Title

Life Cycle Modeling of Technologies and Strategies for a Sustainable Freight System in California

Authors
Ambrose, Hanjiro
Kendall, Alissa

Publication Date
2019-11-01

DOI
10.7922/G2M61HH8

Data Availability
The data associated with this publication are available at: https://doi.org/10.25338/B8NS4T

Life Cycle Modeling of Technologies and Strategies for a Sustainable Freight System in California

November 2019

A Research Report from the National Center for Sustainable Transportation

Hanjiro Ambrose, University of California, Davis

Alissa Kendall, University of California, Davis

National Center for Sustainable Transportation

ITS UCDAVIS INSTITUTE OF TRANSPORTATION STUDIES

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
NCST-UCD-RR-19-07	N/A	N/A

4. Title and Subtitle
Life Cycle Modeling of Technologies and Strategies for a Sustainable Freight System in California

5. Report Date
November 2019

6. Performing Organization Code
N/A

7. Author(s)
Hanjiro Ambrose, PhD https://orcid.org/0000-0002-6502-5191
Alissa Kendall, PhD https://orcid.org/0000-0003-1964-9080

8. Performing Organization Report No.
UCD-ITS-RR-19-37

9. Performing Organization Name and Address
University of California, Davis, Institute of Transportation Studies
1605 Tilia Street, Suite 100
Davis, CA 95616

10. Work Unit No.
N/A

11. Contract or Grant No.
USDOT Grant 69A3551747114

12. Sponsoring Agency Name and Address
U.S. Department of Transportation
Office of the Assistant Secretary for Research and Technology
1200 New Jersey Avenue, SE, Washington, DC 20590

13. Type of Report and Period Covered
Final Report (October 2017 – March 2019)

14. Sponsoring Agency Code
USDOT OST-R

15. Supplementary Notes
DOI: https://doi.org/10.7922/G2M61HH8
Dataset DOI: https://doi.org/10.25338/B8NS4T

16. Abstract
California's freight transportation system is a vital part of the state's economy but is a significant contributor to greenhouse gas emissions and generates an even higher portion of regional and local air pollution. The state's primary strategy for reducing emissions from the on-road freight sector relies on deploying new vehicle and fuel technologies, such as electric medium- and heavy-duty vehicles. The market for electric truck technologies is developing rapidly. The goal of this research is to quantify the life cycle environmental impacts and life cycle costs for on-road goods movement in California to estimate the abatement potential and economic costs and benefits of electrifying California's freight truck sector. The study compares the emissions and costs of urban conventional gasoline and diesel Class 3–8 vehicles with electric heavy-duty vehicles (i.e., electric trucks) for a range of freight and commercial vocations. A model of freight vehicle operations is developed based on representative vehicle location data, and linked with life cycle emissions inventory, technology cost, and pollution health damage cost data. The model is then used to assess energy and capacity requirements for electric trucks and battery systems and explore the impacts of a range of charging strategies and vehicle duty cycles (i.e., vocations) on energy, costs, and emissions between 2020 and 2040. Where emissions occur, and how emissions of different pollutants are affected by factors including vocation, duty cycle, powertrain configuration, and fuel pathway, will influence the effectiveness and economic costs of emissions reduction strategies. On a per mile basis, replacing a conventional gasoline or diesel truck can reduce CO_2-equivalent (CO_2e) emissions by 50%–75% compared to conventional gas and diesel vehicles. Statewide, 100% electrification of in-state Class 8 vehicles by 2040 could reduce annual CO_2e emissions by nearly than 30% (50 million metric tonnes per year), and electrification of Class 3 trucks statewide would likely half current PM2.5 emissions from transportation. The costs of emissions abatement from truck electrification ranged from \$0.25 to \$182 per metric tonne of CO_2e for trucks deployed in 2020, but these costs are likely to fall dramatically by 2040. Full electrification of the in-state registered Class 3–8 vehicle fleet by 2040 would significantly reduce criteria pollutants and aerosols emissions; this in turn could reduce pollution related damages in the state by \$507 million per year by 2025, and by some \$1.6 billion by 2040.

17. Key Words
Electric vehicles, goods movement, environmental impact assessment, life cycle costing

18. Distribution Statement
No restrictions.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	64	N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

About the National Center for Sustainable Transportation

The National Center for Sustainable Transportation is a consortium of leading universities committed to advancing an environmentally sustainable transportation system through cutting-edge research, direct policy engagement, and education of our future leaders. Consortium members include: University of California, Davis; University of California, Riverside; University of Southern California; California State University, Long Beach; Georgia Institute of Technology; and University of Vermont. More information can be found at: ncst.ucdavis.edu.

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, by a grant from the U.S. Department of Transportation's University Transportation Centers Program. However, the U.S. Government assumes no liability for the contents or use thereof.

Acknowledgments

This study was funded, partially or entirely, by a grant from the National Center for Sustainable Transportation (NCST), supported by USDOT through the University Transportation Centers program. The authors would like to thank the NCST and USDOT for their support of university-based research in transportation, and especially for the funding provided in support of this project.

Life Cycle Modeling of Technologies and Strategies for a Sustainable Freight System in California

A National Center for Sustainable Transportation Research Report

November 2019

Hanjiro Ambrose, Institute of Transportation Studies, University of California, Davis

Alissa Kendall, Department of Civil and Environmental Engineering, University of California, Davis

NCST

[page intentionally left blank]

TABLE OF CONTENTS

List of Tables

List of Figures

Life Cycle Modeling of Technologies and Strategies for a Sustainable Freight System in California

EXECUTIVE SUMMARY

California's freight transportation system is a vital part of the state's economy but is a significant contributor to greenhouse gas (GHG) emissions and generates an even higher portion of regional and local air pollution. For example, over half of particulate aerosol and nitrogen oxides (NO_X) emissions from highway vehicles are from medium- and heavy-duty vehicles. These vehicles often operate in parts of the state with already poor air quality, exacerbating existing unhealthy conditions. The state's primary strategy for reducing emissions from the on-road freight sector relies on deploying new vehicle and fuel technologies. The majority of emissions reductions from freight activities are expected to come from the deployment of new emissions control devices on combustion-based powertrains, efficiency improvements, and on-road zero emissions vehicle technologies. Given the rapidly developing market for electric truck technologies, and recent focus on electrification strategies for heavy-duty vehicles (HDVs) in California policymaking, this report focuses on truck electrification. Where emissions occur, and how emissions of different pollutants are affected by factors including vocation, duty cycle, powertrain configuration, and fuel pathway, will influence the effectiveness and economic costs of emissions reduction strategies. Thus, these are all important considerations in the research approach.

The goal of this research is to quantify the life cycle environmental impacts and life cycle costs for on-road goods movement in California to estimate the abatement potential and economic costs and benefits of electrifying California's freight truck sector. The focus of this report is on urban, as opposed to long-haul, freight vehicle vocations that rely on a range of medium- and heavy-duty commercial vehicles (vehicle Classes 3–8). The study also evaluates the potential impacts of operational strategies through a parametric simulation of freight vehicle data and assessment of electric freight vehicle charging strategies.

The modelling tool developed for this research considers seven vocations and five vehicle classes for conventional gasoline and diesel trucks and electrified trucks. Embedded in this tool is a model of freight vehicle operations developed based on a set of representative vehicle location data to estimate electric truck battery capacity requirements and costs as a function of a range of charging strategies and vehicle duty cycles. The model is then linked with life cycle cost and environmental inventory data to evaluate total fuel cycle emissions and costs of electrification across the truck classes and vocations assessed. Finally, the results are combined with a forecast of freight truck population and travel for California to quantify the total costs and abatement potential of truck electrification through the year 2040.

On a per mile basis, replacing a conventional gasoline or diesel truck can reduce CO_2-equivalent (CO_2e) emissions from between about 0.4–1 kg CO_2e/mile (on average over the assessment period), with the lower bound for Class 3 and the higher bound for Class 8 trucks. This represents a 50%–75% reduction from conventional gas and diesel vehicles. Air quality pollutants including NO_X and $PM_{2.5}$ are also substantially lower for electric trucks. Emissions abatement potential for electrification increases over time are due largely to a decarbonizing electricity grid, and partly due to technology improvements over time. For example, statewide, 100% electrification of Class 8 vehicles alone could reduce CO_2e emissions by more than 50 million metric tonnes per year in 2040, a 30% reduction from the business as usual scenario. Electrification of Class 3 trucks could reduce PM2.5 emissions by more than 2500 tonnes, on average, and up to 5000 tonnes at the upper bound in 2040, or a nearly 50% reduction from the business as usual case.

The costs of emissions abatement from truck electrification ranged from $0.25 to $182 per metric tonne of CO2-eq for trucks deployed in 2020. By 2040, the costs of Class 6 and 8 trucks in local delivery applications were significantly lower than conventional alternatives, and abatement costs for GHGs were negative, from -$3.80 to -$9.14 per tonne. Another key potential benefit of GHG abatement from truck electrification is co-reduction of criteria pollutants and aerosols. Total pollution related health damages from operation of conventional Class 3–8 vehicles were estimated to range from to $971 million to $2,179 million per year. As discussed in this study, 100% electrification of in-state registered Class 3–8 trucks could reduce pollution related damages by $507 million per year by 2025, and by some $1.6 billion on average by 2040.

Introduction

Today's transportation system relies on technologies that impose pollution on the local environment and contribute to global warming through greenhouse gas emissions (GHGs). This is particularly true for goods movement through heavy-duty vehicle (HDV) systems. While HDVs are less than 5% of the total U.S. vehicle fleet, they account for 18% of transportation energy use, close to 80% of on-road diesel use, and well over half of particulate aerosol and nitrogen oxides (NO_X) emissions from highway vehicles [1]. Liquid fuel use from medium- and heavy-duty vehicles has increased more rapidly in both relative and absolute terms than consumption by other sectors [2]. With increasing demand for on-road freight transportation, and a seeming lack of cost effective substitutes, these trends are expected to continue into the near future [3].

California has a history of critical air quality issues, including persistent non-attainment areas for federal ozone and airborne particulate matter standards. HDVs are of particular concern as they emit high levels of particulate matter and a complex mixture of pollutants including ozone precursors [4–6]. The state's freight transportation system and related industries are a vital part of the state's economy but constitute the majority of on-road diesel fuel use and generate a high portion of local pollution in parts of the state with poor air quality. On-road goods movements by vans, trucks, tractors, and other HDVs contribute the largest share of GHG and criteria emissions from freight activities. In recognition of these challenges, a number of policies, plans, and orders have been issued. Governor Brown's Executive Order B-32-15 encourages adoption of freight vehicle technologies and infrastructure that allow for reductions in these impacts and the use of alternative energy and fuels. The California Department of Transportation (Caltrans), the California Air Resources Board, and other agencies have contributed to the development of a Sustainable Freight Action Plan (SFAP) for the state. The SFAP identifies two primary strategies: increasing freight efficiency and transitioning to zero-emission technologies.

The state's primary strategy for reducing emissions from the freight sector relies on deploying new vehicle and fuel technologies. California has outlined its plan to reduce NO_X, PM, and toxics from heavy-duty mobile sources over the next decade in the State Implementation Strategy (SIP). This includes a call to reduce emissions of NO_X in the South Coast and San Joaquin air districts by 80% by 2032. California has also set a target to reduce GHG emissions by 40% by 2030 under the Global Warming Solutions Act, Senate Bill 32. To achieve these regulatory objectives, California facilitates the deployment of zero-emission and near-zero emission vehicles and equipment into the heavy-duty sector. Zero-emission vehicle technologies include battery electric medium- and heavy-duty vehicles (BEVs) and fuel cell electric vehicles (FCEVs), while *near-zero* emission technologies include low NO_X engines paired with renewable fuels, and engines and vehicles with greater efficiencies.

Comparing technology performance and ensuring the integrity of reductions across the HDV sector requires assessing the costs and benefits of technology deployment, including impacts on the environment. A transition to advanced HDVs and low-carbon fuels is likely to increase the importance of a life cycle perspective in vehicle policy, as has been demonstrated in the light-duty sector. Shifting of emissions between life cycle stages may occur when a change to a process or input causes new impacts to emerge at different stages in a product's life cycle. For zero-emission HDVs running electricity, hydrogen, or biofuels, the majority of emissions are expected to occur upstream of the vehicle's tailpipe. This poses important questions for the distribution of costs and transfer of benefits from policy action, and necessitates a life cycle framework for calculating costs and benefits.

Compared to fossil fuels, the emissions and environmental impacts of renewable fuel pathways and vehicle supply chains are more complex and difficult to estimate [7–10]. There has been considerable scholarly debate over the emissions reductions potential of biofuels [11], particularly for heavy-duty vehicles [12–18], and the proper methodology for estimating the emissions of grid-tied electric vehicles [19–23]. The performance of emissions control devices for criteria pollutants and toxics can also be highly uncertain, occasionally resulting in inverse trends between quantity of emissions and toxicity due to ambient conditions, maintenance, load, or age [24–26].

There are further methodological and practical challenges to quantifying the environmental impacts of transportation technology policies. These can include characterizing the innovation or diffusion of new technologies [27, 28], quantifying the impacts of incentives or funding [29], and the market structure of specific industries [30]. Substitution and other market-mediated effects also complicate prediction of impacts on pollution from technology change [12]. In total, these issues come down to capturing uncertainty and tradeoffs in the effects of technology change or the appropriate direction to incentivize change [12, 13, 31].

Life cycle assessment (LCA) is a standardized methodology for assessing the environmental impacts of a product system [32]. The scope of LCA is typically limited to environmental impacts, but the life cycle framework is also used to assess costs (as in life cycle costs (LCC)) and other metrics for sustainability [33, 34]. LCC applies life cycle principles to evaluate the economic impacts of decision-making [35, 36]. Taken together, LCC and LCA provide a robust framework for assessing costs and benefits of decision-making over time, in addition to the potential for capturing spatio-temporal tradeoffs in impacts.

