.607	-3.00%
Scenario 7	VMT-10-100	75%	19.561	-0.647	-3.20%
Scenario 5	VMT-20-500	25%	19.396	-0.811	-4.01%
Scenario 6	VMT-10-500	25%	19.389	-0.818	-4.05%
Scenario 7	VMT-10-100	100%	19.358	-0.850	-4.20%
Scenario 8	EJ -20-500	75%	19.281	-0.926	-4.58%
Scenario 8	EJ -20-500	100%	18.979	-1.229	-6.08%
Scenario 5	VMT-20-500	50%	18.579	-1.629	-8.06%
Scenario 6	VMT-10-500	50%	18.577	-1.630	-8.07%
Scenario 5	VMT-20-500	75%	17.771	-2.436	-12.06%
Scenario 6	VMT-10-500	75%	17.754	-2.453	-12.14%
Scenario 5	VMT-20-500	100%	16.947	-3.260	-16.14%
Scenario 6	VMT-10-500	100%	16.922	-3.285	-16.26%

As expected, because of the technological developments in the vehicles, fuel extraction, and energy production, even though the total VMT has increased by more than

15% from 2020 to 2040, we can see a reduction in the overall emissions over the years. In the year 2020, the base scenario emitted a total of 22.455 MMT/year, and, on the other hand, in 2040, the annual total emission fell to 20.207 MMT/year.

Additionally, the reduction percentage for the eHighway scenarios increased substantially after 20 years, with the best-case scenario coming from approximately 8% to 16% for the same scenarios based on VMT and a total of 500 miles of eHighway. These results prove that the benefits in terms of emissions are expected to improve even more after the years.

For the NO_x emissions, we applied the same methodology, and Table 12 presents the results.

Again, it is possible to notice a considerable reduction in total emission for the base scenario comparing 2020 to 2040 (from 52.9 kMT/year to 11.6 kMT/year). However, different from before, the reduction percentage of each scenario compared to the base was virtually the same for both target years. All the scenarios are still producing fewer emissions than a scenario with no eHighway, but the difference between them remained the same.

Table 12. Annual NO_x well-to-wheel emissions for heavy-duty trucks per scenario for 2040. The table presents the total emissions in thousand metric tons (kMT) per year for each scenario with different adoption rates. It also shows the difference in emissions between each scenario with the base scenario (with no eHighway implemented), and the percentage change to the base scenario. The scenario name is defined as [type of optimization, VMT for vehicle miles traveled, and EJ for environmental justice]-[minimum eHighway length]-[total eHighway length]. For example, VMT-10-100 was defined to maximize vehicle miles traveled covered by the network with minimum eHighway length of 10 miles and a total eHighway length of 100 miles.

NO _x					
Scenario		Adoption rate	Total Emission (kMT/year)	Change to base (kMT/year)	Change to base (%)
Base	no eHighway	-	11.607	0.000	0.00%
Scenario 7	VMT-10-100	25%	11.450	-0.157	-1.35%
Scenario 8	EJ -20-500	25%	11.390	-0.217	-1.87%
Scenario 7	VMT-10-100	50%	11.295	-0.312	-2.69%
Scenario 8	EJ -20-500	50%	11.166	-0.441	-3.80%
Scenario 7	VMT-10-100	75%	11.144	-0.463	-3.99%
Scenario 5	VMT-20-500	25%	11.016	-0.591	-5.09%
Scenario 6	VMT-10-500	25%	11.015	-0.592	-5.10%
Scenario 7	VMT-10-100	100%	10.986	-0.621	-5.35%
Scenario 8	EJ -20-500	75%	10.943	-0.664	-5.72%
Scenario 8	EJ -20-500	100%	10.725	-0.882	-7.60%
Scenario 5	VMT-20-500	50%	10.433	-1.174	-10.11%
Scenario 6	VMT-10-500	50%	10.426	-1.181	-10.18%
Scenario 5	VMT-20-500	75%	9.848	-1.759	-15.16%
Scenario 6	VMT-10-500	75%	9.837	-1.770	-15.25%
Scenario 5	VMT-20-500	100%	9.260	-2.347	-20.22%
Scenario 6	VMT-10-500	100%	9.248	-2.359	-20.32%

Lastly, Figure 40 and Figure 41 depict the total emissions broke down by emissions sources (eHighway emissions, non-eHighway WTP, and non-eHighway PTW) for each scenario for the CO₂ and NO_x pollutants, respectively. Here, non-eHighway WTP incorporates both non-eHighway trucks as well as eHighway trucks when not connected to the catenary system. Also, the eHighway emissions account for the emissions from generating additional electric energy to power the eHighway system. The scenarios are presented in order of higher to lower (left to right) total emissions.

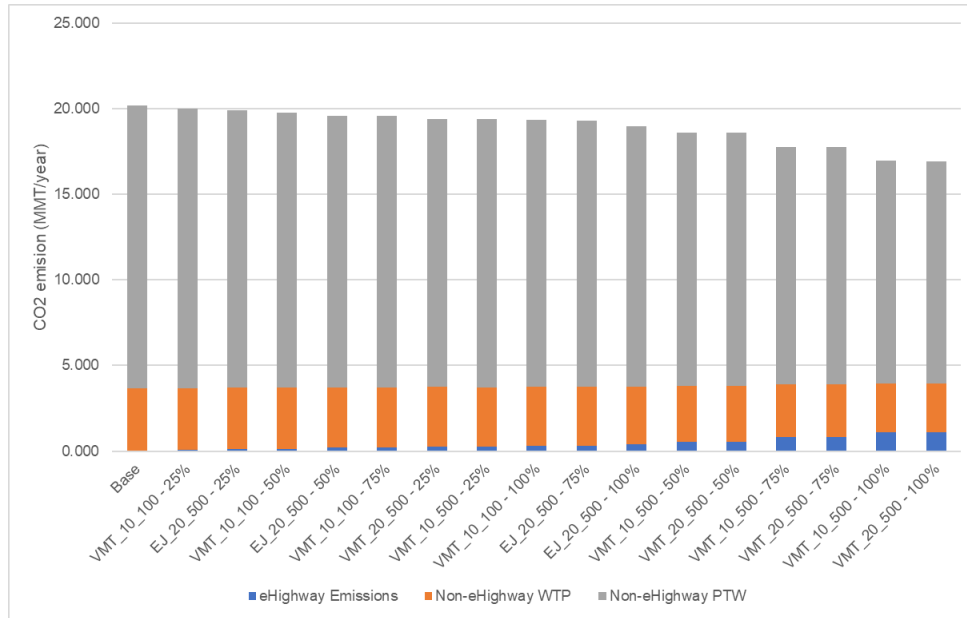


Figure 40. Annual CO₂ emissions divided by well-to-wheel stages for 2040 scenarios. In gray are the pump-to-wheel emissions that include both non-eHighway trucks as well as eHighway trucks when not connected to the catenary system (when in the catenary system, there are not pump-to-wheel emissions for eHighway trucks). In orange, the well-to-pump emissions for non-eHighway trucks. In blue, the emissions from generating additional electric energy to power the eHighway system.

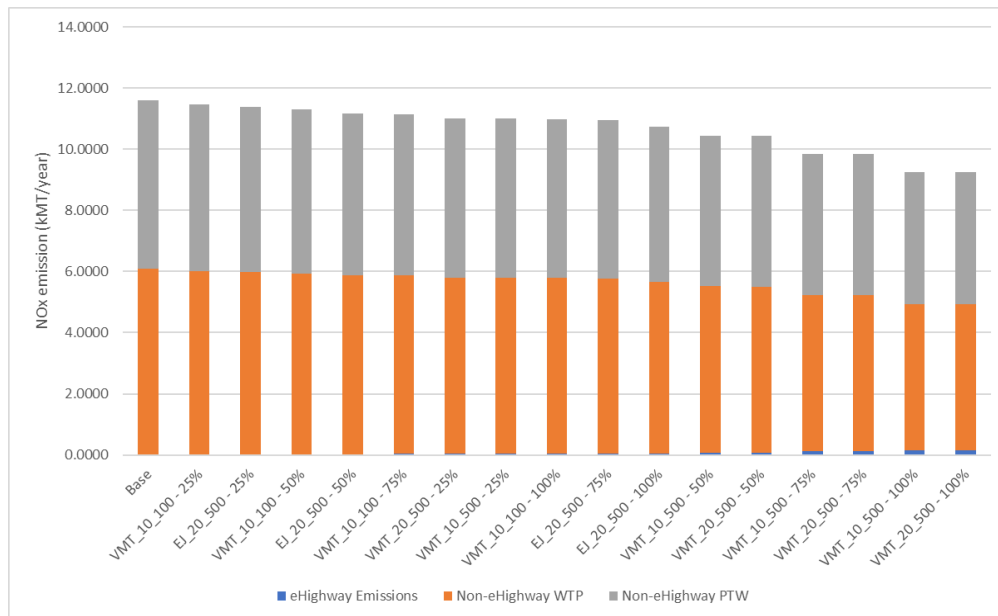


Figure 41. Annual NO_x emissions divided by well-to-wheel stages for 2040 scenarios. In gray are the pump-to-wheel emissions that include both non-eHighway trucks as well as eHighway trucks when not connected to the catenary system (when in the catenary system, there are not pump-to-wheel emissions for eHighway trucks). In orange, the well-to-pump emissions for non-eHighway trucks. In blue, the emissions from generating additional electric energy to power the eHighway system.

The same characteristics found in Figure 38 and Figure 39, persist on these figures, where the eHighway emissions increase as the scenarios improve their performance, however at a lower rate than the WTP and PTW for the non-eHighway decrease.

The total CO₂ emission presented a decrease of around 10% between 2020 and 2040 for the base scenario, reaching an 18% decrease for best eHighway scenario presented based on VMT with a minimum length of 20 miles and total eHighway length of 500 miles.

There was a more significant reduction in NO_x emission. One of the main differences when comparing to the NO_x emissions for 2020 cases is the proportion coming from the WTP and PTW stages for non-eHighway trucks. Due to a significant decrease in the NO_x emission rate from 2020 to 2040, the PTW stage for non-eHighway trucks presented a steep decrease even with a higher VMT in the 2040 model. As it can be seen in Figure 41, the gray bars (that represent the non-eHighway PTW) and the orange bars (that show the non-eHighway WTP emissions) have almost the same size, which means their emissions are practically the same. This large decrease in the NO_x emission rate brought this total pollutant emission from approximately 53 kMT/year to less than 12 kMT/year for the base scenario in this 20-year gap.

5.8 Local emissions for the EJ scenarios

In the results presented in Sections 5.5 and 5.6, it is noticeable the scenarios based on EJ did not perform as well as the scenarios based on VMT with the same total length of 500 miles. This factor can be explained by the total VMT covered in each scenario, which was maximized in the VTM scenarios. The scenarios 1 and 2 that were based on VMT and total eHighway length of 500 miles, covered about 20.4% and 20.6%, respectively. Meanwhile, scenario 4, based on EJ, also with a total eHighway length of 500 miles, covered only 9.0% of the total VMT on the model. Therefore, in terms of statewide emissions, scenarios 1 and 2 were expected and did emit less pollution for both CO₂ and NO_x. Similar results were seen for scenarios based on the year of 2040.

However, because of the incentives and laws surrounding the disadvantage communities, public and private agencies, there would likely be interest in investing the eHighway system in those areas. For that, estimating local, instead of statewide, emissions may be a more relevant way to analyze these scenarios. Therefore, this section explores the potential environmental benefits for the scenarios based on EJ, considering the local emissions around the eHighway roads.

First, we evaluated the percentage of heavy-duty truck VMT covered in each of the census tract zones, as shown in Figure 42. The highlighted regions (blue squares) on the map show the eHighway deployment locations (in red) for scenario 4 (that was optimized for EJ, with a total of 500 miles and minimum eHighway length of 20 miles) using a 100% adoption rate (lower adoption rates would result in proportional change to the results presented here). In the middle, a zoom-in to each of the highlighted eHighway locations is presented, showing the percentual eHighway coverage in each census tract zone. Darker green tract zones mean higher eHighway VMT coverage (that is, most of the trucks going through this tract zone are connected to the catenary system) and lighter green lower VMT eHighway coverage. To the left, we present the map again with environmental justice scores for each tract zones (red tract zones have worse scores, that is, are more polluted than the green zones) with the same regions highlighted.

The figure shows that many of the low scoring tract zones have a high percentage of the heavy-duty truck VMT covered by the eHighway system. This is important as most of the pollution (in particular NO_x, but also CO₂) comes from the PTW stage. As catenary-connected trucks have no PTW emissions, it is expected that these regions would have a reduction in local emission and an increase in air quality.

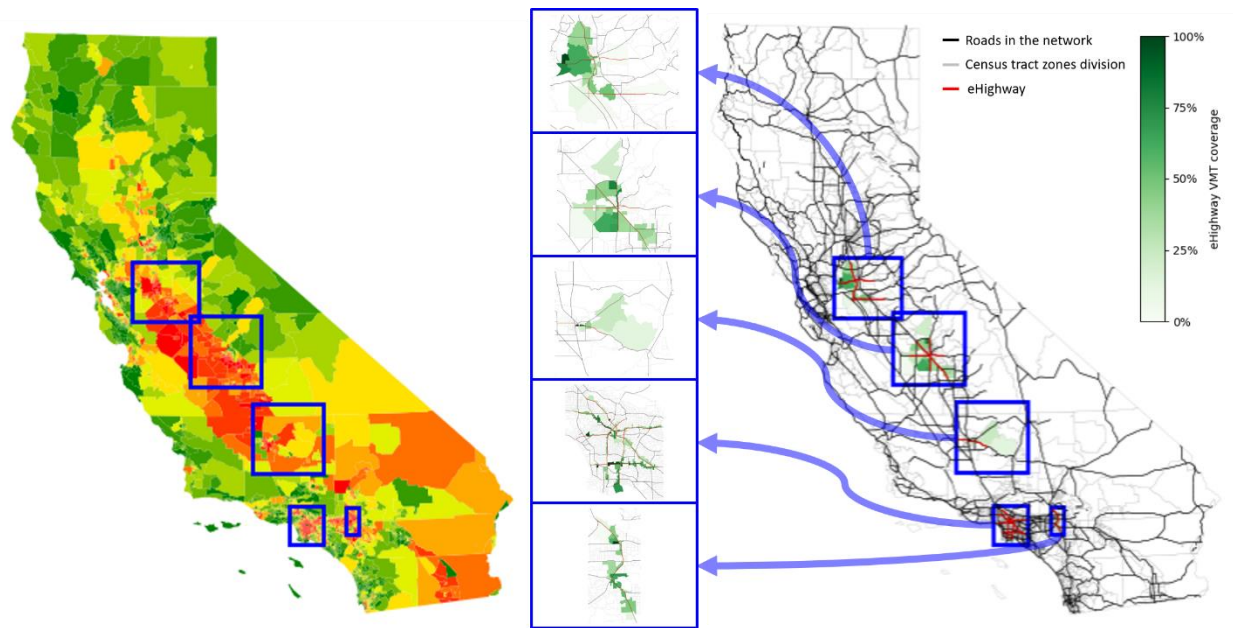


Figure 42. Percentage of heavy-duty truck vehicle miles traveled per census tract zones. Black lines show all the roads in the model with red lines representing eHighway deployed for scenario 4 using a 100% adoption rate, and gray lines show the census tract zones divisions. The areas of interest in the map are highlighted and zoomed in in the middle. Census tract zones are color-coded based on the percentage of total heavy-duty truck vehicle miles traveled covered by the eHighway system (darker green represents higher coverage). On the left, the census tract zones are colored based on their percentile of environmental justice score (red is a lower score) with the same areas of interest highlighted.

However, high VMT percentage coverage does not mean high emission reduction, as some of these tract zones might already have low emission from the tailpipe (e.g., a highly industrial zone with low truck traffic). Figure 43 shows a similar format to Figure 42, but here the census tract zones are color-coded to the amount of pollutant reduction. In the middle part of the figure, darker blue means tract zones with an absolute higher reduction in CO₂ and NO_x (in kg) per day, and lighter blue represent lower reduction. This emission reduction accounts for the percentage of VMT covered and the actual VMT in that region.

In particular, we see a high pollution reduction in the tract zone close to the Los Angeles and Long Beach ports, as these regions have high heavy-duty truck VMT.

If we look at only the tract zones directly affected by this eHighway system (those that contain an eHighway) these air quality improvements would benefit around 2 million

people that live in these areas, which is 5% of the California population and, in this case, mostly composed by unprivileged groups.

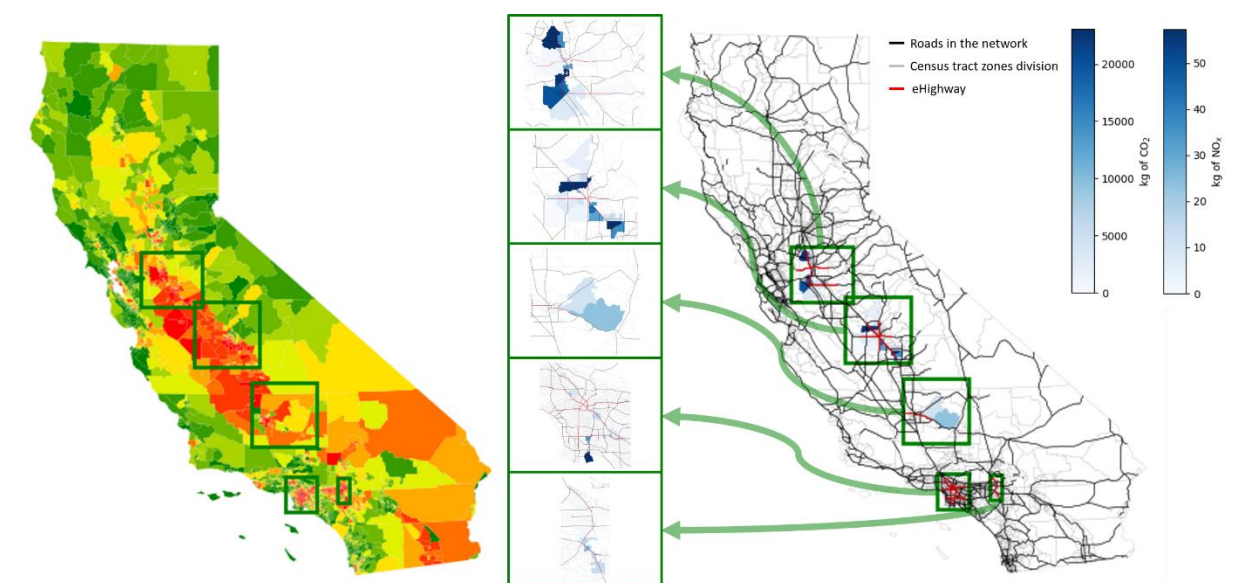


Figure 43. Absolute emission reductions from the eHighway system per census tract zones. Black lines show all the roads in the model with red lines representing eHighway deployed for scenario 4 using a 100% adoption rate, and gray lines show the census tract zones divisions. The areas of interest in the map are highlighted and zoomed in in the middle. Census tract zones are color-coded based on total absolute emission reduction in terms of CO₂ and NO_x (darker blue represents higher reduction). On the left, the census tract zones are colored based on their percentile of environmental justice score (red is a lower score) with the same areas of interest highlighted.

However, even though we are presenting an emission reduction only on tract zones containing an eHighway, these local emissions are likely to affect surrounding areas and populations. Moreover, it is worth remembering that besides the reduction in the local emissions, those scenarios are also reduction the statewide emissions as presented in Section 5.5. Similar results would be expected for the 2040 target year.

5.9 Conclusions

The emissions analysis is one of the most important aspects of this study since the main objective of an eHighway system is its potential in air pollution reduction. Therefore, estimating emission reduction should one of the first steps to support the deployment of such infrastructure. However, even though this seems like a central and logical step, to our knowledge, no available studies are performing this analysis. Thus, this chapter

aimed to fill the literature gap on this subject and presents a well-to-wheel (WTW) analysis for different eHighway implementation scenarios in California.

Electric vehicles have no tailpipe emissions; however, they still emit pollution through the energy generation process necessary to the new demand for this type of vehicle. Therefore, a WTW emission analysis, which accounts for the emission made through the vehicle operations and the fuel generation process, is necessary to guarantee a more realistic emission analysis.

This section introduced the well-to-wheel analysis, divided into a well-to-pump and pump-to-wheel stages, as well as the models used to estimate those types of emissions (the GREET model and the CARB's Vision model). It also presented the HiGRID model that was used to estimate the emissions related to the energy generation for the eHighway trucks. The whole methodology for estimating the total emissions for each scenario was detailed and discussed during the section.

The results were presented in terms of the two target years (2020 and 2040) for CO₂ and NO_x pollutants. The emissions for each eHighway scenario was then compared to a base scenario with no eHighway system. For all the scenarios evaluated, there was a reduction in total CO₂ and NO_x emissions when compared to the base scenario. This result showed the benefit of the implementation of the eHighway system in terms of these emissions. It demonstrated that the emissions from the additional energy generation needed to power the eHighway system are smaller than the emissions removed due to their lack of tailpipe emission. That is, it has a positive net benefit in terms of emission, supporting the main goal of this technology of reducing total emissions of heavy-duty trucks.

Considering the cost of carbon in California, we can estimate how much the eHighway could save with the CO₂ reduction. The best scenario in terms of emission reduction for 2020 could save up to 90 million dollars per year, which would pay off the initial costs of the eHighway infrastructure in around 13 years.

Comparing the analyzed scenarios, the ones based on VTM with a total eHighway length of 500 miles presented the best results in terms of CO₂ and NO_x emission reduction

statewide. However, since the difference between them is virtually zero, the choice of one over the other should take into consideration other aspects, such as total infrastructure costs, construction constraints, investment preferences, etc.

The scenarios with only 100 miles in total eHighway length presented better emission results proportionally to the total length of the eHighway. However, the total absolute emissions statewide, even though it obtained a reduction compared to the case with no eHighway, was not as pronounced as the scenarios with 500 miles in total eHighway length. These results show the potential for these shorter eHighways for cost-constrained projects or earlier phases of larger projects.

Between the 20-year gap analyzed, an additional emission reduction is obtained for all scenarios, which showed that as the years pass and more technological improvement is made, the benefits from the overhead catenary system tend to increase.

As expected, the scenarios based on environmental justice did not perform as well as the VMT scenarios in the statewide emission analysis; therefore, a local emission analysis was conducted. It showed that the eHighway could have significant impacts on local emission, especially in disadvantage communities, benefitting around 2 million people directly.

CHAPTER 6. POWER GRID ANALYSIS

As presented in CHAPTER 5, the eHighway will demand a new load of electric energy to power the trucks on the catenaries. This demand will have environmental consequences in terms of emissions; however, there are other types of impacts an eHighway deployment could have on the electric grid. In this chapter, we will analyze what these impacts are and how they are distributed across the current California electric grid. With that goal, we first review the characteristics of the California electric grid and then determine a methodology to calculate the additional loads in California's substations to supply the energy necessary to power the eHighway system.