In the context of LCA, a life cycle encompasses the relevant stages of the life of a product, i.e., "all activities, or processes, in a product's life result in environmental impacts due to consumption of resources, emissions of substances into the natural environment, and other environmental exchanges" [37]. LCA has previously been used to identify significant drivers of emissions for vehicle and fuel technologies (i.e., hotspots), identify risks of burden shifting (where emissions may be reduced at one stage or location, but increased at another), and to assess potential systems and substitution effects (i.e., attributional or consequential impacts) [38–41]. A transition to advanced HDVs and low-carbon fuels is likely to increase the importance of a life cycle perspective in vehicle policy, as has been demonstrated in the light-duty sector.

This research quantifies the life cycle emissions and costs of heavy-duty truck electrification across a range of goods movement vocations and operational strategies. The study focuses on the effects of duty cycle on battery capacity requirements and charging strategies. These results are also used to estimate the magnitude and costs of potential abatement for California based on state-wide vehicle population data.

Methods

This research uses LCA and LCC methods to quantify the environmental impacts and costs of adopting battery electric heavy-duty trucking used for urban delivery and intermodal operations in California. The goal of the study is to compare the costs, performance, and emissions of electric and conventional trucks for goods movement applications. A specific focus of the study is estimating the costs of avoided emissions from electrification of freight vehicles on a life cycle basis, here-after termed life cycle abatement cost.

To implement a LCA and LCC, modeling is required to represent relevant vehicle types (class and vocation), operations, and related technical and infrastructure systems. A vehicle's vocation will determine both the vehicle class and type, as well as its expected duty cycle (i.e., operations). A model of freight vehicle operations was developed based on a set of representative vehicle location data. Battery capacity requirements and costs are then analyzed across a range of charging strategies and vehicle duty cycles. Changes in key background technical systems, namely battery specific energy and electricity generation technologies, were also evaluated between 2020 and 2040. Finally, the results were combined with a forecast for California of freight truck population and travel to quantify the total costs and abatement potential of truck electrification.

The scope of the cost assessment included:

- Purchase Costs
- Scheduled and Unscheduled Maintenance
- Repower/Refurbishment
- Fuel Costs
- Powertrain Efficiency
- Infrastructure Costs
- Vehicle Life
- Policy Subsidies

The scope of the environmental assessment included the total fuel cycle (production, delivery, and combustion), and vehicle operating emissions including evaporative emissions. The production of the vehicle frame, body, and powertrain were excluded from the system boundary. The variety of truck types considered and a lack of previous research characterizing different HDVs prevented their inclusion. Previous research has often shown that fuel cycle impacts cause the majority of impacts for on-road vehicles. In addition, comparison of the conventional and electrified trucks would be nearly identical with the exception of the powertrain.

The results are reported in three reference, or functional, units:

- Per mile: divided by lifetime vehicle miles travelled by vehicle class
- Per ton-mile: divided by effective cargo capacity per average mile travelled
- Statewide: weighted by in-state truck population and truck activity by class

Given the diversity of truck types, configurations, and cargo capacities, per mile impacts may not be comparable across vehicle classes. Therefore, emissions are also reported based on the average loaded capacity over the duty cycle.

The life cycle abatement costs for each class is estimated as the difference in life cycle costs for each truck class and fuel pathway (i.e., diesel, gasoline, and electric) on a per mile basis, divided by the difference in the life cycle emissions for each pollutant type. For all scenarios, a 4% discount rate is used to estimate life cycle costs. The overall result is a vector of cost per unit emissions avoided by pollutant species.

Vehicle Classes and Specifications

Medium- and heavy-duty trucks service a variety of diverse vocations and are often heavily customized to fit specific applications. Unfortunately, the Federal Highway Administration, U.S. Census Bureau, and Environmental Protection Agency maintain different definitions of heavy-duty vehicles by gross vehicle weight, which can lead to confusion [42, 43]. Table 1, adapted from Giuliano et al. (2018), describes the types of vehicles in these classes as well as the range of vehicle weights when loaded vs. unloaded (in pounds). The weight of the vehicle is one of the primary factors influencing fuel requirements, but it varies considerably during the duty cycle due to the need for return links or ‘dead-heading’ in most goods distribution vocations.

Table 1. Description of vehicle weight and capacity by vehicle class

FHWA Vehicle Class	Description	Min Vehicle Weight (Unloaded)	Max Vehicle Weight
3	Heavy-duty pick-up, small box truck, walk-in van, step vans	8000	14000
4	Heavy-duty pick-up, small box truck, city and parcel delivery, large walk-in van	8000	16000
5	Two-axle, six-tire, single-unit trucks, large walk-in van, city delivery truck	10000	19500
6	Two-axle, six-tire, single-unit trucks, beverage trucks, parcel delivery	12000	26000
7	Four or fewer axles, refuse trucks, semi-tractor, less than truckload cargo (containers)	12000	33000
8	Four or more axle single-trailer trucks, heavy semi-tractor, dump truck, refrigerator truck	33001	80000

Figure 1 shows the estimated population of Class 3–8 in-state registered vehicles and total annual vehicle miles travelled (VMT) by vehicle class and year from 2018 to 2040 (EMFAC

2017). For the vehicle population considered, light commercial vehicles represent about 68% of vehicles and 58% of annual VMT. Total VMT across these vehicle categories is expected to increase between 2020 and 2040, primarily due to increased use of medium and heavy commercial vehicles. For example, VMT from Class 6 in-state registered vehicles is expected to increase by 2.7 million VMT annually by 2040.

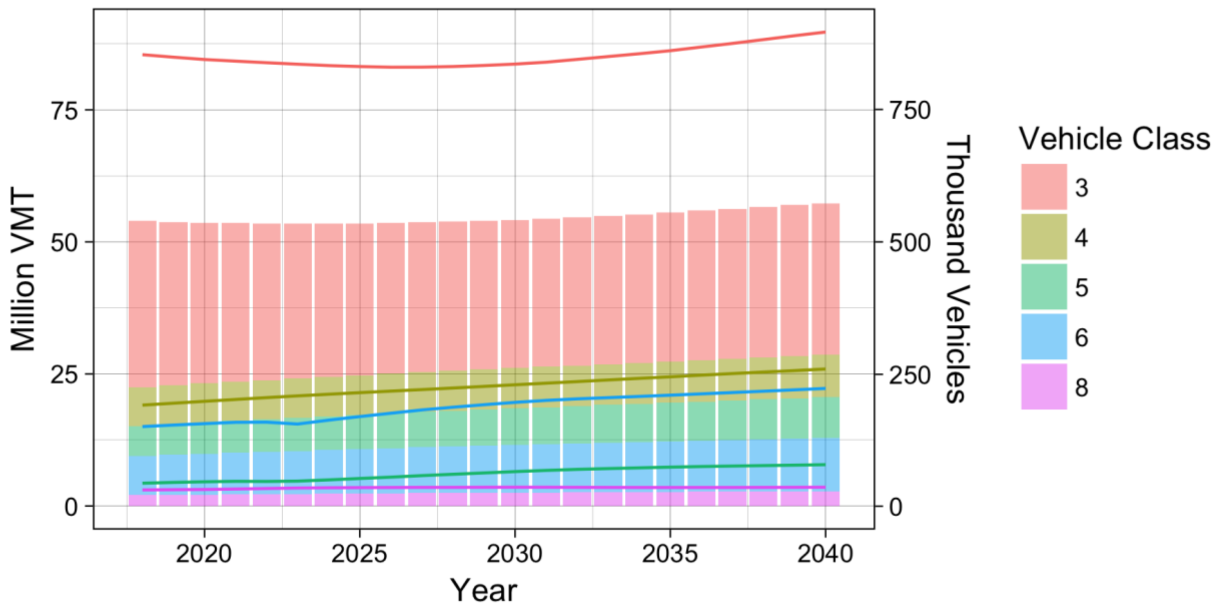

Figure 1. Vehicle population (lines) and annual miles travelled by vehicle class [44]

Goods Movement Vocations

Costs and emissions were estimated for each vehicle class across a representative set of vocation data. Many of the vocations and duty cycles that HDVs are designed for involve high power requirements, brake and tire wear, and other operational inefficiencies that increase vehicles' fuel requirements and use-phase emissions rates [45]. The significant factors that affect emissions from HDVs include: vehicle class and weight, driving cycle, vehicle vocation, fuel type, engine exhaust aftertreatment, vehicle age, and terrain [24]. Studies have established the close links between duty cycle, fuel type, and vehicle energy demands [46, 47]. In fact, duty cycle can be the most significant driver of uncertainty in operational emissions estimates from HDVs [48].

Data on freight vehicle operations were analyzed in order to evaluate the impacts of duty cycle, vehicle class, and load on costs and emissions. Freight vehicle operations data were obtained from the National Renewable Energy Lab Fleet DNA Data Project (Fleet DNA) [49]. Fleet DNA data is gathered from remote dynamometer trackers providing driving conditions and location at one second intervals. Table 2 describes the vehicle data used in this study. As evidenced in Table 2, similar vehicle classes can travel 2 to 3 times as many miles per day across vocations, and average daily travel may not well reflect the routes and travel requirements of many vehicles in the fleet.

In addition to daily travel distances, the driving route and driving conditions also influence fuel requirements. The fuel required to operate a vehicle is primarily driven by physical forces (e.g., air resistance, rolling resistance, and inertia), vehicle efficiency, and auxiliary loads. Figure 2 shows the duty cycle data by average speed and acceleration for each vocation and vehicle class. Higher average acceleration is associated with more frequent stops per mile and lower fuel economy. Air resistance at higher average speeds can also be a significant driver of fuel consumption

Table 2. Fleet DNA vehicle drive cycle data by vocation and vehicle type

Vehicle Class	Vehicle Description	Vocation Description	Vehicle Records	Total Trips	Average Daily Driving Distance (mi)	Max Daily Driving Distance (mi)
3	Service Van	Telecom	29	281	32.8	63.9
8	Tractor	Beverage Delivery	722	7480	70.6	339.2
6	Straight Truck	Warehouse Delivery	60	1076	93.0	191.5
4	Step Van	Parcel Delivery	271	2547	55.7	131.9
6	Straight Truck	Parcel Delivery	117	1079	28.28	85.2
5	Walk-in	Parcel Delivery	299	4080	42.8	231.8
4	Step Van	Linen Delivery	291	3887	64.8	200.9
6	Straight Truck	Linen Delivery	19	76	62.3	90.8
5	Walk-in	Linen Delivery	113	1775	77.7	261.7
6	Straight Truck	Food Delivery	357	3099	38.9	81.2
8	Tractor	Food Delivery	136	1453	164.4	568.3
8	Tractor	Local Delivery	292	3866	127.3	248.9

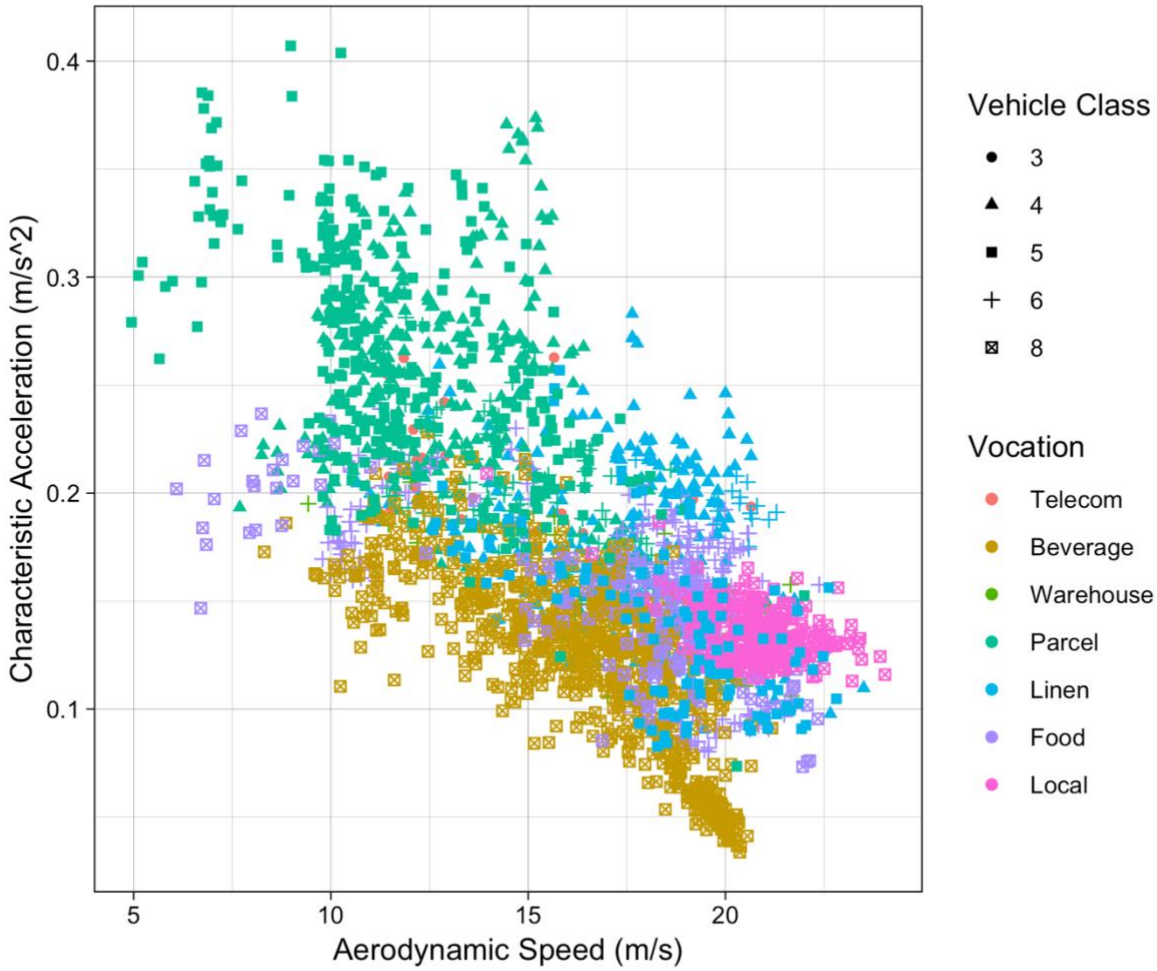

Figure 2. Average speed and acceleration by duty cycle and vehicle class in Fleet DNA composite data

Vehicle energy demands, or average fuel consumption per unit distance-mass travelled (specific fuel consumption (SFC)), can be estimated from these data through Equation 1:

Equation 1

$$SFC = \frac{C_{aero} * v_{aero}^2 + C_{rolling} + \overline{\alpha}(1 - \eta_{regen})}{\eta_{powertrain}} + \frac{E_{auxfuel}}{M_{veh} * D}$$

$$C_{aero} = \frac{\frac{1}{2} * \rho C_D FA}{M_{veh}}$$

$$C_{rolling} = RRC * g$$

Where:

$$v_{aero} = aerodynamic\ speed$$

$$\overline{\alpha} = characteristic\ acceleration$$

$$SFC = \frac{Fuel}{Mass * D}$$

$$C_{aero} = aerodynamic\ resistance$$

$$C_{rolling} = rolling\ resistance$$

$$RRC = coefficient\ of\ rolling\ resistance$$

$$\rho = air\ density$$

$$g = gravity$$

$$C_D = coefficient\ of\ aerodynamic\ resistance$$

$$\eta_{powertrain} = powertrain\ efficiency$$

$$\eta_{regen} = braking\ regeneration\ efficiency$$

$$M_{veh} = vehicle\ mass$$

$$D = trip\ distance\ travelled$$

SFC was estimated for each vehicle observation for empty and loaded masses as described in Table 2. The efficiency of the electric drive motor and regeneration motor are assumed to be 92% and 85% respectively, based on values from Schwertner and Weidmann (2016) and O'Keefe et al. (2007) [50, 51]. For comparison, the assumed powerplant efficiency of an equivalent diesel engine is 38%. The estimated vehicle energy requirements in kWh per mile are shown in Figure 3. Comparison with diesel vehicle efficiency is discussed in the results section.

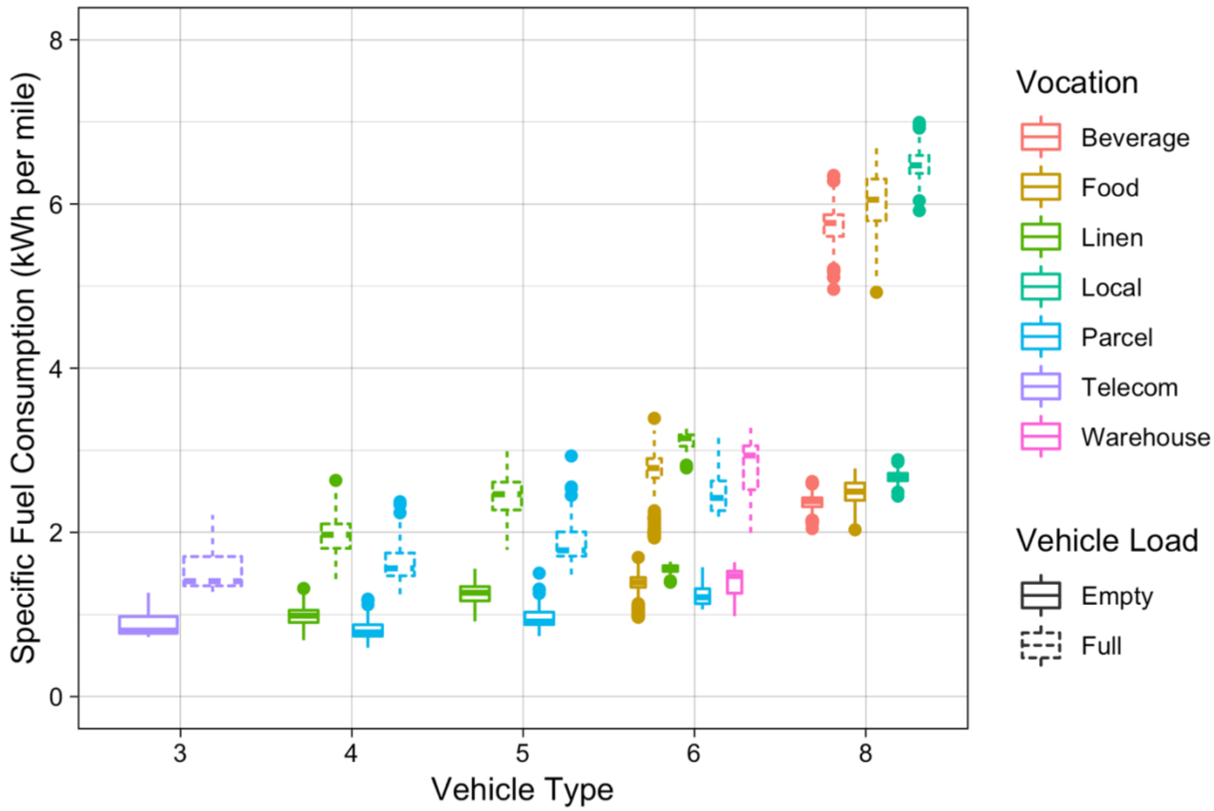

Figure 3. Estimated electric truck energy demands per mile

Vehicle Purchase and Operating Costs

Vehicle purchase and operations cost data were drawn from the AFLEET model and other existing data sources [52]. Electric truck purchase costs are broken down into three categories: the chassis (e.g., vehicle body and powertrain), the battery system, and charging infrastructure. The battery system, which can represent 50%–70% of the cost of new electric freight vehicles [53], is discussed in the next section. Charging infrastructure is discussed with electricity costs in the section on charging strategies. Table 3 shows the assumed purchase costs for the average (diesel) conventional alternative used to estimate abatement costs. The electric chassis cost is assumed to represent the total vehicle purchase cost lest the battery system. Battery cost and charging infrastructure costs are discussed in the following sections. The purchase cost of conventional trucks is assumed to increase by 2% per year based on tightening emissions standards, while maintenance and repair costs are assumed to be constant over the study period.

Table 3. Purchase and maintenance cost assumptions

Vehicle Class	Conventional Purchase Cost	Conventional Maintenance Cost (per mile)	Electric Chassis Purchase Cost	Electric Maintenance Cost (per mile)	Tires (per axel/ mile)	Repairs (per mile)
3	$39,500	$0.204	$27,650	$0.151	$0.04	$0.08
4	$46,500	$0.201	$32,550	$0.139	$0.04	$0.06
5	$65,000	$0.201	$45,500	$0.137	$0.04	$0.06
6	$75,000	$0.204	$52,500	$0.162	$0.04	$0.05
8	$90,000	$0.194	$63,000	$0.173	$0.04	$0.10

Note: battery system and charging infrastructure costs are variable and handled through scenario analysis described separately

Battery Costs and Performance

A forecast was developed to assess potential improvements in the cost and mass of future battery systems. Reduction in the costs of emerging energy technologies can result from increasing production scale, maturing supply chains, new efficiency gains, and new innovations. The effects of industrial learning and knowledge acquisition can be characterized by technology experience curves [54]. Experience curves have a long history of use for examining the relationship between deployment of a technology and the price of a technology [55]. Equation 2 shows the form of an experience curve, *C(U),* which is the unit cost of a lithium ion battery (LIB) in $/kW or $/kWh as a function of a given level of cumulative deployment (U).

Equation 2

$$C(U) = C_0 * (U/U_0)^{-a}$$

Where C_0= the initial cost, U_0= the initial production factor, and *a* = the coefficient of learning. The Learning Rate (LR), shown in Equation 3, represents the reduction in the unit cost of a technology with every increase in production. It is commonly estimated using a base of two, and as such represents the reduction in costs of a technology with each doubling of cumulative production:

Equation 3

$$LR = 1 - 2^{\alpha}$$

The technology experience curve has been widely applied to photovoltaic [56, 57], gas [58], and energy storage technologies [59, 60]. While traditionally used for retrospective studies, the LR model provides insight into the magnitude of impacts on technology prices from further increases in the rate of technology production

We take the average of two potential scenarios for learning based on Niikvist [61]: 1) a whole industry average for large-format LIBs; and 2) LIBs designed for high power/performance. These scenarios are used to capture the range of potential cost improvements across submarkets for vehicle LIBs. The Whole Industry Average scenario assumes an initial price of C_0= $1,585 USD/kWh (2011 USD) with an average LR=14%. The High Performance scenario assumes an initial price of $725 USD/kWh and a LR=6%. As 18% learning rates are common in many emerging technologies [62], these represent relatively conservative assumptions.

Historical sales and production data were combined with forecasts of manufacturing capacity to estimate cumulative production (Figure 4). The forecast for annual production of LIBs is based on current and planned LIB cell manufacturing facilities constructions or expansions, as well as publicly available data on global LIB production capacity [63, 64]. All production facilities are assumed to produce 90% of their rated capacity. From now to 2030, annual production increases at an average rate of 5.5% per year. After 2030, annual production grows linearly at 2% per year through 2040. The low-price scenario represents learning across all applications of large format LIBs, and quickly declines to reflect the lowest market price as production increases. This is contrasted with the high price scenario, where the initial price more closely reflects the entry point of high-power, large format LIBs into the vehicle market.

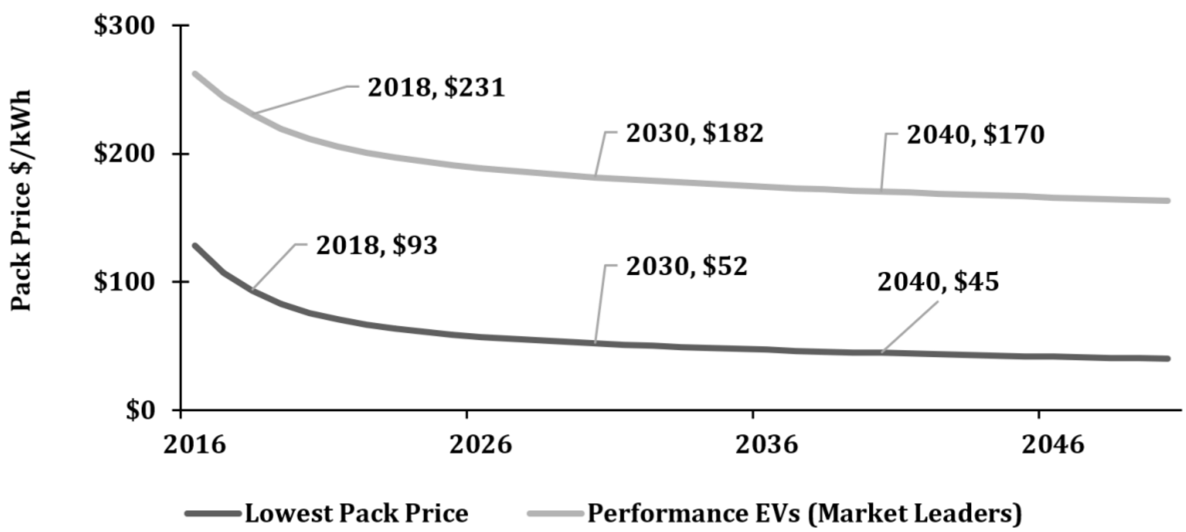

Figure 4. Estimated vehicle battery pack costs 2015 to 2050

In addition to continued reductions in the costs of LIB systems, the specific energy, power, and cycle life of LIBs are also expected to increase over time. A range of proprietary cathode chemistries, cell sizes, and architectures are used to build LIB packs for vehicles. The effective battery pack energy density is a function of both cell performance and battery/thermal management systems, and there are significant opportunities for improvement. LIB pack energy densities in passenger electric vehicles increased by some 50% compared to initial model offerings, while further increases in the cell energy densities by factors of 2 and 3 are possible with today's LIB technologies [65]. Figure 5 illustrates the potential improvements in cell cathode energy density from transition to new anode materials and reductions in anode quantity. The magnitude and rate of improvements in LIB pack energy density were forecasted based on theoretical values for current automotive cathode materials and technology development targets set by the Department of Energy for LIB cells and packs [66]. Current pack energy density was estimated using the BatPAC Model for a pack based on nickel manganese cobalt cells [67]. Based on improvements observed in light-duty vehicle applications, pack energy density is assumed to increase by 3% per year between now and 2040, increasing from 110 Wh/kg to almost 260 Wh/kg.

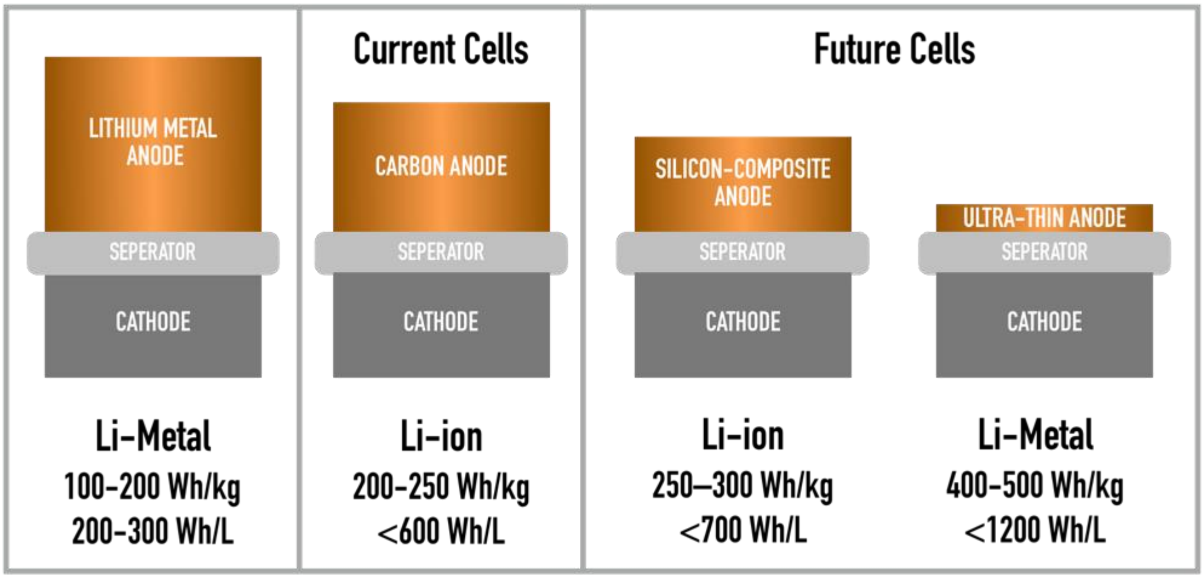

Figure 5. Potential improvements in Li-ion cell energy density

Charging Strategies and Battery Capacity

The types and location of charging infrastructure, combined with vehicle charging schedules, influence both the costs and emissions attributable to vehicle charging events. The availability of charging infrastructure also influences the battery capacity requirements for a given duty cycle. Electric vehicle system charging levels (e.g., Levels 1, 2, and 3) are commonly used to characterize the different levels of power provided from charging systems. For medium- and heavy-duty systems, higher power charging systems are likely to be required to meet duty cycle requirements given the larger capacity of batteries and high utilization of vehicles. For each vocation, four charging infrastructure scenarios were evaluated: managed Level 2 overnight depot charging for a small fleet; managed Level 2 overnight depot charging for a large fleet; managed depot DC Fast Charging; and finally, opportunistic DC fast charging. Table 4 shows the key systems and costs for charging infrastructure considered.