6.1 California electric grid

An electricity generation and distribution system must continually generate electricity to balance the daily energy demand with potential hourly peaks and demand oscillations during the day [96]. California's electric power system is comprised of around 1480 operating power plants utilizing a broad array of technologies, almost 35 thousand miles of transmission lines, and over 3200 operational substations throughout the state [97].

From 2002 to 2018, California generated an average of 292,368 gigawatt-hours (GWh) in total annual electricity. The amount of electricity produced is dependable for several factors that happen during the year. The most important one is the energy demand. In recent years, the electricity demand has been flat or slightly declining as energy efficiency programs (such as the use of private solar photovoltaic systems) have resulted in energy savings [98].

Figure 44 presents the California annual electric generation from 2002 to 2018. The in-state generation accounts for all the energy produced using power plants physically located in the state of California, Northwest imports uses energy produced in power plants located in Alberta, British Columbia, Idaho, Montana, Oregon, South Dakota, Washington, or Wyoming, and Southwest imports are the ones generated in

Arizona, Baja California, Colorado, Mexico, Nevada, New Mexico, Texas, or Utah. The yellow line represents the sum of the three columns, and it is the total California energy mix generation in GWh [98].

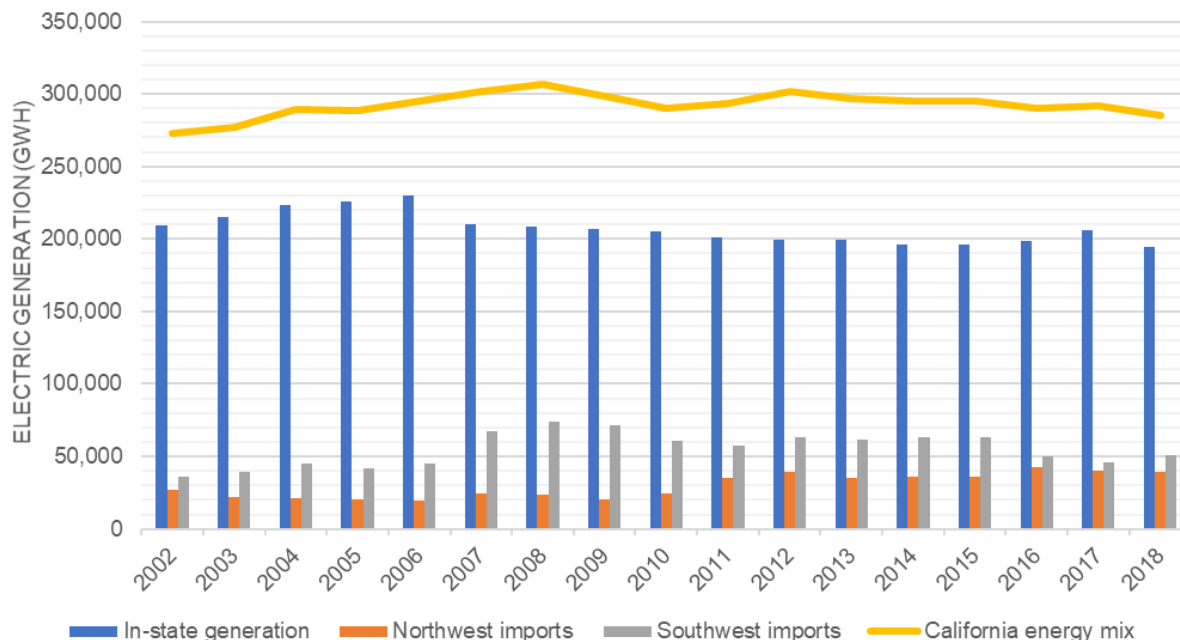


Figure 44. California's annual energy generation in GWh from 2002 to 2018.

The most current data available are for the year of 2018, in which the state generated 285,488 GWh in a total of electricity. For that, 68.25% was produced in the state of California, 13.84% was imported from Northwest, and 17.91% imported from the Southwest region [98]. A breakdown of the major resource mix serving California the same year is depicted in Figure 45.

The largest contributor to the generation mix is natural gas at 34.91%, with renewables in the closest second place with 31.36%. Large hydroelectric power plants considered a zero-carbon resource and provided an additional 10.68% of the total energy mix. The unspecified sources of power account for 10.54%, and it refers to electricity that is not traceable to a specific generating facility. In other words, it is the electricity that the source of fuel can no longer be determined. They are typically a mix of resource types and may include renewables too. Even though there is only one active nuclear power plant in California (the Diablo Canyon located in San Luis Obispo), this resource is the

fifth contributor at around 9%. The last resources are coal with 3.30%, oil with 0.01%, and others that include petroleum coke and waste heat with 0.15% [98].

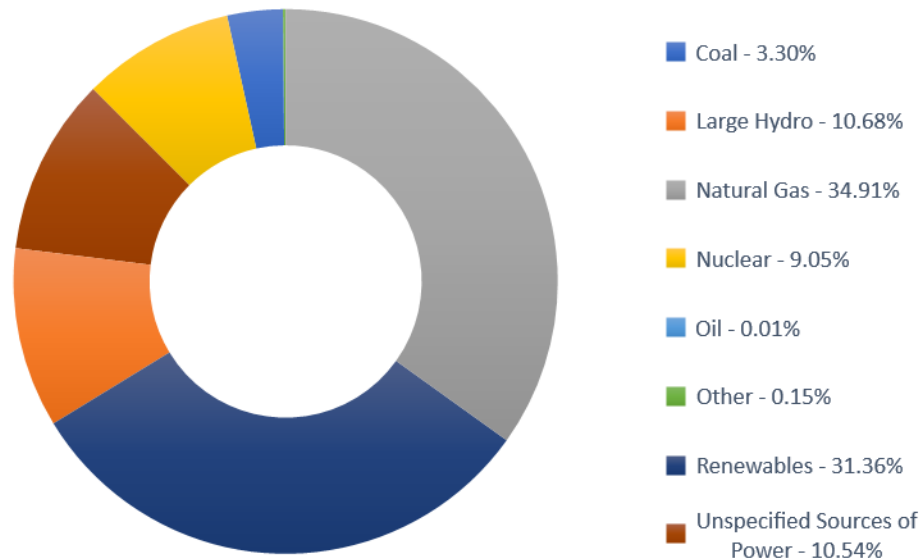


Figure 45. California energy mix for 2018.

Although natural gas is still the leader on energy generation, California's vast growth in a utility-scale renewable generation has helped reduce the state's reliance on natural gas, favoring those power plants that produce fewer emissions. This fact supports the expansion of electric-powered vehicles, as the electric generation becomes less pollutant.

Renewable energy is the energy derived from natural processes that do not involve the consumption of exhaustible resources such as fossil fuels and uranium. Consequently, they offer the opportunity for enhanced energy independence and security while reducing criteria pollutant and GHG emissions. The most common examples are hydroelectricity, wind power, solar, and geothermal. It can be divided into two types: dispatchable, that can be used on-demand at the request of the power grid (such as hydroelectric and geothermal), and non-dispatchable ones that cannot be controlled (such as solar and wind power) [96]. The renewables portion on the overall California mix

for 2018 can be further divided, and Figure 46 presents the percentage of each renewable source [98].

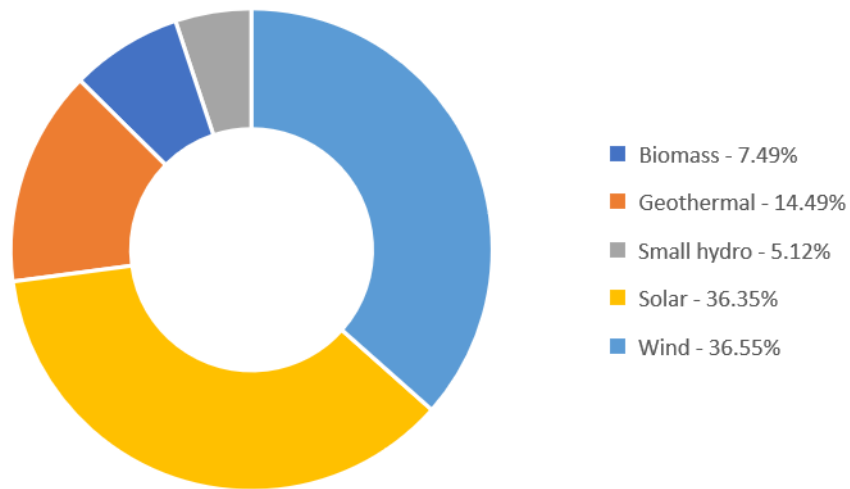


Figure 46. Renewable sources in the California mix for 2018.

Solar and wind combined represent most of the renewable source's generation, with 22.86% on the entire California mix for 2018 (72.9% of the 31.36% of renewables). Geothermal also accounts for a considerable share of renewable generation with 14.49%, followed by biomass (7.49%) and small hydroelectric (5.12%).

The capacity factors for renewables are very dependent on the temperature and precipitations in the area. For example, in a drier year, the annual hydroelectric generation will probably fall, while experiencing higher solar radiation will grow the generation through solar power plants. Because of its favored geographic location, California has a promising capability of benefiting from the use of renewable resources. This significant potential can be further observed comparing to the state's energy mix with the national for the same year [99]. In 2018, the generation of electricity from utility-scale generators in the United States was about 4.2 million GWh (compared to about 285 thousand GWh in California) Figure 47 shows the breakdown of the United States energy mix for 2018 by source.

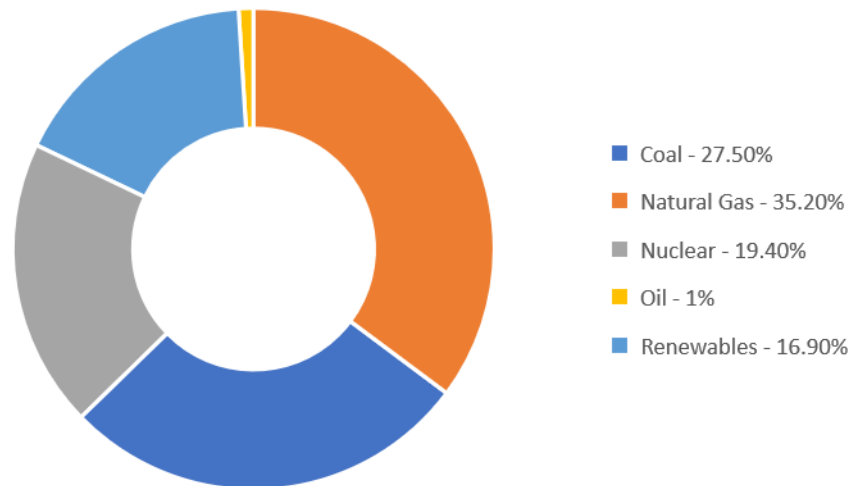


Figure 47. United States energy mix for 2018.

The natural gas portion on the energy mix is virtually the same in California and the United States as a whole. However, the most prominent difference can be seen comparing the use of coal in a national perspective. In the California mix, coal accounts for 3.3%, while nationwide, they represent more than 27%. On the other hand, renewables in California are the second-largest source in the mix with 31.36% and only the fourth source (with 16.90%) for the entire country. This matter also supports the implementation of new electric technologies, such as the eHighway system in California [99].

The California Independent System Operator (CAISO or California ISO) is a non-profit entity responsible for operating the state's power system, transmission lines, and electricity market. It manages the flow of electricity, ensuring safe and reliable transportation of electricity on over 80 percent of the California power grid. The California ISO has two control centers in the state where it supervises the generation resources and transmission efficiency [100].

Another important role of the CAISO is to forecast electrical demand and dispatch the lowest cost generator to meet this demand. Their system has two different types of prediction: the day-ahead, which the needed generation is calculated approximately 14 hours before the desired operating day, and the hour-ahead prediction, which happens around 75 minutes ahead of the beginning of the hour. Both forecasted and current

demand for the state is publicly available and updated every 5 minutes. Their website also presents current CO₂ emissions per resource, current marginal energy cost per location in the state, and the electric supply curve per hour per source. Figure 48 presents an example of a weekday in January 2020 [101].

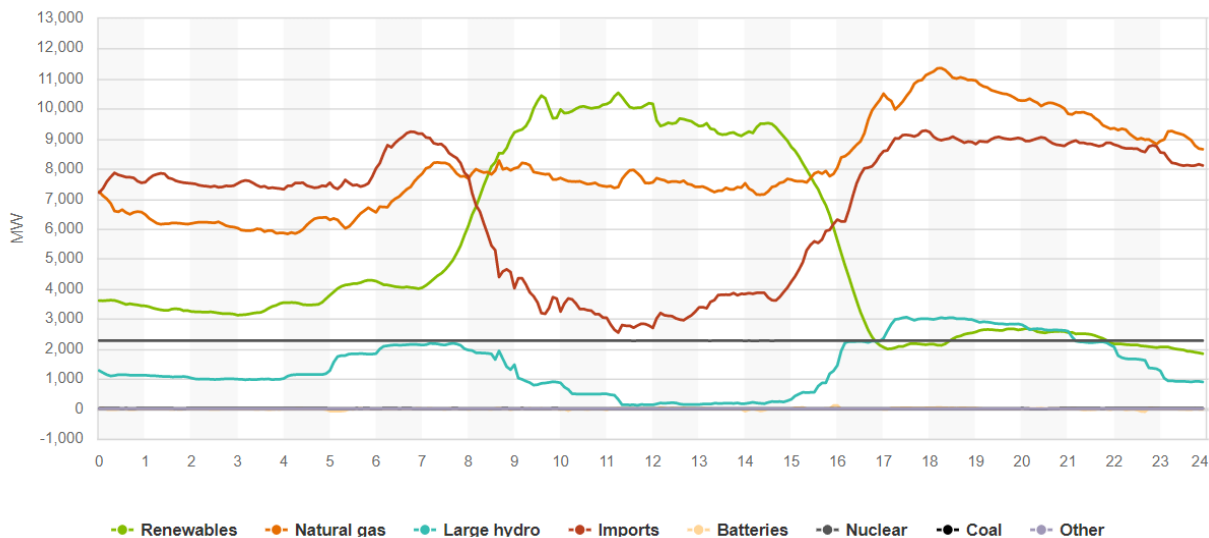


Figure 48. California electric supply trend for January 2020.

One of the possible disadvantages of the eHighway system is the higher electric demand during working hours. It aligns with current daily energy consumption and, therefore, understating the additional load from the eHighway system during these hours is another important aspect to be explored before implementing this technology.

6.2 Methodology for analyzing the impact of the eHighway system on the electric grid

The main objective of this chapter is to propose a methodology to determine which power substations connected to California's electric grid are used to energize the eHighway system as well as calculate energy demand from these substations.

From the literature review presented in CHAPTER 2, we learned that the catenaries are powered by smaller substations constructed along the roadway. Likewise, those substations are electrified by their connection to the electric grid. However, the

methodology used to create these connections in the pilot studies are not thoroughly described in the technical reports and may not apply to a larger scale system like the one proposed here. However, a parallel with the light rail system can be applied, and we propose using the same methodology for this study.

A light rail system is a form of an urban rail of medium capacity, also known as a technological outgrowth form of streetcars or trams. They usually use electric rail cars and operate in the exclusive right-of-way, separated from other traffic. The vast majority of light rail systems are powered by overhead electrical wires, avoiding passengers stepping on an electrified third rail [102], similar to the eHighway system.

A study conducted by Grenier and Page (2012) analyzed the impacts of having a new fleet of electric vehicles, or a light rail system could cause on the electric grid of the city of Christchurch in New Zealand [103]. According to their research, the catenary system for the light rail is electrified through traction power substations located along the rail that is powered by the electric grid substations of the city. Therefore, the same methodology can be applied to the eHighway system, where the catenaries are electrified through the eHighway substations that are consecutively powered by the current substations in California.

To apply this methodology to our eHighway model, the first step is to gather information about California substations, which can be done through the California Energy Commission (CEC) database [97]. The CEC was created in 1974 and serves as the primary energy policy and planning agency in the state. The main agency's responsibility is to create a clean and modern energy system through investments and developments in energy innovation, renewable resources, energy infrastructure, and transportation. It also provides geographic and geospatial information services for various topics, such as substations, power plants, transmission lines, natural gas pipelines, and renewable energy.

Through this database, we now have the exact location of each operational substation in California. However, one important limitation of the power substations database is that the information regarding current demand and capacity of the substations

is not publicly available, and our efforts to obtain that data have not been successful. Therefore, we will present a methodology of how to link the eHighway substations to the power substation as well as calculate the energy demand for each substation, but we are unable to conclude if these substations can handle the additional energy supply.

The next step is defining the distance between eHighway substations. Siemens has not disclosed the maximum distance in any of its public reports. Moreover, none of the pilot studies required multiple substations on the same eHighway. The ELISA project, in Germany, had two substations, but they were required due to the eHighway be located on the outmost right lane, and each substation was then used for a different side of the road. For the methodology implemented here, the maximum distance between substations is an input variable. Using this distance, we divide each eHighway into the minimum possible number of segments of the same length that are shorter than the maximum distance. We calculate the middle point between the beginning and end of the segment. This middle point is our reference point for this segment, and where the eHighway station would be located.

Now, we find the closest substation available by looking for the minimum distance between the reference point and all the substations. Multiple segments are allowed to use the same substation if it happens to be the closest one. As the VMT and the energy consumption rate of the eHighway trucks are known from the model and the literature estimates (as presented in previous chapters), we can calculate the energy demanded from each substation.

This methodology was applied to one of the scenarios presented in CHAPTER 4. Here, we chose to use scenario 1, with 500 miles of total eHighway length and minimum eHighway length of 20 miles using a 100% adoption rate for the target year of 2020. This scenario was chosen as it is the one with the highest energy consumption and can best exemplify the methodology, and the results are presented in Figure 49. Only one of the scenarios is tested here as the methodology would be the same for any other one. The Python code to reproduce this methodology and results can be found in APPENDIX D.

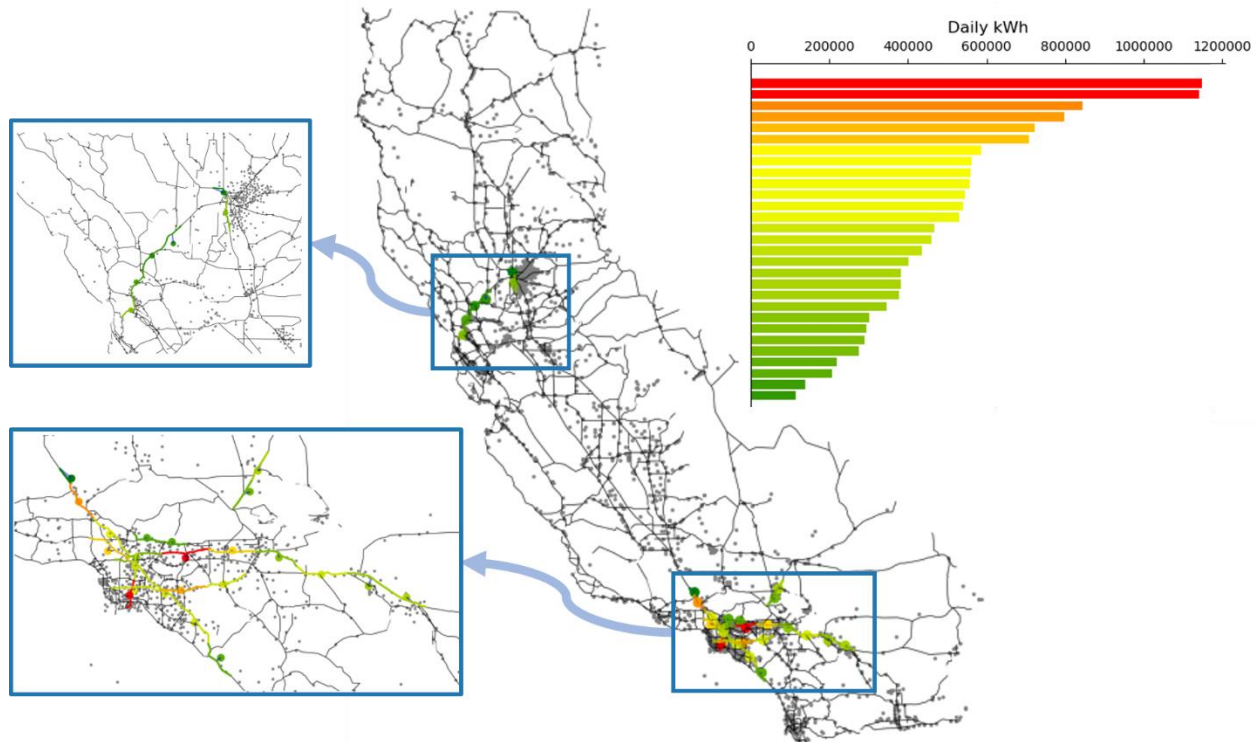


Figure 49. California's substations energy demand. Black lines show all the roads in the model. Colored lines represent the eHighway deployed for scenario 1 using a 100% adoption rate where the color represents the amount of energy demanded (red represents more energy). The colored circles show the substations connected to the eHighway of matching color. The bars on the right represent each of these substations (also color-matched), showing the amount of daily energy demanded. The gray circles represent the power substations not connected to the eHighway system.

In Figure 49, all the roads in the model (black line) are presented in the middle of the figure. California's substations that are not connected to any eHighway are presented as a gray dot. The power substations connected to an eHighway are shown as a colored dot. The color of the connected substations depends on how much energy is being demanded by the eHighway system, with more energy demanded from the red substations and less energy from the green substations, as shown in the figure's bar plot. To the left, we show a zoom-in of the two areas of interest where the eHighways are concentrated. The color of the eHighway and their linked substations are matched.

Some substations are being demanded over 1 MWh of energy in one day. However, as discussed above, the capacity of these substations is not publicly available, so it is not possible to compare these demands with current availability and hence not

possible to draw any conclusion from the current data. However, this presents the methodology that would be used to do so.

6.3 Conclusions

In this chapter, we presented an overview of the current energy generation sources in California. We showed how California is suitable to implement new technologies that rely on electricity due to its high injection of renewable and clean energy.

We then presented a methodology to calculate eHighway energy demand of specific power substations using the current California electric grid. We exemplified this methodology by applying it to one of the previous scenarios, showing that some substations would require extra of upwards to 1 MWh of daily energy to power the eHighway system. However, due to the unavailability of public data on California's substations' current demand and capacity, we could not draw conclusions in terms of the ability of these substations to handle such demands.

Nevertheless, the methodology presented here could, and should, be applied to understand if the current electric grid could handle the demands of the eHighway system before its implementation.