Table 4. Electric truck charger system costs [52]

Charging System Level	*Level 2*	*DC Fast 50kW*	*DC Fast 250kW*
Description	*Single Station (Cost per charger)*	*Cost per charger*	*Cost per charger*
Hardware	$1,360	$15,000	$23,000
Electrical Materials	$0	$500	$500
Other Materials	$100	$500	$500
Electrician Labor	$220	$2,500	$2,500
Other Labor	$0	$14,000	$14,000
Mobilization	$140	$1,000	$1,000
Permitting	$20	$200	$200
Transformer	$0	$9,000	$18,000
Maintenance Cost (per year)	$720	$1,200	$1,200
Power Output (kW)	19	50	250
Managed Charging ($/kWh)	$0.05–$0.12	$0.05–$0.12	$0.08–$0.14
Unmanaged Charging ($/kWh)	$0.07–$0.20	$0.08–$0.26	$0.08–$0.26
Demand Rate ($/kW)	$0	$8	$8

The cost of electricity consumed during charge events is a function of the utility rate schedule, which traditionally has two components for commercial customers: demand charges, which correspond to the highest level of power (i.e., kW) demand during the billing period; and usage charges, which is the rate charged per kWh of energy supplied. Managed charging and lower power systems can be used to decrease the costs of charging vehicles by reducing demand charges for high-power, opportunistic charging that can occur during peak demand periods. Charging costs are estimated from California utility rate data obtained from the draft Battery Electric Truck and Bus Charging Cost Calculator (Version 3.0) created by the California Air Resources Board.

Two main charge scheduling strategies were assessed—depot managed and opportunistic charging—as described in the scenarios above. In depot charging scenarios, vehicles are assumed to have a single charge event per duty cycle, occurring overnight, and managed to minimize demand charges. In opportunistic charging, vehicles are assumed to utilize high-power DC fast chargers while the vehicle is idle during the duty cycle to supplement electric range, with additional depot charging at lower power levels between duty cycles. A key potential benefit of the opportunistic or on-route charging is to decrease the size of the vehicle traction battery system. To evaluate the opportunistic charging scenarios, we assessed the duration of stops and dwell times from the Fleet DNA data. Figure 6 shows the average dwell time trips by vehicle class with a single stop exceeding 30 minutes per trip. For the opportunistic charging scenarios, we assume vehicles could be charged when the vehicle dwell time at the stop exceeds 30 minutes. This results in approximately 12 to 18 minutes of average on-route charging time assuming no deviation in route or duty cycle. This implicitly assumes that charging infrastructure is available at the stop location.

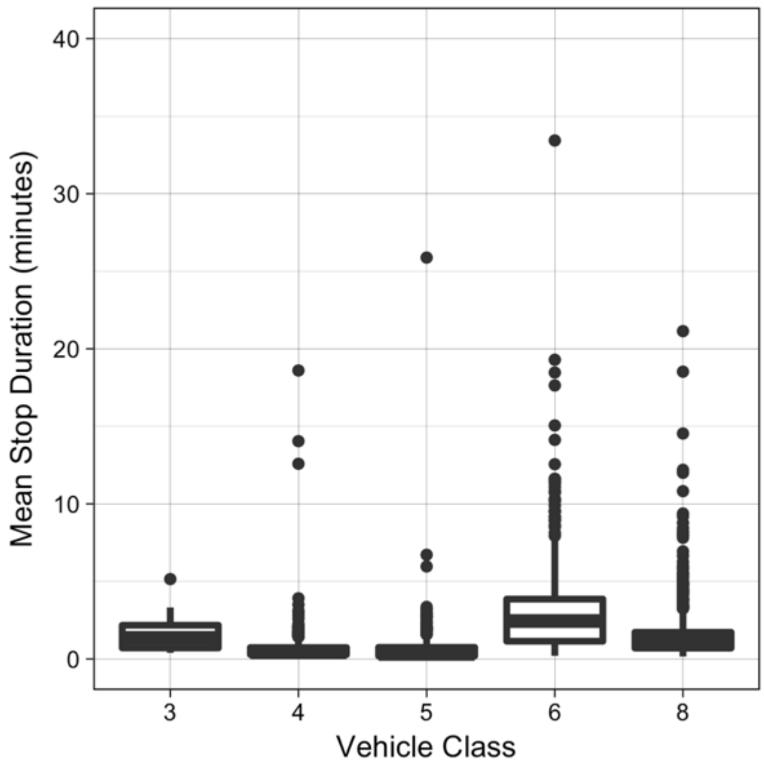

Figure 6. Average dwell time at stops in minutes

Based on the charging strategy, we then evaluated the potential battery capacities required to meet each duty cycle. Figure 7 shows the percentage of trips by total fuel energy requirement for electric trucks by vehicle class, based on the trips observed in the Fleet DNA database. The intersection of the curves (color) and the horizontal dashed line indicates the energy required to deliver 90% of trips described. This is assumed as the cut-off value or target for the design of battery pack requirements and charging systems.

For the depot charging scenario, the battery capacity must be sufficient to meet the 90% vehicle energy requirement for the duty cycle. It is also important to restrict the depth of discharge of the battery to prevent damage to the battery system. Therefore, the depth of discharge for battery packs is assumed to be restricted to 80%. In the opportunistic charging scenarios, the battery capacity is estimated to be the daily energy requirement, less energy delivered during opportunistic DC fast charge event(s). The minimum battery size is constrained at 25 kWh for all scenarios.

For all scenarios, the maximum duration of overnight depot charging was assumed to be 11 hours. For Level 2 charging systems, this results in approximately 200 kWh in potential charging (e.g., 11 hours at 19 kW, or 209 kWh per day). For Class 8 vehicles, the minimum duty cycle energy requirement exceeded the maximum deliverable energy and Level 2 charging was not considered for the Class 8 vehicle scenarios.

The cost of charger installation and equipment are amortized over their expected service life based on the total delivered energy. Charging systems have a service life of 12 years, or approximately twice the expected service life of the trucks. Charging systems are assumed to be active approximately 30% of the time or eight hours for every average service day. One potentially significant cost for high-power charging not considered in this study relates to the need for further upgrades to utility distribution and transmission equipment to support the load of charging systems. It is unclear how these costs would be passed through to a fleet owner by the utility, if at all. As noted in Table 4, an additional $9,000 dollars for transformer upgrades is included in the 250 kW scenario.

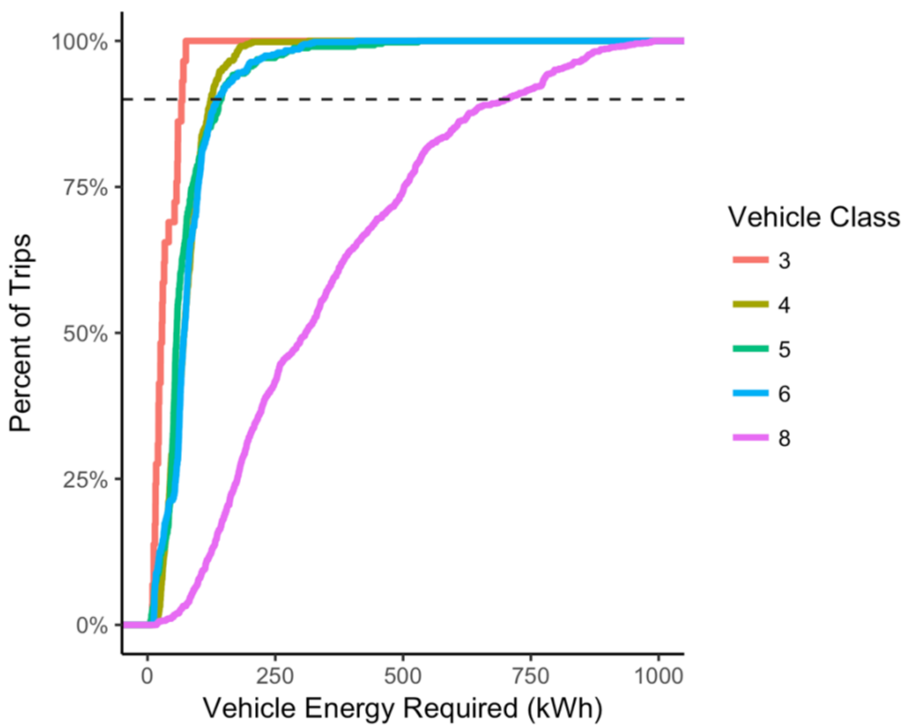

Figure 7. Energy required by duty cycle and daily travel distance

Generation of Electricity

A key factor in estimating emissions from the operation of electric freight vehicles is quantifying the emissions associated with generation of electricity for vehicle charging. Emissions from electricity were estimated based on a forecast of average utility generation mix. Even for a particular resource, emissions and combustion efficiency can vary significantly between generator technologies. For example, combined cycle natural gas generators are more than twice as efficient as conventional combustion turbines [68]; therefore, not only the resource mix, but the generator technology mix must be modeled. The projected electricity generation by fuel source was obtained from the Energy Information Agency's (EIA) Annual Energy Outlook (2018) and National Energy Model regional electricity generation module for the California sub-region of the Western Electricity Coordinating Council region (CAMX). Emissions were evaluated under the reference case or business as usual (BAU) scenario. The average Emissions Factor (*EF*) is estimated with Equation 4, and defined as the mass of GHG equivalent emissions per unit of delivered energy, where the weighted generation by year (t) and fuel source (x) is multiplied by the life cycle inventories (LCI) of emissions species (e) by fuel type (x), and the impact characterization factors for each species (m).

Equation 4

$$EF_t = \frac{Fuel_{tx}}{\sum_x Fuel_{tx}} * LCI_{xe} * m_e$$

The resource mix was broken into five fuel source categories: coal, natural gas, renewables, nuclear, and fuel oil. Generator technology LCI data were drawn from the GREET 1 model [69], and a representative LCI was estimated for each fuel source based on the net generation by generator type for each regional scenario [70]. Figure 8 shows the total electricity generation by fuel source (A) and average GHG emissions per kWh of delivered electricity for residential and commercial end uses (B), for the period 2018 to 2050. The U.S. national average mix for the same set of projections from the EIA Annual Energy Outlook is provided for reference.

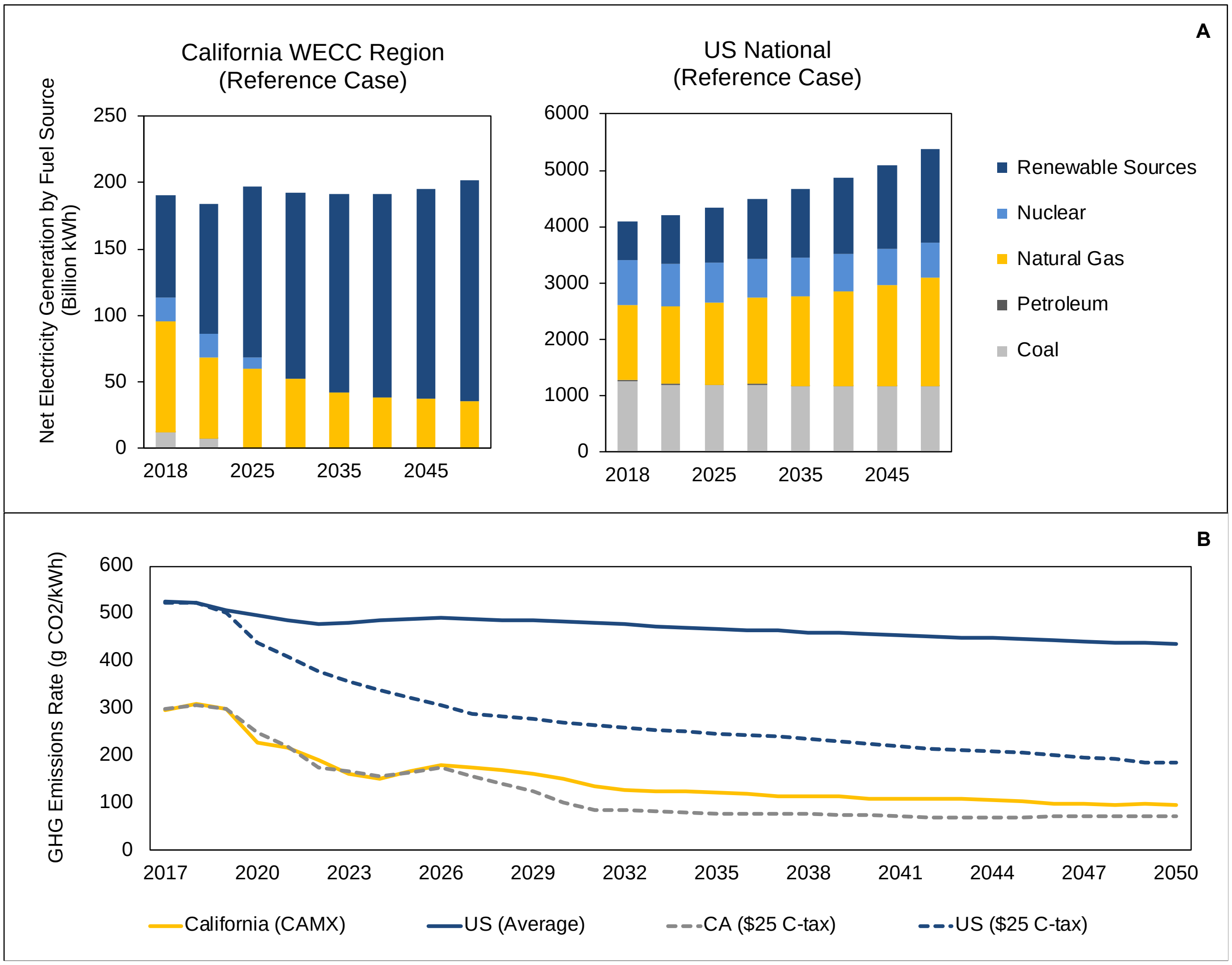

Figure 8. Electricity generation by fuel source (A) and GHG emissions rate for delivered electricity (B), 2018 to 2050.