CHAPTER 7. CONCLUSIONS AND MAIN CONTRIBUTIONS

The eHighway systems have already been tested in Europe and in the United States to show its feasibility and collect data for future implementations. The benefits in terms of tailpipe emissions are clear since the technology uses a zero-emissions electric vehicle. Some reports broadly discuss technical aspects of catenary systems, such as infrastructure and vehicle characteristics; however, there have been no studies looking at well-to-wheel emissions and power grid implications of large-scale implementation. This gap in the literature (presented in CHAPTER 2) is the focus of this research, where we evaluated and presented the benefits and drawbacks of the implementation of this technology.

Here, for the first time, we introduce a new comprehensive framework that combines a methodology for optimally selecting eHighway placement, estimating the well-to-wheel (WTW) emissions of heavy-duty trucks once the eHighway is deployed, and analyzing the impacts such technology can have on the power grid. This methodology was applied to different implementation scenarios in California, using data from the California Statewide Freight Forecasting Model (CSFFM). The roads included in the original CSFFM were aggregated, filtered, and ordered, making the eHighway road selection possible, in which we analyzed other impacts of deploying the overhead catenary system.

To optimize the road selection, we proposed an algorithm with two data inputs: the total eHighway length and the minimum eHighway length. A total of eight different scenarios were explored using two optimization metrics (road vehicle miles traveled (VMT) and environmental justice (EJ)) and two target years (2020 and 2040). The algorithm was able to select the more suitable roads in the model for each one of them: 1) for the VMT metric, we showed that with a low percentage of total miles with an eHighway deployed covered a much higher percentage of the total VMT in the model. 2) for the EJ, we visually compared the selected roads with the map of environmental justice scores and showed that the eHighways aligned with the most disadvantage communities.

We then presented a methodology on how to estimate the WTW emissions for heavy-duty trucks. The well-to-pump (fuel generation emissions) and pump-to-wheel (tailpipe emissions) emissions were calculated for each truck in the model, according to their powered fuel. We later applied this methodology to all the scenarios and estimated their total emissions in terms of CO₂ and NO_x. The results demonstrated the potential benefits an eHighway implementation could have in California in terms of emission reductions since all the scenarios that had a catenary system deployed produced fewer emissions than a scenario with no eHighway.

Among all the scenarios, the ones based on VTM with a total eHighway length of 500 miles presented the best results in terms of CO₂ and NO_x emission reduction statewide. For this best-case scenario, the savings in terms of cost of carbon would add up to 90 million dollars per year. The scenarios with only 100 miles in total eHighway length presented better emission results proportionally to the total length of the eHighway, confirming their potential for cost-constrained projects or earlier phases of larger projects. The scenarios based on environmental justice did not perform as well as the VMT scenarios in the statewide emission analysis; however, a local emission analysis proved their benefits on specific areas, such as the disadvantage communities, by substantially reducing the CO₂ and NO_x emission locally, benefiting around 2 million people directly.

Moreover, between the target year of 2020 and the year of 2040, an additional emission reduction was presented, showing the benefits from the eHighway tend to increase as the years go by, and the vehicle's technical aspects improve.

Lastly, an analysis to calculate eHighway energy demand and identify substation to generate that extra demand is presented. Even though we could not conclude the grid impacts in California due to the lack of information available, the methodology introduced can be implemented once the California data become available or for any other state's power grid.

The results presented in the study support the deployment of an overhead catenary system in California. However, there are still some aspects to be considered before large-scale implementation. The results from the pilot projects around the world

can also predict potential issues that could be encountered during the construction or testing phases; therefore, positive feedback from them would be instrumental. Cost wise the system implementation is also dependable on political decisions, international cooperation and standardization, as well as contributions from the automotive industry, national and state government, and many other stakeholders. However, since there is an urgent need for making road freight transport more sustainable, among currently available technologies, the eHighway system, as presented in this research, is a promising solution worth further exploration.

7.1 Model limitations and future directions

The eHighway system is still a new technology, and, as discussed throughout this work, the literature around this system is limited, and many aspects have not been made public. Therefore, the conducted study assumed or did not consider some characteristics of the system.

Here, we present some of the model limitations that could be improved in future research:

- Energy consumption model. This study used a fixed energy consumption rate estimated from previous overhead catenary systems for all the trucks connected to the eHighway. Therefore, acceleration profile and load differences across trucks were not accounted for (including regenerative braking to store or feedback energy into the grid, for example).
- Cost analysis. The total spent in some of the pilot projects is the only public information regarding the eHighway system cost. Even those are many times discrepant between different sources. Ideally, the eHighway costs would be a constraint or a new objective to be optimized in the road selection algorithm; however, the costs (broken down by infrastructure parts) need to be known for this analysis.

- Dependency on the CSFFM. All the results presented in this study are based on projected data from the CSFFM that have not been fully validated after the 2010 data calibration.
- Pollutants. The HiGRID model estimates the eHighway emissions in terms of CO₂ and NO_x, and, to allow for WTW analysis, only these two pollutants were considered in this study. Other important pollutants could be analyzed to estimate better the effects of the eHighway system (e.g., particulate matter (PM), the volatile organic compound (VOC), sulfur dioxide (SO₂), etc.).
- California grid impacts. As explained in CHAPTER 6, the substations capacity and current load are not publicly available in California; therefore, we could not conclude the current and projected impacts of the eHighway system on the state's power grid. However, we present a methodology for this analysis (as well as the algorithms to run it), which could be implemented once the data become available.

7.2 Research contributions

This study intends to cover the literature gap on overhead catenary systems, introducing its concept and characteristics, as well as presenting the past, current, future pilot projects around the world. The research also gives insights on the effects of deploying an electric highway system in California, providing guidance to public and private agencies about the viability of this solution in terms of supporting efficient operations for freight movements.

New methodologies were presented to address three main issues: 1) optimal placement and length to deploy an eHighway system in California, 2) effects on WTW emissions once the eHighway is implemented, and 3) its potential impacts on the state's power grid. Even though the methodology was applied in California, we provided the source code of each algorithm used in the study so that the same process can be applied to any other location in the world.

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APPENDIX A. SOURCE CODE FOR CHAPTER 3

```
# CSFFM Preprocessing
@author: msebastiani
```

```
This file loads a CSFFM shape file, process the file to leave only
main roads, find connected links for each road, and organize them in
the correct order. The cleanup data is saved as a shape file and
as a csv file.
```

```
"""
```

```
# %% load libraries
import numpy as np
from sklearn.decomposition import PCA
import geopandas as gp
import os, sys
```

```
# %% load utility functions
os.chdir(os.path.pardir(os.path.realpath(__file__)))
sys.path.append(".")
```

```
from util_ej import get_ej, get_ej_data, add_ej
from util_elevation import get_elevation_data, get_elevation
from util_csffm import get_csffm_data, get_tams_tod
from util_functions import remove_parallels, update_road_df
```

```
# %% create output dataframe to be filled in with the columns:
# A, B - beginning and end node of each link (from original file)
# ROAD - road name (from original file)
# LINK ID - unique ID for the link (from original file)
# DIRECTION - cardinal direction (N, S, E, W) calculated using PCA
# DISTANCE - length (in miles) of the link (from original file)
# VMT_C[X] - VMT for commodity X (see document for details), (from original file)
# VMT - total VMT for that link (from original file)
# TAMS_ID - ID of closest daily traffic profile available
# EJ - Environmental Justice score for the link
# EJ_tracts - Census tracts that the link crosses (or is within)
# ELEV_START - elevation at the start of the link
# ELEV_END - elevation at the end of the link
# fac_[H] - rate of traffic expected at hour H in that link (from TAMS)
# geometry - geometry of the link for plotting (from original file)
```

```
year = 2040
```

```

if year == 2020:
    input_file = r"data_input/2020/assignment_loaded_AON_2020.shp"
    output_file = "data_preprocessed/2020/all_roads_2020_AoN_countyvmvt"
else:
    input_file = r"data_input/2040/assignment_loaded_AON_2040.shp"
    output_file = "data_preprocessed/2040/all_roads_2040_AoN_countyvmvt"

columns = ["A", "B", "ROAD", "LINK_ID", "DIRECTION", "DISTANCE"]
commodity_columns = []

for commodity_number, i in enumerate(range(3, 60, 4)):
    commodity_columns.append("VMT_C" + str(commodity_number + 1))
columns += commodity_columns

columns += ["VMT", "TAMS_ID", "EJ", "EJ_tracts", "ELEV_START", "ELEV_END", "COUNTY"]
fac_columns = ["fac_{:02d}".format(c) for c in range(24)]
columns += ["geometry"]
df_output = gp.GeoDataFrame(columns=columns)

# %% load data into dataframes
roads_grouped = get_csffm_data(file_name=input_file)
df_tams, factors = get_tams_tod(
    file_name_tams=r"data_input/TAMS Deployed Sites/deployedsites_lanecoverage.shp",
    file_name_tod=r"data_input/TOD Factors.csv",
)
df_ej = get_ej_data(ej_file=r"data_input/EJ/CES3June2018Update.shp")
# elev_data = get_elevation_data()

# %% go through each road group and process it
roads = roads_grouped.groups
for r in roads:
    this_road_output = gp.GeoDataFrame(columns=columns)
    # get items belonging to this road
    this_road = roads_grouped.get_group(r)
    coordinates = None

    # for each link in the road, get coordinates
    for i, link in this_road.iterrows():
        if coordinates is None:
            coordinates = np.transpose(np.array(link.geometry.xy))
        else:
            cord = np.transpose(np.array(link.geometry.xy))
            coordinates = np.vstack((coordinates, cord))

```

```

# apply PCA on the coordinates (see document for details)
pca = PCA(n_components=1)
pca.fit(coordinates)
transformed = pca.transform(coordinates)

# define direction based on PCA components
if abs(pca.components_[0][0]) > abs(pca.components_[0][1]):
    print(str(r) + ": East/West")
    if pca.components_[0][0] > 0:
        forward_direction = "E"
        backward_direction = "W"
    else:
        forward_direction = "W"
        backward_direction = "E"
else:
    print(str(r) + ": North/South")
    if pca.components_[0][1] > 0:
        forward_direction = "N"
        backward_direction = "S"
    else:
        forward_direction = "S"
        backward_direction = "N"

# for each road, define one direction as forward and another as backward (with the P
C)
forwards = []
backward = []
for i in range(len(transformed) // 2):
    if transformed[i * 2] < transformed[i * 2 + 1]:
        forwards.append(i * 2)
    else:
        backward.append(i * 2)

forwards = np.array(forwards)
backward = np.array(backward)

# now we need to remove links that don't belong to the main road (e.g. off ramps, on r
amps, etc)
# this is done by looking at the connectivity between links
# e.g. stretch of roads that end too soon are likely on or off ramps
# when there are roads that reconnect to the main road (parallel roads),
# we remove those with inconsistent VMT
# See documents for details
try:

```

```

forwards = remove_parallels(
    forwards, transformed, this_road, forward_or_backward="F"
)
backward = remove_parallels(
    backward, transformed, this_road, forward_or_backward="B"
)

elevations_forward = elevations_backward = 0

this_road_output = update_road_df(
    r,
    this_road_output,
    transformed,
    forwards,
    this_road,
    elevations_forward,
    df_tams,
    factors,
    fac_columns,
    forward_direction,
)
this_road_output = update_road_df(
    r,
    this_road_output,
    transformed,
    backward,
    this_road,
    elevations_backward,
    df_tams,
    factors,
    fac_columns,
    backward_direction,
)
df_output = df_output.append(this_road_output, ignore_index=True)
except:
    pass

df_output = add_ej(df_output, df_ej)

# %% create output files
df_output.to_file(output_file + ".shp")
df_output.to_csv(output_file + ".csv", index=False)

```

```
#Utility functions
```

```
@author: msebastiani
```

```
This file contains utility functions to process CSFFM links,  
removing parallel links that are not part of the main highways  
and update the dataframe output by the CSFFM preprocessing file  
.....
```

```
# %% load libraries
```

```
import pandas as pd
```

```
import geopandas as gp
```

```
import numpy as np
```

```
from collections import OrderedDict
```

```
# %% define parallel removal function
```

```
def remove_parallel(positions, transformed, df_road, forward_or_backward="F"):
```

```
    parallels_to_remove = [0]
```

```
    while len(parallels_to_remove) > 0:
```

```
        begins = transformed[positions]
```

```
        ends = transformed[positions + 1]
```

```
        parallels_to_remove = []
```

```
        for i in positions:
```

```
            if forward_or_backward[0].lower() == "f":
```

```
                parallels = np.where(
```

```
                    np.logical_and(
```

```
                        begins >= transformed[i], begins < transformed[i + 1]
```

```
                    )
```

```
                )[0]
```

```
            else:
```

```
                parallels = np.where(
```

```
                    np.logical_and(
```

```
                        begins <= transformed[i], begins > transformed[i + 1]
```

```
                    )
```

```
                )[0]
```

```
        if len(parallels) > 1:
```

```
            if len(parallels) > 1: # prioritize links connected at the end
```

```
                connected = []
```

```
                for p in parallels:
```

```
                    connected.append(np.any(ends[p] == begins))
```

```
                connected = np.array(connected)
```

```
                if any(connected) and not (all(connected)):
```

```
                    parallels = parallels[np.where(connected == False)]
```

```
                # print(connected)
```

```

    if len(parallels) > 1: # prioritize links connected at the beginning
        connected = []
        for p in parallels:
            connected.append(np.any(begins[p] == ends))
        connected = np.array(connected)
        if any(connected) and not (all(connected)):
            parallels = parallels[np.where(connected == False)]
        # print(connected)

    if len(parallels) > 1: # prioritize links with a streetname
        street_name = df_road.iloc[positions[parallels] // 2][
            "STREET_NAME"
        ].values
        if any(street_name != None) and not (all(street_name != None)):
            parallels = parallels[np.where(street_name == None)]

    # if we want to use real VMT:
    # vmts = df_road.iloc[positions[parallels]//2]["V3_1"].values * df_road.iloc[positions[parallels]//2]["DISTANCE"].values
    vmts = df_road.iloc[positions[parallels] // 2]["V3_1"].values
    connected = []
    if len(vmts) > 1:
        vmts_ordered = np.argsort(vmts)
        for j in vmts_ordered[:-1]:
            parallels_to_remove.append(parallels[j])
    else:
        parallels_to_remove.append(parallels[0])
    last_size = len(positions)
    positions = np.delete(positions, parallels_to_remove)
    print(
        "{} from {} to {}".format(forward_or_backward, last_size, len(positions))
    )
    return positions

def update_road_df(
    road,
    output_df,
    transformed,
    positions,
    road_df,
    elevations,
    df_tams,
    tod_facs,
    fac_columns,

```

```

    direction,
):
    "For each segment copy the necessary information from the original file and add the
    new info in the function parameters."
    position_transformed = transformed[positions]
    position_order = np.argsort(position_transformed[:, 0])
    for i, f in enumerate(position_order):

        # find closest tams_tod device
        this_link = road_df.iloc[positions[f] // 2]
        pos = df_tams.distance(this_link.geometry).idxmin()
        tams_tod_id = df_tams.iloc[pos]["id"]

        # creat dictionary for file
        this_link_dict = dict()
        this_link_dict["A"] = this_link["A"]
        this_link_dict["B"] = this_link["B"]
        this_link_dict["ROAD"] = road
        this_link_dict["LINK_ID"] = i
        this_link_dict["DIRECTION"] = direction
        this_link_dict["DISTANCE"] = this_link["DISTANCE"]

        total_vmt = 0
        for commodity_number, j in enumerate(range(3, 60, 4)):
            this_link_dict["VMT_C" + str(commodity_number + 1)] = (
                this_link["V" + str(j) + "_1"] * this_link["DISTANCE"]
            )
            total_vmt += this_link["V" + str(j) + "_1"] # using volume instead of VMT
        this_link_dict["VMT"] = total_vmt * this_link["DISTANCE"]

        this_link_dict["TAMS_ID"] = tams_tod_id
        this_link_dict["COUNTY"] = this_link["COUNTY"]
        this_link_dict["geometry"] = this_link["geometry"]
        output_df = output_df.append(this_link_dict, ignore_index=True)
    return output_df

```

#CSFFM utility functions

@author: msebastiani

This file contains utility functions to load CSFFM data and TAMS TOD data

"""

import pandas as pd

import geopandas as gp

```

import numpy as np
from collections import OrderedDict
import os

def get_csffm_data(
    county=True, ct_route=True, use=True, ftype=False, grouped=True, file_name=None
):
    df_vmt = gp.read_file(file_name)

    df_vmt.crs = {"init": "epsg:3310"}
    print()
    if county:
        df_vmt = df_vmt.dropna(subset=["COUNTY"])
    if ct_route:
        df_vmt = df_vmt[df_vmt["CT_ROUTE"] > 0]
    if ftype:
        df_vmt = df_vmt[
            (df_vmt["FTYPE"] == 1) | (df_vmt["FTYPE"] == 8)
        ] # keep only freeways
    if use:
        df_vmt = df_vmt[df_vmt["USE"] == 1] # no restriction road
    # fix county names
    df_vmt["COUNTY"] = df_vmt["COUNTY"].str.upper()
    df_vmt[df_vmt["COUNTY"] == "LOS ANGEL"] = "LOS ANGELES"
    df_vmt[df_vmt["COUNTY"] == "CONTRA CO"] = "CONTRA COSTA"
    df_vmt[df_vmt["COUNTY"] == "HUMBOLT"] = "HUMBOLDT"
    df_vmt[df_vmt["COUNTY"] == "SACRAMENT"] = "SACRAMENTO"
    df_vmt[df_vmt["COUNTY"] == "SAN BENIT"] = "SAN BENITO"
    df_vmt[df_vmt["COUNTY"] == "SAN BERNA"] = "SAN BERNARDINO"
    df_vmt[df_vmt["COUNTY"] == "SAN FRANC"] = "SAN FRANCISCO"
    df_vmt[df_vmt["COUNTY"] == "SAN JOAQU"] = "SAN JOAQUIN"
    df_vmt[df_vmt["COUNTY"] == "SAN LUIS"] = "SAN LUIS OBISPO"
    df_vmt[df_vmt["COUNTY"] == "SANTA BAR"] = "SANTA BARBARA"
    df_vmt[df_vmt["COUNTY"] == "SANTA CLA"] = "SANTA CLARA"
    df_vmt[df_vmt["COUNTY"] == "SANTA CRU"] = "SANTA CRUZ"

    if grouped:
        return df_vmt.groupby("CT_ROUTE")
    else:
        return df_vmt

def get_tams_tod(file_name_tams=None, file_name_tod=None, ignore_weekend=True)
:

```

```

# load tams file and transform coordinates
if file_name_tams is None:
    df_tams = gp.read_file(r"../TAMS Deployed Sites/deployedsites_lanecoverage.shp"
)
else:
    df_tams = gp.read_file(file_name_tams)

if file_name_tod is None:
    df_tod = pd.read_csv(r"../TOD Factors.csv", index_col="detstaid")
else:
    df_tod = pd.read_csv(file_name_tod, index_col="detstaid")

df_tams = df_tams.to_crs({"init": "epsg:3310"})

# load csv with TOD
fac_columns = ["csffm3_mean_dir_fac_{:02d}".format(c) for c in range(24)]
if ignore_weekend:
    df_tod = df_tod[df_tod.daytype != "wkend"]

# group by detector id
grouped_ids = df_tod.groupby("detstaid")

# but we'll only use the ids that are also present in the tams file
# obs: there are a few ids that exist in one file and not in the other
# and to make sure we get all the data we need, they must exist in both
tams_tod_ids = []
id_fac = OrderedDict()
for idd in grouped_ids.groups:
    tams_tod_ids.append(idd)
    this_id = grouped_ids.get_group(idd)
    id_fac[idd] = this_id.mean(axis=0)[fac_columns].values

return df_tams[df_tams.id.isin(id_fac.keys())].reset_index(drop=True), id_fac

#Utility EJ
@author: msebastiani

This file contains utility functions to load environmental justice data
and connect links from CSFFM to each EJ region
"""

### load libraries
import geopandas as gp

```

```

import numpy as np
import matplotlib.pyplot as plt
from shapely.geometry import Point, Polygon, LineString

def get_ej_data(ej_file=None):
    " Load EJ data from file and fix county names (make them capital case to match CSS FM"
    df_ej = gp.read_file(ej_file)
    df_ej["California"] = df_ej["California"].str.upper()
    return df_ej

def add_ej(df, df_ej):
    " Calculate EJ score for each segment. Segments inside of a census tract zone take the EJ score from that tract. Segments that cross one or more tracts take the average of the tracts. Tracts are also saved for each segment separated by commas when there are multiple"
    counter = 1
    grouped = df.groupby("ROAD")
    for g in grouped.groups:
        this_road = grouped.get_group(g)
        for _, segment in this_road.iterrows():
            counter = counter + 1
            line = LineString(segment.geometry)

            this_ej = []
            this_ej_tracts = ""

            for _, tract in df_ej.iterrows():
                try:
                    poly_tract = Polygon(tract.geometry)
                except NotImplementedError:
                    pass

                if line.within(poly_tract):
                    this_ej.append(tract.CIscore)
                    this_ej_tracts += str(tract.OBJECTID_1) + ","
                    break
                elif line.crosses(poly_tract):
                    this_ej.append(tract.CIscore)
                    this_ej_tracts += str(tract.OBJECTID_1) + ","

            df.loc[segment.name, "EJ"] = np.mean(this_ej)
            df.loc[segment.name, "EJ_tract"] = this_ej_tracts
    return df

```

APPENDIX B. SOURCE CODE FOR CHAPTER 4

```
#eHighway selection
@author: msebastiani
```

This file loads filtered CSFFM shape file and selects the ehighway positions based on optimization metric, minimum ehighway length, total ehighway length, and target year.

```
"""
```

```
# %% load libraries
import numpy as np
import matplotlib.pyplot as plt
import geopandas as gp
import os, sys
import pandas as pd
```

```
os.chdir(os.path.pardir(os.path.realpath(__file__)))
sys.path.append(".")
```

```
# %% define parameters
"""
```

	optimization	min len	total len	year
Scenario 1 -	VMT	20	500	2020
Scenario 2 -	VMT	10	500	2020
Scenario 3 -	VMT	10	100	2020
Scenario 4 -	EJ	20	500	2020
Scenario 5 -	VMT	20	500	2040
Scenario 6 -	VMT	10	500	2040
Scenario 7 -	VMT	10	100	2040
Scenario 8 -	EJ	20	500	2040

```
"""
```

```
selection_method = "VMT"
min_ehighway_length = 10
ehighway_total_length = 500
year = 2040
```

```
output_file_name = r"./data_output/{}/ehighway_{}_{}_miles.shp".format(
    year, selection_method, min_ehighway_length, ehighway_total_length
)
if year == 2020:
    processed_file = r"./data_preprocessed/2020/all_roads_2020_AoN.shp"
else:
    processed_file = r"./data_preprocessed/2040/all_roads_2040_AoN.shp"
```

```

# %% load data
df = gp.read_file(processed_file)
df["EJ"] = pd.to_numeric(df["EJ"])
grouped = df.groupby("ROAD")

# %% go through each road
fig, ax_vmt_window = plt.subplots()
fig, ax_ehighway_length = plt.subplots()

vmt_f = []
vmt_d = []
x = []

vmts = dict()
miles = dict()
roads = dict()

for r in grouped.groups:
    print("Road: {}".format(r))

    # get this road
    this_road = grouped.get_group(r)

    # get possible directions
    this_road_directions = this_road.DIRECTION.unique()

    # get forward and backward subset
    forward = this_road[this_road.DIRECTION == this_road_directions[0]]
    backward = this_road[this_road.DIRECTION == this_road_directions[1]]

    # get total distance
    total_distance_forward = int(forward.DISTANCE.sum())
    total_distance_backward = int(backward.DISTANCE.sum())
    total_distance = min(total_distance_forward, total_distance_backward)

    # get road miles
    miles_forward = forward.DISTANCE.cumsum()
    miles_backward = backward.DISTANCE.cumsum()

    if total_distance > min_ehighway_length:
        # create vectos for vmt and miles
        vmts[r] = []
        miles[r] = []