Conventional Vehicles and Emissions from Operation

In order to estimate the magnitude and cost of avoided emissions, the performance of gasoline and diesel pathways were also evaluated for the five vehicle classes. For conventional gasoline and diesel freight vehicles, there are a multitude of emissions sources, from fuel production, to fuel combustion, vehicle operation, and vehicle storage. Table 5 describes the categories of operations emissions tracked in the EMFAC database. While electric and conventional freight vehicles will both cause emissions from fuel production and brake and tire wear, there are several sources of exhaust and operational emissions from gasoline and diesel vehicles with different appropriate units of analysis. Emissions associated with starts/stops, storage, or idling, which are key sources of pollution from diesel vehicles, can be highly variable across duty cycles with comparable distances and speeds. To ensure a comparable counterfactual across the duty cycles assessed, the speed weighted emissions for each vehicle class were obtained from the EMFAC database. The average life cycle emissions were estimated for each composite drive cycle using the duty cycle and vehicle speed data.

Table 5. Sources of operations and combustion emissions for freight vehicles [44]

Process Type	Unit	EMFAC Associated Data
Running Exhaust	gram/veh-mile	VMT by Speed Bin
Idle Exhaust	gram/veh-idle hour	Number of Idle Hours
Start Exhaust	gram/veh-start	Number of Starts
Hot Soak Evaporative	gram/veh-start	Number of Starts
Running Loss Evaporative	gram/veh-hour	Vehicle Running Hour
Partial Day Running Loss Evaporative	gram/veh-hour	Vehicle Population
Multi-Day Running Loss Evaporative	gram/veh-hour	Vehicle Population
Partial Day Diurnal Loss Evaporative	gram/veh-hour	Vehicle Population
Multi-Day Diurnal Loss Evaporative	gram/veh-mile	Vehicle Population
Brake Wear	gram/veh-mile	VMT Overall Speed Bin
Tire Wear	gram/veh-mile	VMT Overall Speed Bin

Conventional Fuel Production Emissions

The production of fuel for conventional vehicles requires recovery of raw crude oils, refining, and distribution. An emissions inventory for gasoline and diesel in California was obtained from the GREET Model from Argonne National Laboratory. Values were converted to the per gallon equivalent for diesel or gasoline using the lower heating value for each respective fuel. The U.S. national average gasoline is also provided for comparison in Table 6.

Table 6. Emissions from producing, refining, and distributing gasoline and diesel fuels

Inventory Flow	*Gasoline*	*California Gasoline*	*Low Sulfur Diesel*	*Unit*
Total Energy	31,550	28,252	36,413	Btu/gal
WTP Efficiency	78.1%	79.9%	82.7%	
Fossil Fuels	29,926	26,788	34,539	Btu/gal
Coal	2,314	1,915	2,671	Btu/gal
Natural Gas	18,796	18,074	21,694	Btu/gal
Petroleum	8,815	6,799	10,174	Btu/gal
Water Consumption	6	7	7	gal/gal
CO_2 (w/ C in VOC & CO)	1,652	1,416	1,907	g/gal
CH_4	19	21	22	g/gal
N_2O	0	0	0	g/gal
GHGs	2,313	2,130	2,669	g/gal
VOC	3	3	4	g/gal
CO	2	2	2	g/gal
NO_X	4	5	5	g/gal
PM_{10}	0	1	0	g/gal
$PM_{2.5}$	0	0	0	g/gal
SO_X	3	3	3	g/gal
BC	0	0	0	g/gal
OC	0	0	0	g/gal

Conventional Fuel Prices

A forecast for conventional fuel prices was obtained from the U.S. Energy Information Administration fuel price components analysis for the U.S. pacific region [71]. The price of conventional fuels can be volatile, but average fuel prices are expected to increase steadily over the next two decades (Figure 9).

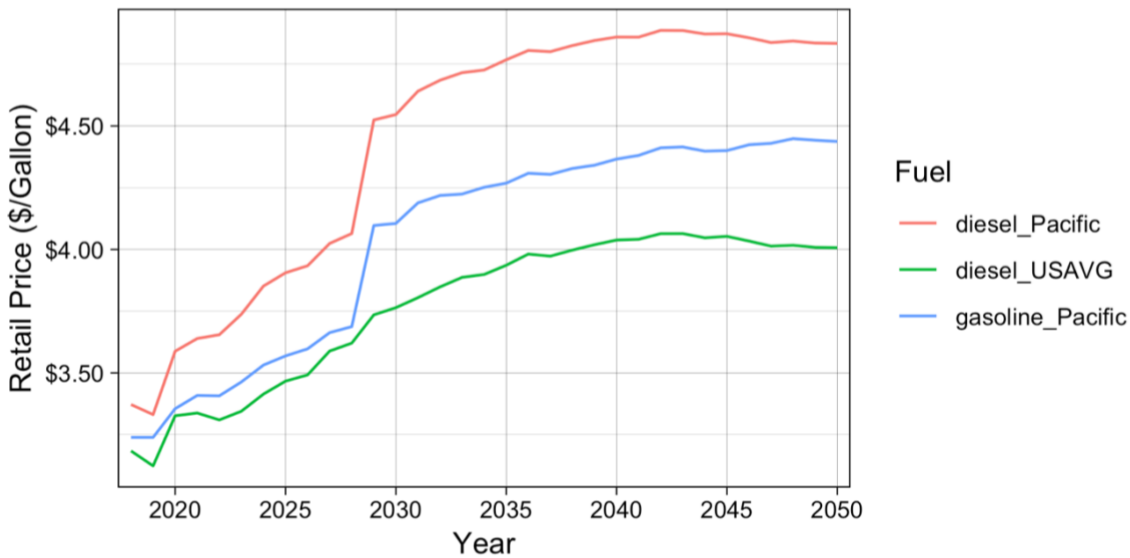

Figure 9. Retail price of gasoline and diesel in California, 2018–2050 [71]

Pollution Damages

Exposure to concentrations of fine particulate matter and other criterial pollutants is associated with negative health impacts, including asthma, increased risk of cancer, and premature mortality [72]. HDVs are of particular concern as they emit high levels of particulate matter and a complex mixture of pollutants including ozone precursors. The South Coast Basin, which includes Los Angeles County, represents approximately 10% of the U.S. population, but 34% of the population-weighted national exposure to ozone above the 8-hour limit. NO_X is a key ozone precursor and a combustion by-product from both diesel and natural gas engines. According to California's Mobile Sources Emissions Inventory and Model, trucks are expected to remain the largest share of daily NO_X emissions in both the South Coast and neighboring San Joaquin Valley for the near future.

The Air Pollution Emission Experiments and Policy analysis (AP2) model is an integrated assessment model that links emissions of air pollution to exposures, physical effects, and monetary damages in the contiguous United States [73]. The AP2 model was used to estimate the cost of pollution damages for ground level sources by air basin for California, adjusted to 2018 dollars using the consumer price index. Two scenarios for pollution and marginal damages were considered: 1) a BAU scenario assuming continued use of conventional diesel and gas vehicles through 2040; and 2) a scenario assuming 100% electrification of Class 3–8 vehicles by 2040.

Results

This section reports the estimated life cycle emissions and costs for both electric and conventional freight vehicles. Emission and costs are reported in two functional units to represent the performance of the technology system, namely per mile travelled and per ton-mile. The ton-mile functional unit reflects the average load and capacity of the vehicle over typical duty cycles. The life cycle abatement costs for each class is defined as the difference in life cycle costs for each truck class (conventional vs. electric), divided by the difference in the life cycle emissions inventories. The result is a vector of cost per unit emissions avoided by emissions category and performance metric. The total baseline emissions for the California population of Class 3–8 vehicles is then compared to the potential emissions reductions from 100% fleet electrification by 2040. Pollution damage costs and avoided damages are then estimated based on projected in-state truck activities.

Conventional Freight Vehicles

The life cycle costs of operating a conventional freight vehicle are primarily variable, namely fuel costs. The average life cycle cost for current Class 3–8 vehicles over an average 12 year service life was found to range from $112,592 for Class 3, to $639,276 for a Class 8 truck. However, the average does not well describe the absolute cost of some observed cases, where high utilization and fuel costs corresponded with total life cycle costs an order of magnitude higher than average (Figure 10). The distribution in Figure 10 represents the range of cases resulting from both the travel distances and vehicle efficiencies reflected in the EMFAC database for in-state registered Class 3–8 trucks. The extremes or outliers of the distribution are driven primarily by fuel costs.

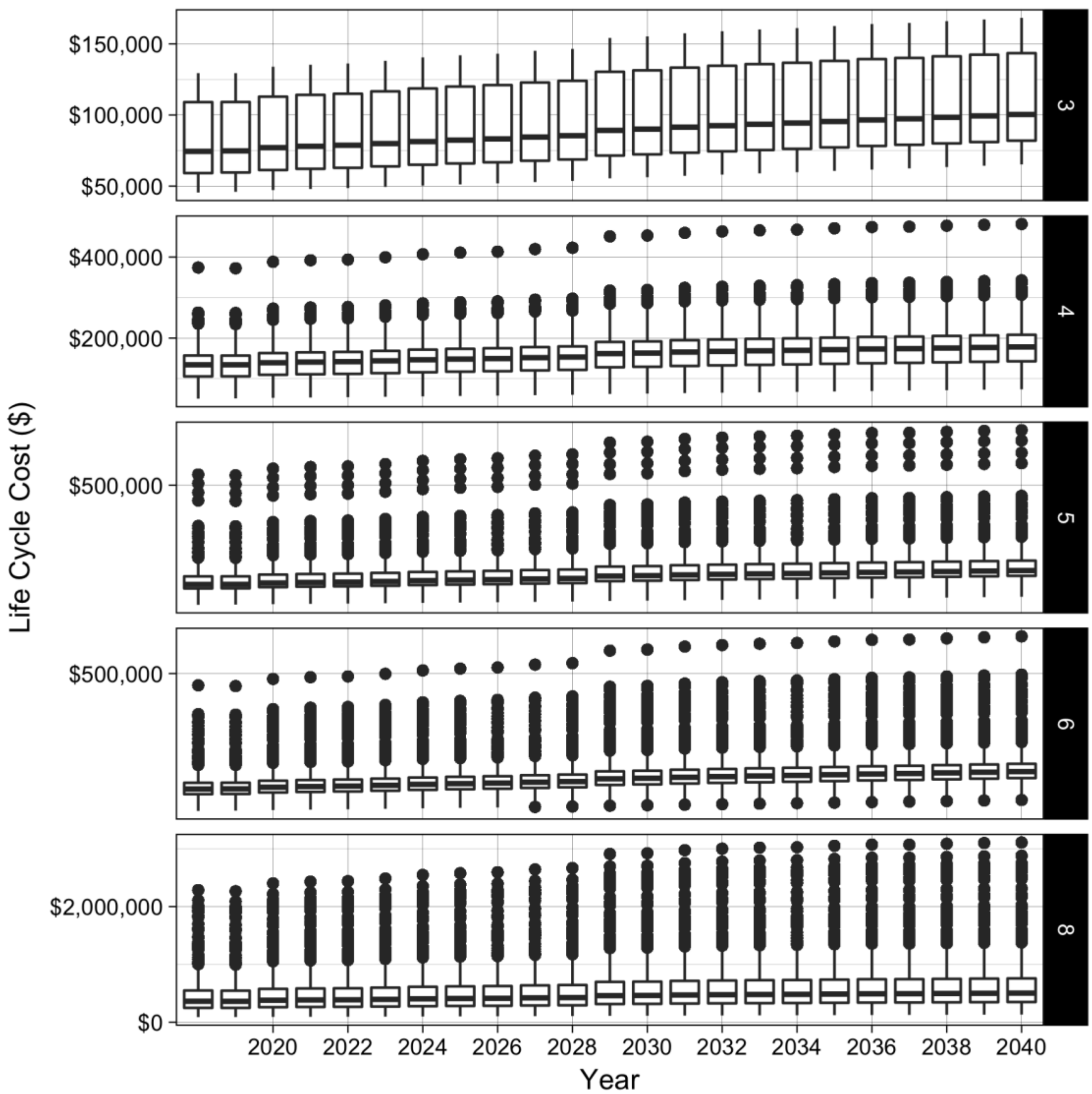

Figure 10. Life cycle cost of conventional (gasoline and diesel) Class 3–8 vehicles

The mean estimated GHG emissions rate of Class 3–8 gasoline and diesel vehicles are shown in Figure 11. For GHGs, emission range from 546 to 1622 g/mile on average. Emissions of oxides of nitrogen (NO_X) were found to range from 0.3 g/mile for service trucks and vans, to 3.4 g/mile for Class 8 tractor trucks on average. Figure 11 also reflects the considerable outliers in some emissions categories related to duty cycles with frequent stops or other inefficiencies.