```

```

# move a window of size min_ehighway_length across the full length of the road calculating the score (dependent on the selection_method variable), this score will be used to select the ehighway stretches later

```

```

for m in range(
    min_ehighway_length // 2, total_distance - min_ehighway_length // 2
):
    beg = m - min_ehighway_length // 2
    end = m + min_ehighway_length // 2

```

```

if selection_method == "VMT":
    vmt_sum = (
        forward[((miles_forward > beg) & (miles_forward < end))].VMT.sum()
        + backward[
            ((miles_backward > beg) & (miles_backward < end))
        ].VMT.sum()
    )

```

```

elif selection_method == "EJ":
    vmt_sum = np.max(
        forward[((miles_forward > beg) & (miles_forward < end))].EJ.max()
        + backward[
            ((miles_backward > beg) & (miles_backward < end))
        ].EJ.max()
    )

```

```

vmt_d.append(
    (
        forward[
            ((miles_forward > beg) & (miles_forward < end))
        ].DISTANCE.sum()
        + backward[
            ((miles_backward > beg) & (miles_backward < end))
        ].DISTANCE.sum()
    )
    / 2
)

```

```

vmt_f.append(vmt_sum)
vmts[r].append(vmt_sum)
miles[r].append(m)
x.append(m)

```

```

ax_vmt_window.plot(x, vmt_f)
ax_vmt_window.set_ylabel("TOTAL VMT")
ax_vmt_window.set_xlabel("MILE")

```

```

ax_ehighway_length.plot(x, vmt_d)
ax_ehighway_length.set_ylabel("E-HIGHWAY STRETCH (MILES)")
ax_ehighway_length.set_xlabel("MILE")
plt.show()

# %% put all metrics into one vector
all_vmts = [] # vmts
all_roads = [] # road ids
all_miles = [] # locations
for r in vmts:
    for vm, m in zip(vmts[r], miles[r]):
        all_vmts.append(vm)
        all_roads.append(int(r))
        all_miles.append(m)

# %% order all VMTs
vmt_order = np.argsort(all_vmts)
ehighway_locations = dict()
ehighway_lengths = dict()

ehighway_current_length = 0

# go in order of highest to lowest VMT
for link in vmt_order[::-1]:

    # make sure vmt is greater than 0
    if all_vmts[link] > 0:
        road_name = all_roads[link]

    # if total desired ehighway length is yet reached, try to add link to ehighway
    if ehighway_current_length < ehighway_total_length:

        # check if there's an ehighway stretch in this road already, if not, add current link

        if not (all_roads[link] in ehighway_locations):
            ehighway_locations[all_roads[link]] = [all_miles[link]]
            ehighway_lengths[all_roads[link]] = [min_ehighway_length]
        else:
            merged = False
            # there's an ehighway in this road, so check if we should connect this link to c
            urrent ehighway
            # or create new ehighway
            for i, (loc, leng) in enumerate(
                zip(ehighway_locations[road_name], ehighway_lengths[road_name])
            ):

```

```

        # if distance between this stretch and other ehighways in this road is less than
        # min_ehighway_length connect them
        if abs(all_miles[link] - loc) <= (
            leng // 2 + min_ehighway_length // 2 + min_ehighway_length
        ):
            new_beg = min(
                loc - leng // 2, all_miles[link] - min_ehighway_length // 2
            )
            new_end = max(
                loc + leng // 2, all_miles[link] + min_ehighway_length // 2
            )
            new_leng = new_end - new_beg
            new_loc = (new_beg + new_end) // 2
            print("{} --> {}".format(loc, new_loc))
            ehighway_locations[road_name][i] = new_loc
            ehighway_lengths[road_name][i] = new_leng
            merged = True

        # if there was a merge, we need to see if the new merged ehighways should
        # also be merged
        if len(ehighway_locations[road_name]) > 1:
            for k, (loc2, leng2) in enumerate(
                zip(
                    ehighway_locations[road_name],
                    ehighway_lengths[road_name],
                )
            ):
                if k != i:
                    if abs(new_loc - loc2) <= (
                        leng2 // 2 + new_leng // 2 + min_ehighway_length
                    ):
                        new_beg = min(
                            loc2 - leng2 // 2, new_loc - new_leng // 2
                        )
                        new_end = max(
                            loc2 + leng2 // 2, new_loc + new_leng // 2
                        )
                        new_leng2 = new_end - new_beg
                        new_loc2 = (new_beg + new_end) // 2

                        ehighway_locations[road_name][k] = new_loc2
                        ehighway_lengths[road_name][k] = new_leng2
                        del ehighway_locations[road_name][i]
                        del ehighway_lengths[road_name][i]

```

```

        if not (merged):
            ehighway_locations[all_roads[link]].append(all_miles[link])
            ehighway_lengths[all_roads[link]].append(min_ehighway_length)

    ehighway_current_length = 0
    for r in ehighway_locations:
        ehighway_current_length += np.sum(ehighway_lengths[r])
    print(ehighway_current_length)
else:
    break
else:
    print("NaN")

#add highway number to identify each highway on the shapefile

print("ehighway_locations=")
print(ehighway_locations)
print("ehighway_lengths=")
print(ehighway_lengths)
### print locations
for r in ehighway_locations:
    for loc, leng in zip(ehighway_locations[r], ehighway_lengths[r]):
        print("Road: {}".format(r))
        print(
            "Location: from mile {} to mile {}".format(loc - leng // 2, loc + leng // 2)
        )
        print("Length: {} miles".format(leng))

# %% plot roads
ehighway_locations
ehighway_lengths
fig, ax = plt.subplots()
df.plot(ax=ax)
for r in ehighway_locations:
    this_road = grouped.get_group(str(r))
    # get possible directions
    this_road_directions = this_road.DIRECTION.unique()

    # get forward and backward subset
    forward = this_road[this_road.DIRECTION == this_road_directions[0]]
    backward = this_road[this_road.DIRECTION == this_road_directions[1]]

    # get road miles
    miles_forward = forward.DISTANCE.cumsum()
    miles_backward = backward.DISTANCE.cumsum()

```

```

for loc, leng in zip(ehighway_locations[r], ehighway_lengths[r]):
    forward[
        (miles_forward > (loc - leng // 2)) & (miles_forward < (loc + leng // 2))
    ].plot(ax=ax, color="r")

plt.show()

# %% create shapefile
output_file = None
this_ehighway = None
ehighway_number = 0
for r in ehighway_locations:
    this_road = grouped.get_group(str(r))
    # get possible directions
    this_road_directions = this_road.DIRECTION.unique()

    # get forward and backward subset
    forward = this_road[this_road.DIRECTION == this_road_directions[0]]
    backward = this_road[this_road.DIRECTION == this_road_directions[1]]

    # get road miles
    miles_forward = forward.DISTANCE.cumsum()
    miles_backward = backward.DISTANCE.cumsum()

    for loc, leng in zip(ehighway_locations[r], ehighway_lengths[r]):
        this_ehighway = forward[
            (miles_forward > (loc - leng // 2)) & (miles_forward < (loc + leng // 2))
        ]
        this_ehighway.append(
            backward[
                (miles_backward > (loc - leng // 2))
                & (miles_backward < (loc + leng // 2))
            ]
        )
        this_ehighway["EHIGHWAY"] = ehighway_number
        ehighway_number += 1
    if output_file is None:
        output_file = this_ehighway
    else:
        output_file = output_file.append(this_ehighway)

output_file.to_file(output_file_name)

```

APPENDIX C. SOURCE CODE FOR CHAPTER 5

```
#Energy calculation for HiGRID
@author: msebastiani
```

```
This file loads the eHighway selection from one of the scenarios and calculate the energy demand for different adoption rate.
"""
```

```
#%% import libraries
import pandas as pd
import datetime
from collections import OrderedDict
import numpy as np
import geopandas as gp
import matplotlib.pyplot as plt
```

```
# %% parameter selection
selection_method = "VMT"
min_ehighway_length = 10
ehighway_total_length = 500
year = 2020
scenario = "ehighway_{ }_{ }miles".format(
    selection_method, min_ehighway_length, ehighway_total_length
)
scenario_file = r"./data_output/{ }/{ }.shp".format(year, scenario)
```

```
file_output_name = scenario + "_energy"
```

```
#%% load file
dateparse = lambda x: pd.datetime.strptime(x, "%Y-%m-%d %H:%M:%S")

df_tod = pd.read_csv(
    r"./data_input/TOD Factors.csv", parse_dates=["month"], date_parser=dateparse
)
fac_columns = ["csffm3_mean_dir_fac_{:02d}".format(c) for c in range(24)]
```

```
df_ehighway = gp.read_file(scenario_file)
# %% iterate dates
vmts_per_day = OrderedDict()
d = datetime.date(year, 1, 1)
d_end = datetime.date(year, 12, 31)
delta = datetime.timedelta(days=1)
while d <= d_end:
    vmts_per_day[d] = np.zeros(24)
```

```

d += delta

total_vmt = 0
for _, link in df_ehighway.iterrows():
    vmt_link = link["VMT"] * link["DISTANCE"]
    tams_link = int(link["TAMS_ID"])
    total_vmt += vmt_link

current_month = 0
for day in vmts_per_day:
    print(day)
    if day.month != current_month:
        current_month = int(day.month)

    this_tod = df_tod[
        (df_tod.detstaid == tams_link) & (df_tod.daytype == "wkday")
    ]
    month_mask = this_tod["month"].map(lambda x: x.month) == current_month
    if np.sum(month_mask) > 0:
        id_fac_wkday = this_tod[month_mask].mean(axis=0)[fac_columns].values
    else:
        id_fac_wkday = this_tod.mean(axis=0)[fac_columns].values

    this_tod = df_tod[
        (df_tod.detstaid == tams_link) & (df_tod.daytype == "wkend")
    ]
    month_mask = this_tod["month"].map(lambda x: x.month) == current_month
    if np.sum(month_mask) > 0:
        id_fac_wkend = this_tod[month_mask].mean(axis=0)[fac_columns].values
    else:
        id_fac_wkend = this_tod.mean(axis=0)[fac_columns].values

    if day.weekday() in [5, 6]:
        vmts_per_day[day] += id_fac_wkend * vmt_link
    else:
        vmts_per_day[day] += id_fac_wkday * vmt_link

# %% calculate energy and put into file depending on target year
header = "date,hour,energy (kwh)"
if year == 2020:
    energy_factor = 2.36931 # kWh/mile
else:
    energy_factor = 1.65405 # kWh/mile

energy = []

```

```

days = []
hours = []
for day in vmts_per_day:
    energy += list(vmts_per_day[day] * energy_factor)
    days += 24 * [day.strftime("%Y-%m-%d")]
    hours += range(24)

for ehighway_factor in [0.25, 0.5, 0.75, 1]:
    this_energy = np.array(energy) * ehighway_factor
    fname = "./data_output/{}/{}_factor-{}.csv".format(
        year, file_output_name, int(100 * ehighway_factor)
    )
    np.savetxt(
        fname,
        np.column_stack((days, hours, this_energy)),
        delimiter=";",
        fmt="%s",
        header=header,
    )
    with open(fname, "wb") as myfile:
        for d, h, e in zip(days, hours, this_energy):
            myfile.writeline("{}{}{}\n".format(d, h, e))

```

#Local emission calculation – EJ scenarios

@author: msebastiani

This file calculates the total VMT in each census tract which can be used to calculate total emission reduction.

"""

load libraries

import geopandas as gp

import numpy as np

import matplotlib.pyplot as plt

import matplotlib.patches as patches

import matplotlib as mpl

import sys, os

os.chdir(os.path.pardir(os.path.realpath(__file__)))

sys.path.append(".")

from csffm_preprocess.util_ej import get_ej_data

```

# %% load data
year = 2040
if year == 2020:
    processed_file = r"./data_preprocessed/2020/all_roads_2020_AoN.shp"
if year == 2040:
    processed_file = r"./data_preprocessed/2040/all_roads_2040_AoN.shp"

ej_file = r"./data_input/EJ/CES3June2018Update.shp"
ej = get_ej_data(ej_file)
df = gp.read_file(processed_file)

election_method = "VMT"
min_ehighway_length = 10
ehighway_total_length = 500
year = 2020

scenario = "ehighway_{}/{}_miles".format(
    selection_method, min_ehighway_length, ehighway_total_length
)
ehighway_file = r"./data_output/{}/{}.shp".format(year, scenario)

ehighway = gp.read_file(ehighway_file)
ej["total_vmt"] = 0
tracts = dict()
for i_seg, seg in df.iterrows():
    if seg.EJ_tract is not None:
        tracts_seg = seg.EJ_tract.split(",")
        for ts in tracts_seg:
            rate = 1.0 / len(tracts_seg)
            if ts != "":
                tsi = int(ts)
                ej.loc[ej.OBJECTID_1 == tsi, "total_vmt"] = (
                    ej[ej.OBJECTID_1 == tsi].total_vmt + seg.VMT * rate
                )

ej["ehighway_vmt"] = 0
ej["ehighway"] = 0
tracts = dict()
fig, ax = plt.subplots()
for i_seg, seg in ehighway.iterrows():
    if seg.EJ_tract is not None:
        tracts_seg = seg.EJ_tract.split(",")
        for ts in tracts_seg:
            rate = 1.0 / len(tracts_seg)
            if ts != "":

```

```

tsi = int(ts)
ej.loc[ej.OBJECTID_1 == tsi, "ehighway_vmt"] = (
    ej[ej.OBJECTID_1 == tsi].ehighway_vmt + seg.VMT * rate
)
ej.loc[ej.OBJECTID_1 == tsi, "ehighway"] = int(seg.EHIGHWAY) + 1

ej["ehighway_rate"] = ej.ehighway_vmt / ej.total_vmt

#here, we can use eHighway VMT to calculate emission based on the emission rate pre
sented in the dissertation

```

APPENDIX D. SOURCE CODE FOR CHAPTER 6

```
#Substations
```

```
@author: msebastiani
```

```
This file splits the ehighway in segments that are powered by a single ehighway substati  
on and connect the to a power substation in the California grid  
,,,,,
```

```
#%% load libraries
```

```
import pandas as pd
```

```
import geopandas as gp
```

```
import numpy as np
```

```
from collections import OrderedDict
```

```
import matplotlib.pyplot as plt
```

```
import matplotlib.patches as patches
```

```
import matplotlib as mpl
```

```
from shapely import wkt
```

```
from shapely.geometry import Point, LineString
```

```
import sys, os
```

```
import math
```

```
os.chdir(os.path.pardir(os.path.realpath(__file__)))
```

```
sys.path.append(".")
```

```
from csffm_preprocess.util_ej import get_ej_data
```

```
# %% define variables
```

```
selection_method = "VMT"
```

```
min_ehighway_length = 10
```

```
ehighway_total_length = 500
```

```
year = 2020
```

```
scenario = "ehighway_{ }_{ }miles".format(  
    selection_method, min_ehighway_length, ehighway_total_length  
)
```

```
ehighway_file = r"./data_output/{ }/{ }.shp".format(year, scenario)
```

```
powerplant_file = (  
    r"./data_input/California_Electric_Substation/California_Electric_Substation.shp"  
)
```

```
max_road_length_per_powerplant = 20
```

```
powerplants = dict()
```

```
processed_file = r"./data_preprocessed/2020/all_roads_2020_AoN.shp"
```

```
df = gp.read_file(processed_file)
```

```

link_to_powerplant = gp.GeoDataFrame()

# %% load files
ehighway_df = gp.read_file(ehighway_file)
powerplant_df = gp.read_file(powerplant_file)
powerplant_df = powerplant_df.dropna(subset=["geometry"])
powerplant_df = powerplant_df.to_crs({"init": "epsg:3310"})
powerplant_df = powerplant_df[powerplant_df["Status"] == "Operational"]
powerplant_df = powerplant_df[powerplant_df["State"] == "CA"]
powerplant_df = powerplant_df[
    (powerplant_df["kv_12_TO_3"] == "YES") | (powerplant_df["kv_33_TO_9"] == "YES"
)
]

# %% get each segment, find the correct powerplant based on the expected distance between
ehighway_df["powerplant"] = 0
grouped = ehighway_df.groupby(["ROAD", "DIRECTION"])

for road in grouped.groups:
    this_road = grouped.get_group(road)

    this_division = np.where(np.diff(this_road.LINK_ID.astype(int)) != 1)[0]
    if len(this_division) > 0:
        all_ehighways = [0, this_division[0] + 1, len(this_road)]
    else:
        all_ehighways = [0, len(this_road)]

    for i in range(len(all_ehighways) - 1):
        this_ehighway = this_road.iloc[all_ehighways[i] : all_ehighways[i + 1]]
        n = math.ceil(this_road.DISTANCE.sum() * 1.0 / max_road_length_per_powerplant)
    )
    this_max_road_length_per_powerplant = this_road.DISTANCE.sum() / n

    # find strechs of road inside the this_max_road_length_per_powerplant
    this_stretch_vmt = 0
    this_stretch_distance = 0
    this_stretch_x0, this_stretch_x1 = None, None
    this_stretch_y0, this_stretch_y1 = None, None
    this_stretch_xm, this_stretch_ym = None, None
    list_of_links_powerplant = []
    for ln, link in this_ehighway.iterrows():
        this_stretch_vmt += float(link.VMT)
        this_stretch_distance += float(link.DISTANCE)

```

```

# save links in this powerplant to update csv
list_of_links_powerplant.append(ln)

# if new stretch, get centroid's position
if this_stretch_x0 is None:
    this_stretch_x0 = link.geometry.centroid.x
    this_stretch_y0 = link.geometry.centroid.y

if (
    this_stretch_distance >= this_max_road_length_per_powerplant / 2.0
    and this_stretch_xm is None
):
    this_stretch_xm = link.geometry.centroid.x
    this_stretch_ym = link.geometry.centroid.y

# if end of stretch
if (
    this_stretch_distance >= this_max_road_length_per_powerplant
    or link["LINK_ID"] == this_ehighway.iloc[-1]["LINK_ID"]
):

    if this_stretch_vmt > 0:
        this_stretch_x1 = link.geometry.centroid.x
        this_stretch_y1 = link.geometry.centroid.y
        if this_stretch_xm is None:
            this_stretch_xm = this_stretch_x1
            this_stretch_ym = this_stretch_y1

    # find closest power station
    this_stretch_x = (this_stretch_x0 + this_stretch_x1) / 2.0
    this_stretch_y = (this_stretch_y0 + this_stretch_y1) / 2.0

    pos = np.argmin(
        powerplant_df.distance(
            Point(this_stretch_x, this_stretch_y)
        ).values
    )
    if pos >= len(powerplant_df):
        continue

    powerplant_id = powerplant_df.iloc[pos]["OBJECTID"]
    if powerplant_id in powerplants:
        powerplants[powerplant_id] += this_stretch_vmt
    else:
        powerplants[powerplant_id] = this_stretch_vmt

```

```

        this_dict = {
            "geometry": LineString(
                [
                    powerplant_df.iloc[pos].geometry.centroid,
                    Point(this_stretch_xm, this_stretch_ym),
                ]
            ).wkt
        }
        this_link_to_powerplant = pd.DataFrame(this_dict, index=[0])
        this_link_to_powerplant["geometry"] = this_link_to_powerplant[
            "geometry"
        ].apply(wkt.loads)
        this_link_to_powerplant = gp.GeoDataFrame(
            this_link_to_powerplant, geometry="geometry"
        )
        link_to_powerplant = link_to_powerplant.append(
            this_link_to_powerplant
        )

```

```

# add powerplant to ehighway

```

```

for llp in list_of_links_powerplant:
    ehighway_df.at[llp, "powerplant"] = powerplant_id

```

```

# reset stretch info

```

```

this_stretch_vmt = 0
this_stretch_distance = 0
this_stretch_x0, this_stretch_x1 = None, None
this_stretch_y0, this_stretch_y1 = None, None
this_stretch_xm, this_stretch_ym = None, None
list_of_links_powerplant = []

```

```

# calculate energy used for each power plant

```

```

if year == 2020:

```

```

    energy_factor = 2.36931 # kWh/mile

```

```

else:

```

```

    energy_factor = 1.65405 # kWh/mile

```

```

ehighway_df["energyused"] = 0

```

```

powerplant_df["energyused"] = 0

```

```

for pp in powerplants:

```

```

    powerplant_df.loc[powerplant_df["OBJECTID"] == pp, "energyused"] = (
        powerplants[pp] * energy_factor
    )

```

```

ehighway_df.loc[ehighway_df["powerplant"] == pp, "energyused"] = (

```

```

        powerplants[pp] * energy_factor
    )

    energy_consumed = powerplants[pp] * energy_factor
    print(pp, energy_consumed)
    #%%
    # ax = powerplants_used_df.plot(color='green')
    fig, ax = plt.subplots()
    ax.set_frame_on(False)
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
    df.plot(ax=ax, color="k", linewidth=0.5, alpha=0.5)
    link_to_powerplant.plot(ax=ax, color="blue", alpha=0.5)

powerplants_used_df = powerplant_df[powerplant_df.OBJECTID.isin(powerplants.keys(
))]
cmap = mpl.colors.LinearSegmentedColormap.from_list("", ["green", "yellow", "red"])

powerplant_df[~powerplant_df.OBJECTID.isin(powerplants.keys())].plot(
    ax=ax, color="gray", markersize=1
)
powerplants_used_df.plot(ax=ax, markersize=20, column="energyused", cmap=cmap)

ehighway_df.plot(ax=ax, column="energyused", cmap=cmap)

# show only california
plt.xlim([-500000, 750000])

plt.show()

# %% plot bar
plt.rcParams["xtick.top"] = plt.rcParams["xtick.labeltop"] = True

plt.rcParams["xtick.bottom"] = plt.rcParams["xtick.labelbottom"] = False
plt.rcParams["ytick.left"] = plt.rcParams["ytick.labelleft"] = False

x = range(len(powerplants_used_df))
y = powerplants_used_df.sort_values(by="energyused").energyused.values
plt.barh(x, y, color=cmap(y / np.max(y)))
plt.title("Daily kWh")

plt.show()

```