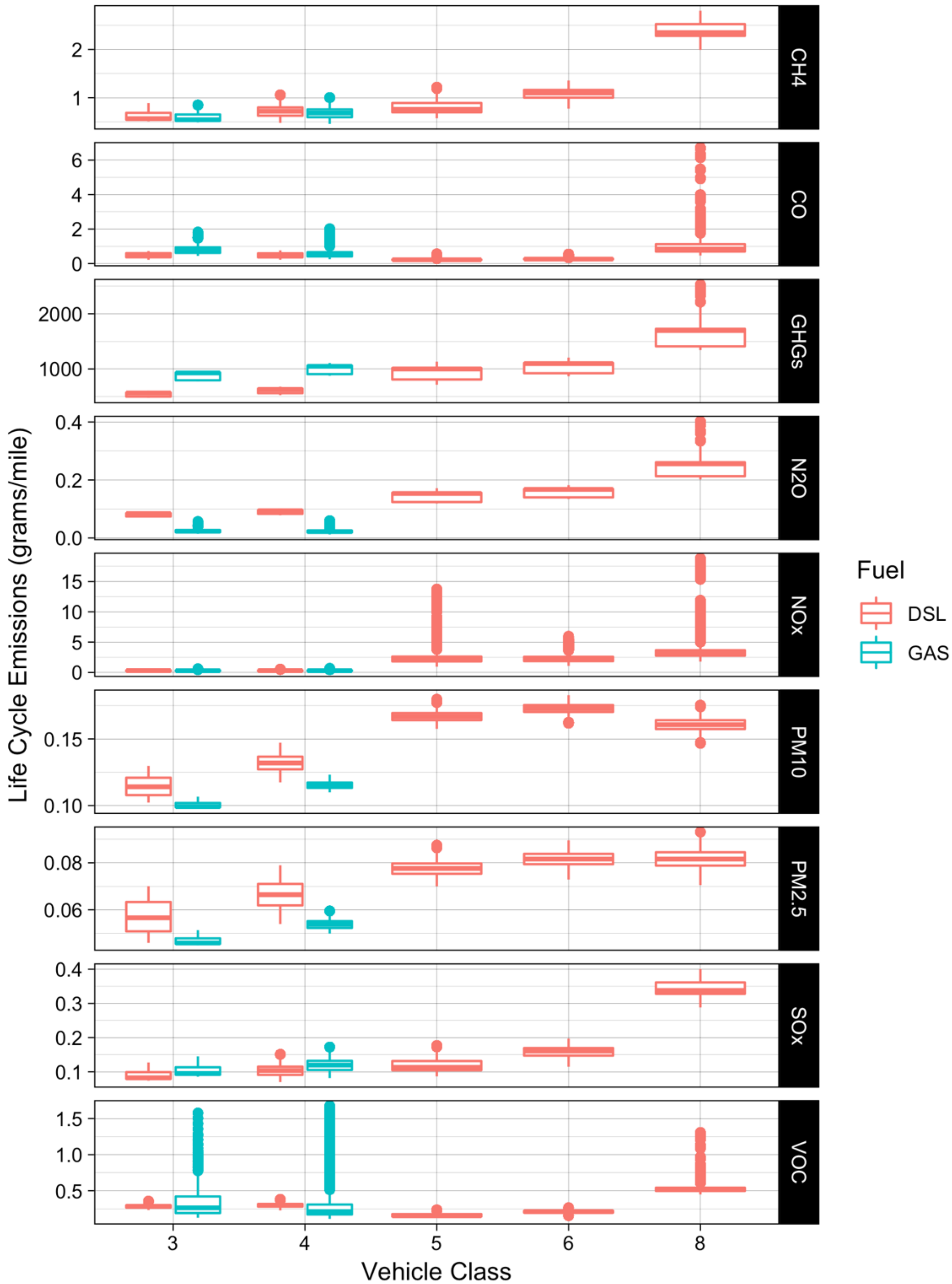

Figure 11. Emissions per mile for conventional Class 3–8 vehicles
(DSL = Diesel, GAS = Gasoline)

To calculate the ton-mile emissions, the emissions rate per mile was divided by the estimated average load for each vehicle class [74]. The average cargo load was calculated based on the vehicle capacity and reflects the need for return links or 'dead-heading' in most cargo distribution. While tank and trailer trucks can operate at maximum loads 80% of the time, vans and service vehicles 'weight-out' less than 20% of the time. Table 7 shows the per ton mile emissions for each of the scenarios. The mid-sized, Class 5 trucks had higher emissions on average due to a combination of their more limited capacity and typical vocations. The Class 8 vehicles have much lower emissions on a per ton mile basis, but require much greater levels of cargo consolidation and are not amendable to all vocations.

Table 7. Average GHG emissions rate (g/ton-mile) for conventional vehicles by year
(DSL = Diesel, GAS = Gasoline)

Fuel	*Emission Type*	*Class 3*	*Class 4*	*Class 5*	*Class 6*	*Class 8*
DSL	CH_4	0.56	0.50	0.47	0.46	0.28
DSL	CO	0.44	0.32	0.13	0.11	0.12
DSL	GHGs	501.72	420.39	544.58	440.85	190.26
DSL	N_2O	0.07	0.06	0.08	0.07	0.03
DSL	NO_X	0.27	0.20	1.52	0.98	0.40
DSL	PM_{10}	0.11	0.09	0.10	0.07	0.02
DSL	$PM_{2.5}$	0.05	0.05	0.05	0.03	0.01
DSL	SO_X	0.08	0.07	0.07	0.07	0.04
DSL	VOC	0.26	0.21	0.09	0.09	0.06
GAS	CH_4	0.54	0.47			
GAS	CO	0.74	0.40			
GAS	GHGs	815.53	692.01			
GAS	N_2O	0.02	0.02			
GAS	NO_X	0.27	0.21			
GAS	PM_{10}	0.09	0.08			
GAS	$PM_{2.5}$	0.04	0.04			
GAS	SO_X	0.09	0.08			
GAS	VOC	0.31	0.19			

Electric Freight Vehicles

The median life cycle cost of electric Class 3–8 vehicles is comparable or equivalent to current conventional vehicles in many applications (Figure 12). The wide distribution of outcomes relates to both variability in electricity prices (e.g., managed vs. unmanaged charging), as well as the variations in duty cycles. For the current model year, the median life cycle cost ranged from $79,000 for Class 3 vehicles to $327,000 for Class 8 tractors. While masked in the wide distribution of outcomes, the median cost of electric Class 3–8 vehicles are expected to decline between 2018 and 2040 due to reductions in the costs of battery systems (Figure 13).

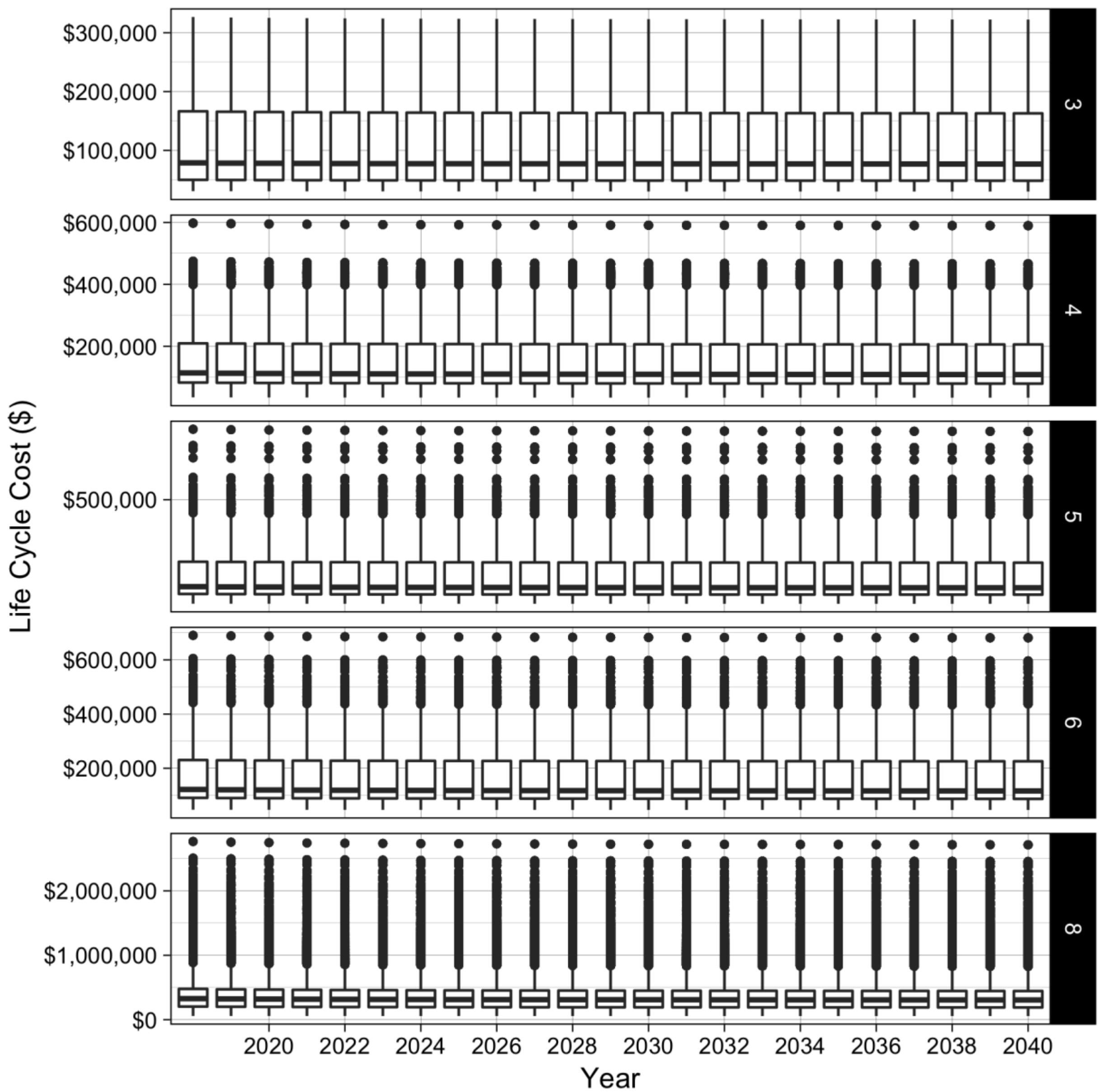

Figure 12. Life cycle costs of electric Class 3–8 vehicles

Figure 13 shows the estimated cost of the battery pack for each vehicle class by model year. Significant reductions in battery pack costs did not correspond with significant decreases in the overall life cycle costs of electric Class 3–8. This is due to the large share of fuel costs for these vehicles, as well as the significant variability in electricity prices for charging, which ranged from a few cents to close to $1 per mile.

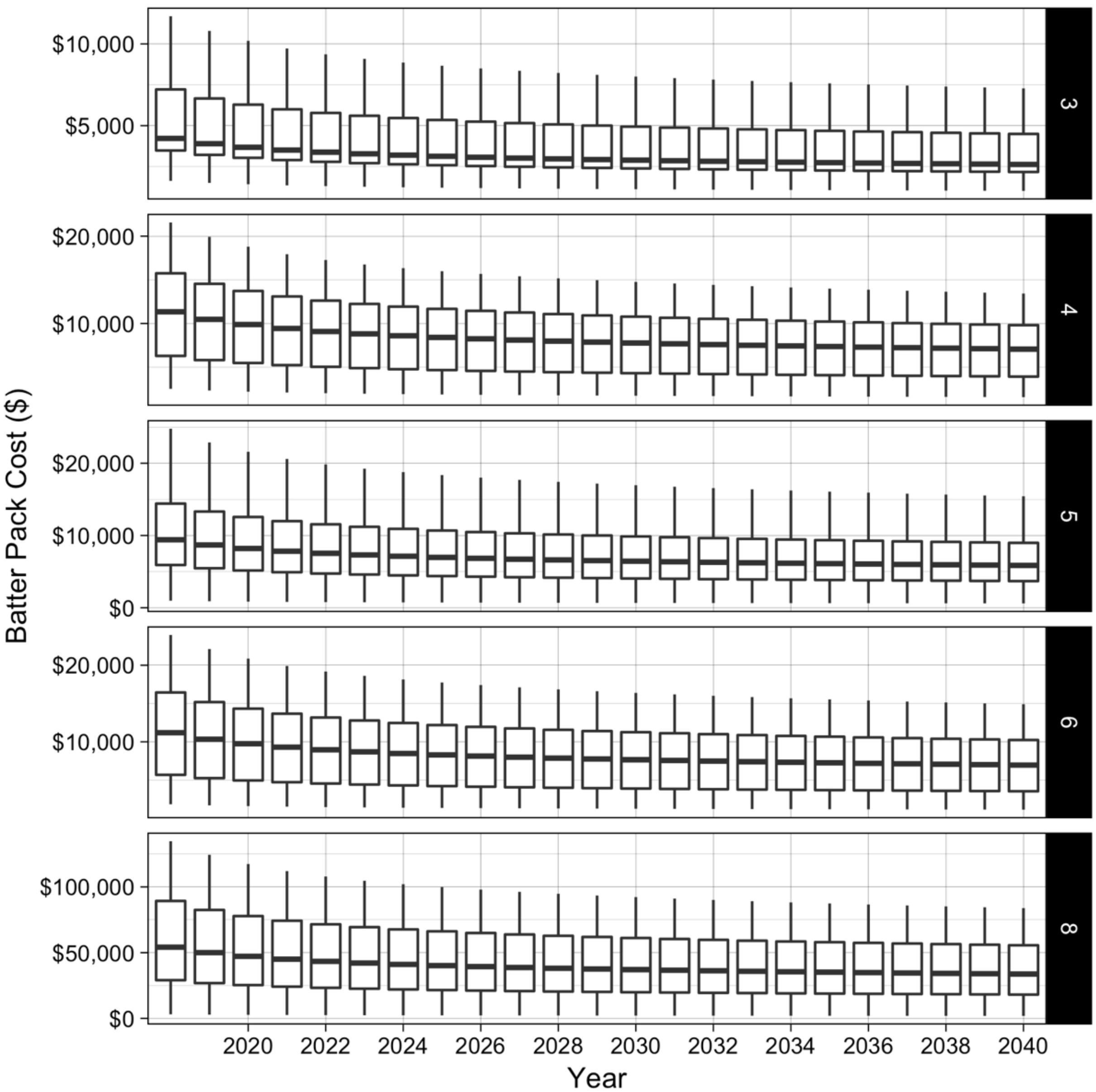

Figure 13. Battery pack cost by year and vehicle class

The emissions rates of both conventional and electric freight vehicles are expected to change over time. For conventional vehicles, this is primarily due to the increased use of emissions control devices and other efficiency improvements. Though not considered in this study, emissions rates could also change due to fuel blending and substitution. For electric vehicles, in addition to potential improvements in efficiency, the technologies and fuel sources used to generate electricity are also changing. Figure 14 shows the emissions rate per mile changing over time in line with these shifts in electricity generation.

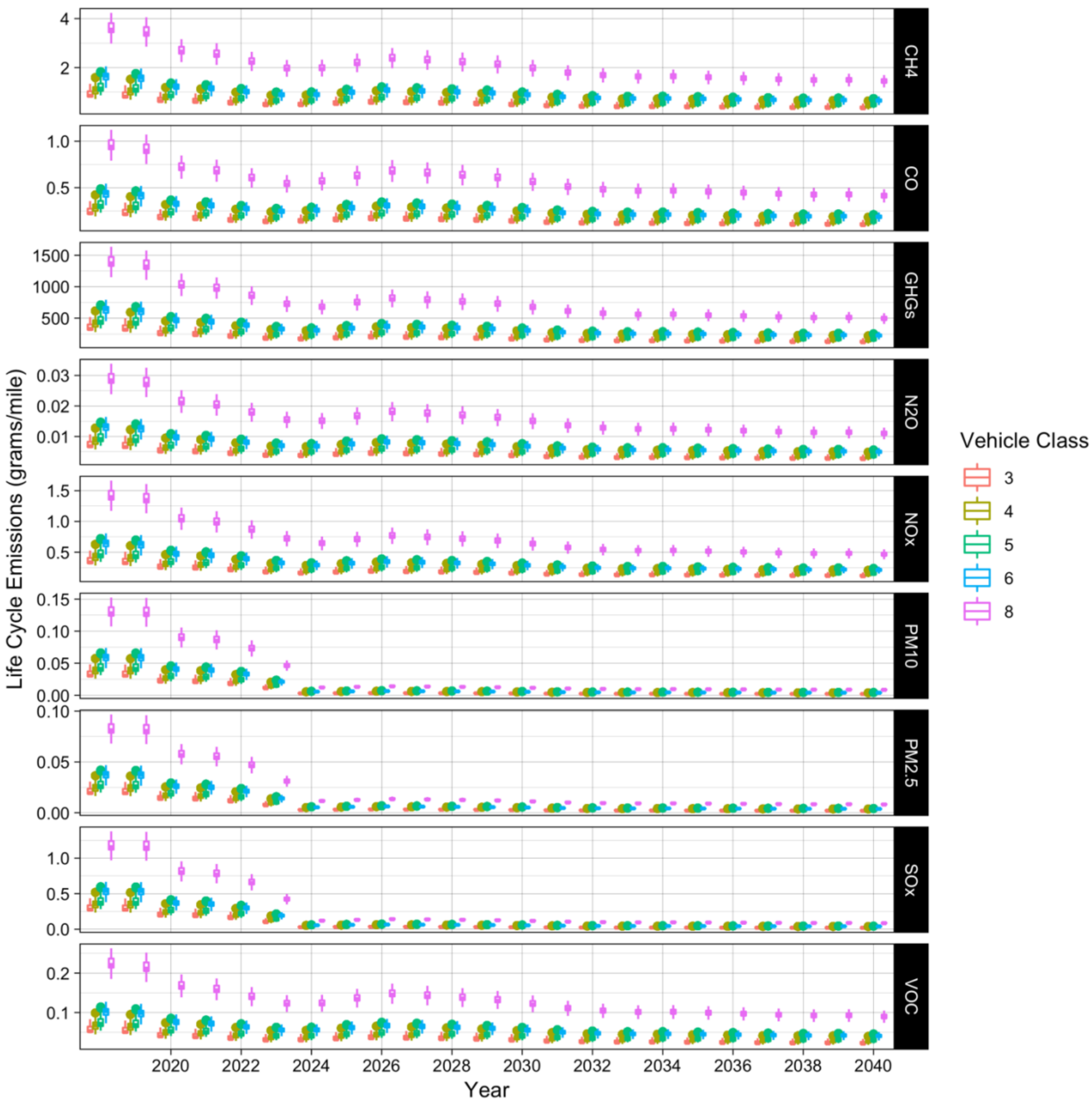

Figure 14. Emissions per mile for electric trucks, 2018–2040

Table 8 shows the average emissions rate for electric trucks divided by the effective cargo capacity for electric trucks operating in the current grid (present to 2020). While the emissions rates for electric trucks change dramatically, they are relatively constant after 2024, compared with the prior decade. The values in Table 9 then primarily reflect the estimated emissions rate for electric trucks operating in a future (cleaner) grid, averaged over the period 2030 to 2040.

Table 8. Emissions per ton-mile for 2020 electric Class 3–8 vehicles (g/ton-mile)

Emission Type	*Class 3*	*Class 4*	*Class 5*	*Class 6*	*Class 8*
CH_4	0.76	0.67	0.64	0.62	0.38
CO	0.20	0.18	0.17	0.17	0.10
GHGs	293.86	260.05	246.00	240.02	147.27
N_2O	0.01	0.01	0.01	0.00	0.00
NO_X	0.30	0.26	0.25	0.24	0.15
PM_{10}	0.03	0.02	0.02	0.02	0.01
$PM_{2.5}$	0.02	0.02	0.01	0.01	0.01
SO_X	0.25	0.22	0.21	0.20	0.12
VOC	0.05	0.04	0.04	0.04	0.02

Table 9. Emissions per ton-mile for electric Class 3-8 vehicles, 2030–2040 (g/ton-mile)

Emission Type	*Class 3*	*Class 4*	*Class 5*	*Class 6*	*Class 8*
CH_4	0.45	0.40	0.38	0.37	0.23
CO	0.13	0.11	0.11	0.10	0.06
GHGs	158.44	140.21	132.92	129.69	79.58
N_2O	0.00	0.00	0.00	0.00	0.00
NO_X	0.15	0.13	0.13	0.12	0.08
PM_{10}	0.01	0.01	0.00	0.00	0.00
$PM_{2.5}$	0.00	0.00	0.00	0.00	0.00
SO_X	0.05	0.05	0.05	0.04	0.03
VOC	0.03	0.02	0.02	0.02	0.01

Per-mile Emissions Abatement

Emissions abatement represents the avoided emissions from electrification of a class of freight vehicles. As unit reductions (e.g., replacement of a specific vehicle or fleet) and system wide reduction are both of concern, emissions abatement is estimated per mile travelled and for the system wide emissions reductions for California given electrification of the in-state Class 3–8 vehicle population. As emissions from electric vehicles and conventional vehicles both change over time, we first estimated the emissions avoided for deploying an electric truck in any vehicle class in each year between 2018 and 2040.

Figure 15 shows the emissions abatement achieved by replacing conventional trucks with electric trucks in grams per mile across the vehicle and powertrain scenarios considered. Most emissions, including GHGs (which include CO_2, CH_4, and N_2O reported in units of CO_2-equivalent (CO_2e)), show that electrification reduces emissions; however, electrification could result in increased emissions of CH_4 and SO_X under some use cases. These tended to be limited outliers, and the potential reduces over time with a further shift toward renewable electricity generation.

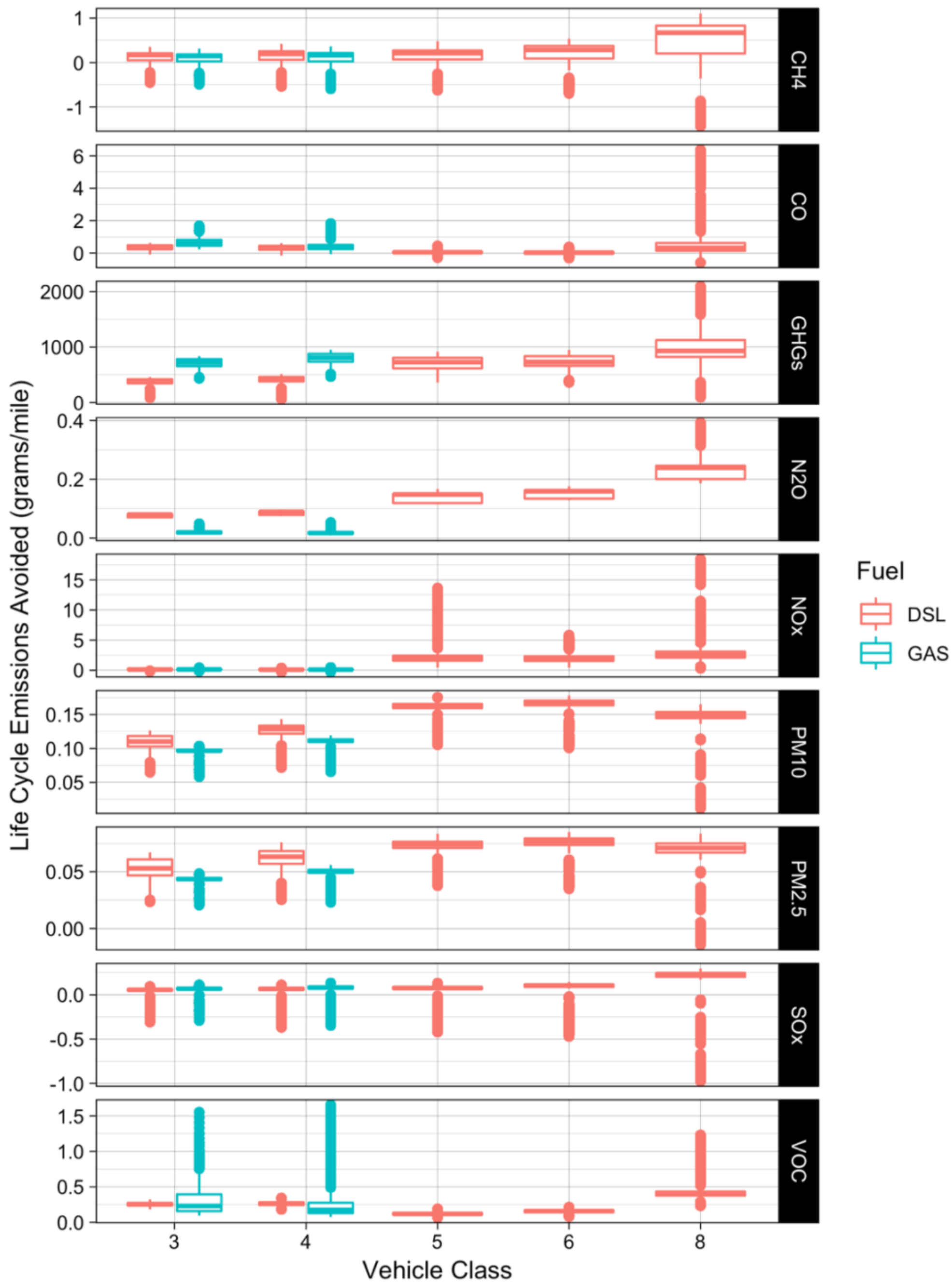

Figure 15. Emissions abatement (grams/mile) from electrification of diesel (DSL) and gasoline (GAS) trucks by vehicle class

Statewide Results

Now we assess the total magnitude of potential abatement from truck electrification, as well as the avoided pollution damages. Combining the forecasted vehicle population and activity data shown in Figure 1 with emissions rates for conventional vehicles by model year, we first estimated a baseline emissions inventory representing BAU (Figure 16). Under this BAU case, life cycle emissions remain flat across most categories despite increasing vehicle activity. This is due to the gradual adoption of more efficient vehicles and emissions control technologies for conventional gas and diesel vehicles.

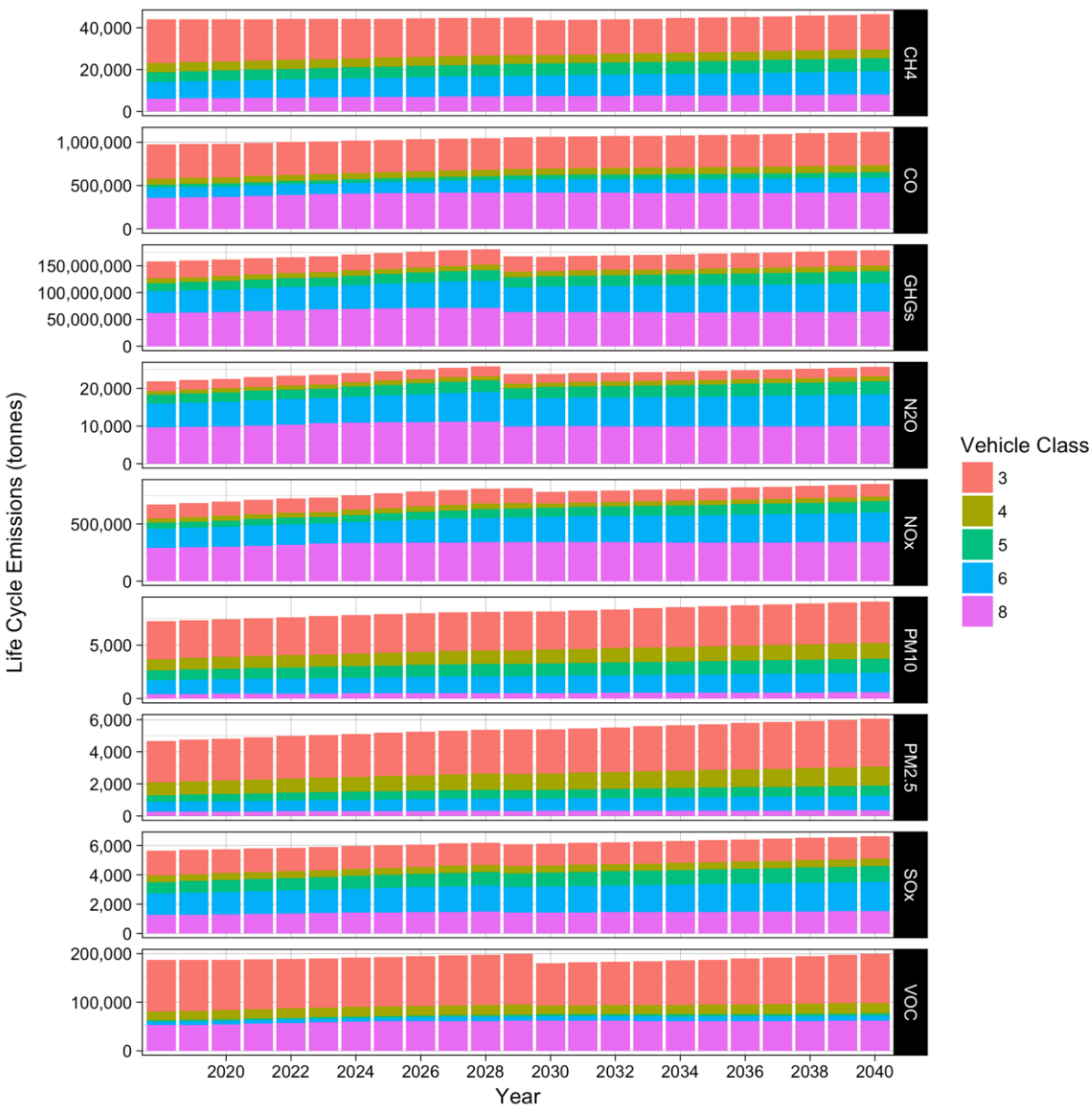

Figure 16. BAU statewide emissions from conventional Class 3–8 trucks

In order to estimate the potential abatement from a state-wide fleet electrification target, we assume 100% of VMT must be electric by 2040 with a linear rate of increase in fleet size from 2020 to 2040 (Figure 17). This translates to a target fleet of over 250,000 Class 3–8 electric vehicles deployed by 2030, and 500,000 by 2040.

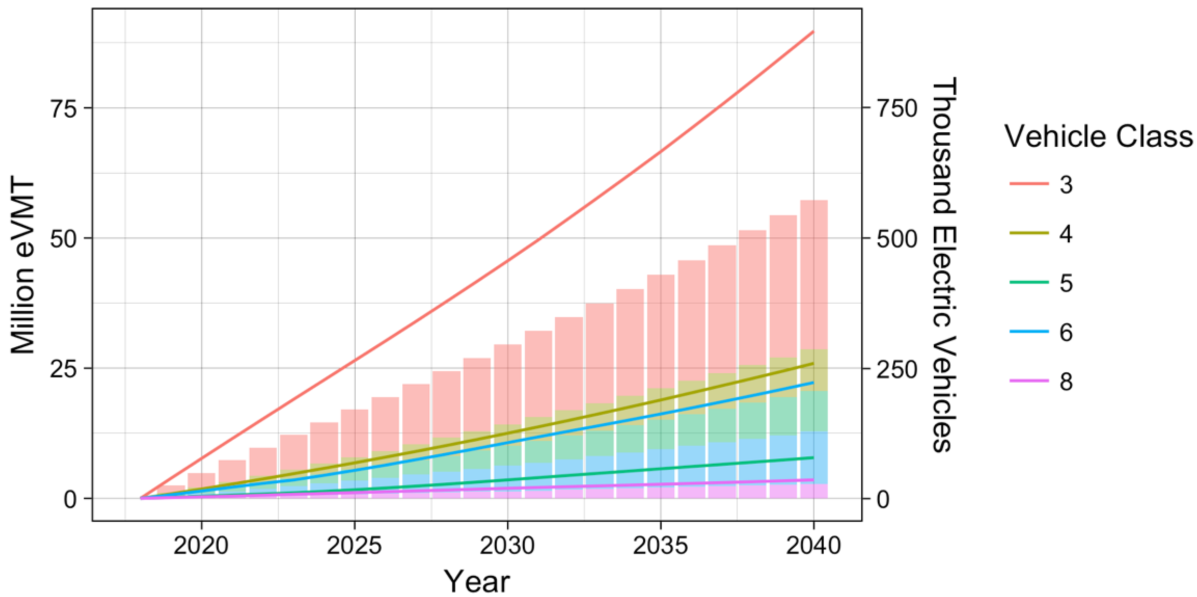

Figure 17. Assumed electric truck eVMT (bars) and vehicle population (lines)

Given the deployment trajectory in Figure 17, we then estimated the emissions abatement and damages avoided given a 100% electrification by 2040. As the fleet costs for electric was generally lower than the conventional BAU, average abatement costs trended toward or below zero. As distribution of electric truck costs was much wider and skewed higher than conventional alternatives, the mean or average becomes a poor test statistic to compare abatement potential and cost. Figure 18 shows the upper probability interval (95%) on the cost of abatement in dollars per ton. We can observe that abatement costs are likely higher for light commercial (Class 3 and 4) vehicles as compared to Class 6–8.

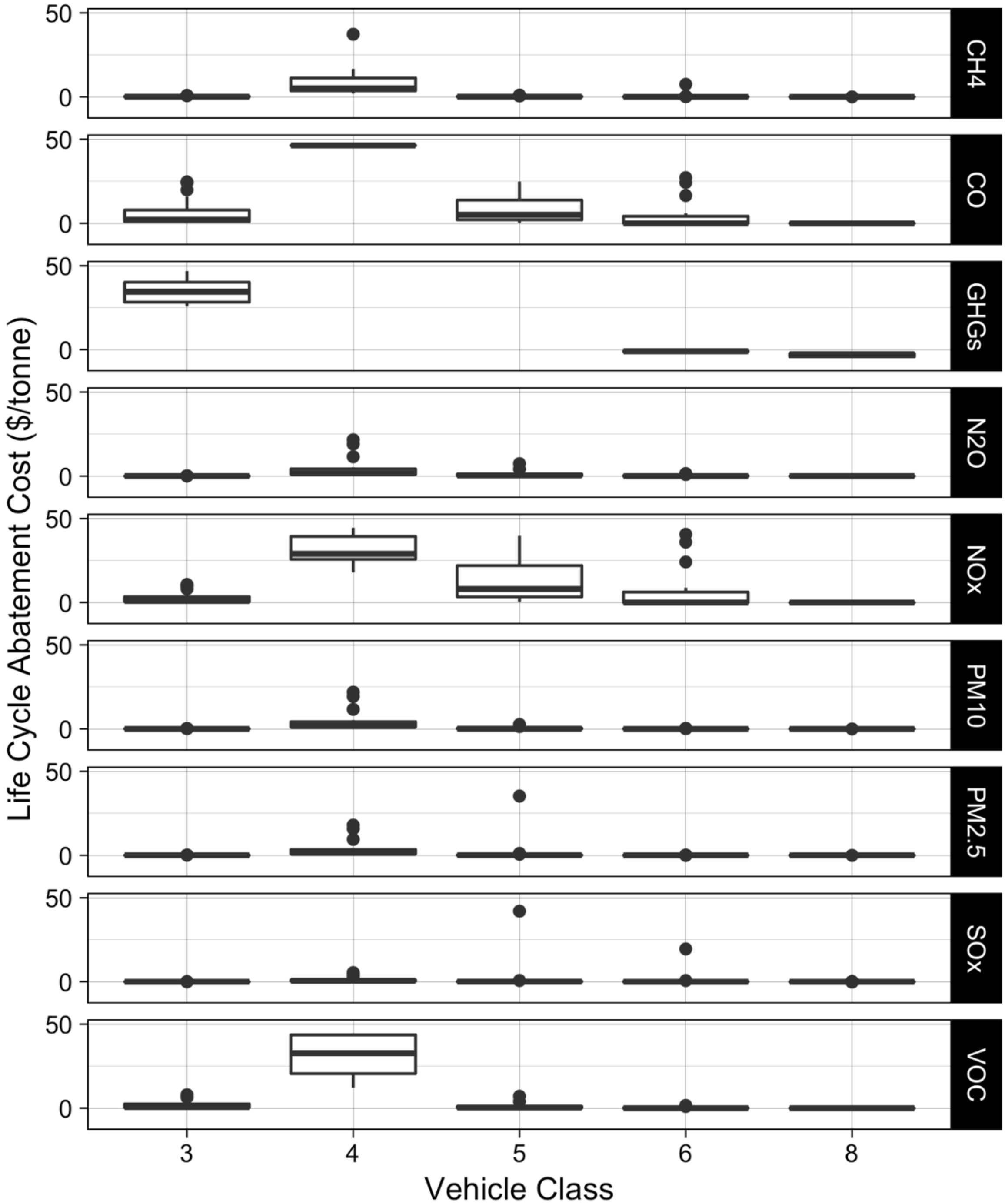

Figure 18. Abatement costs for 100% electrification by 2040 ($/tonne)

The estimated range of avoided emissions in metric tons per year by vehicle class is shown in Figure 19. For GHGs (CO_2e emissions), the largest share of potential abatement comes from electrification of Class 6–8 vehicles, where efficiency gains are greatest. The relative certainty of GHG emissions benefits from truck electrification is contrasted with the wide intervals suggested for abatement of key pollutants like fine and ultrafine particulate matter. Class 3 and

4 vehicles are large contributors to PM and VOC emissions. Electrification of medium sized (Class 3 and 4) vehicles resulted in a wide range of potential outcomes. Full electrification by 2040 results in a reduction in GHG emissions of 102 to 148 million metric tonnes of CO_2e per year, and approximately 10,000 metric tonnes of fine and ultra-fine particulate matter.

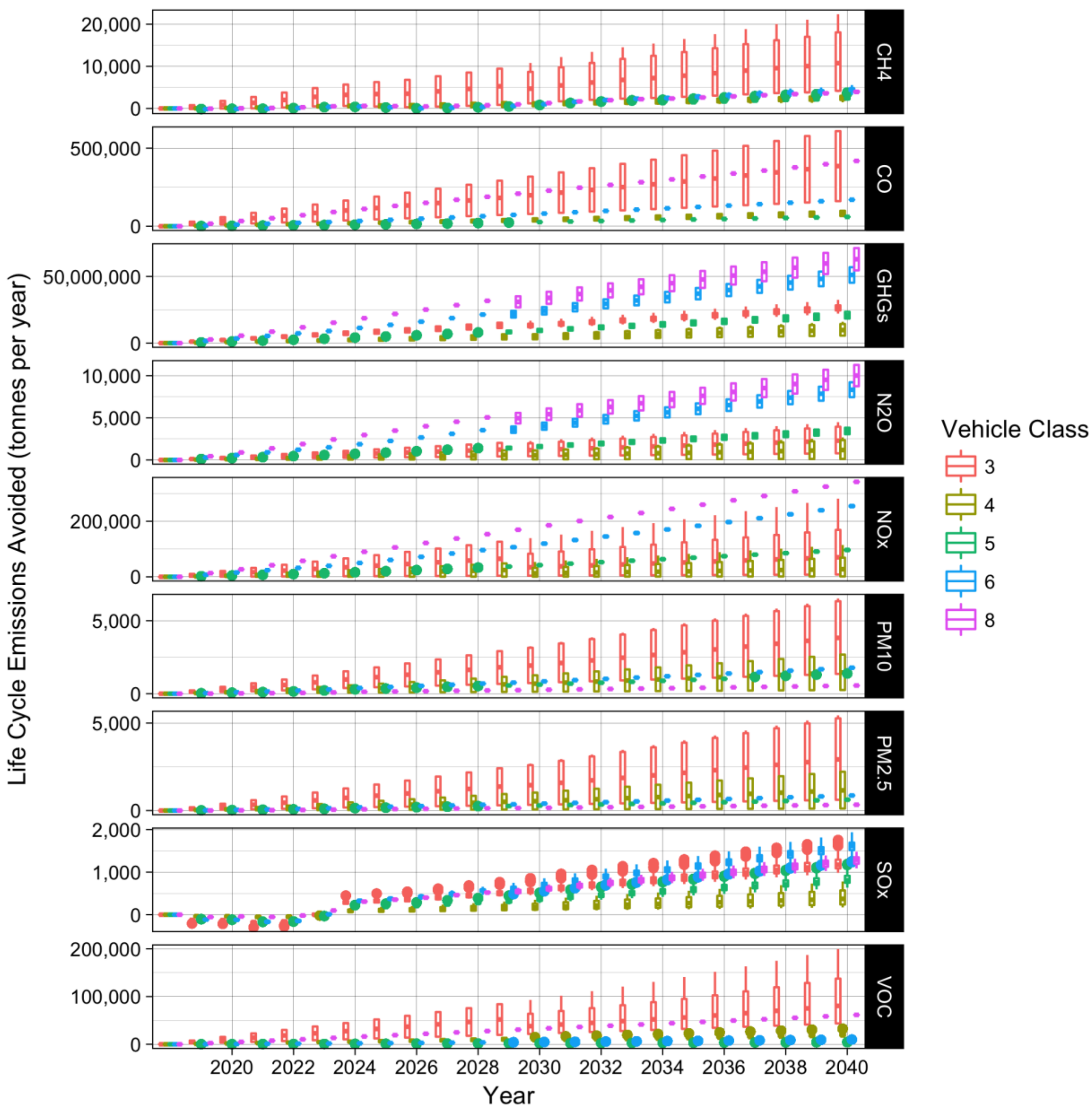

Figure 19. Statewide emissions abatement from electrification of Class 3–8 trucks

Reductions in emissions from truck electrification would have additional societal benefits in the form of reductions in the incidents of negative health impacts or premature mortality from conventional truck pollution. While the benefits of GHG emissions abatement are global, avoided air quality pollutants benefits local communities. This is particularly true in communities that already experience disproportionately high concentrations of pollutants. The avoided cost of damages in Figure 20 is estimated for in-state Class 3–8 vehicles, modelled based on the weighted pollution damages and truck activity in each air basin.

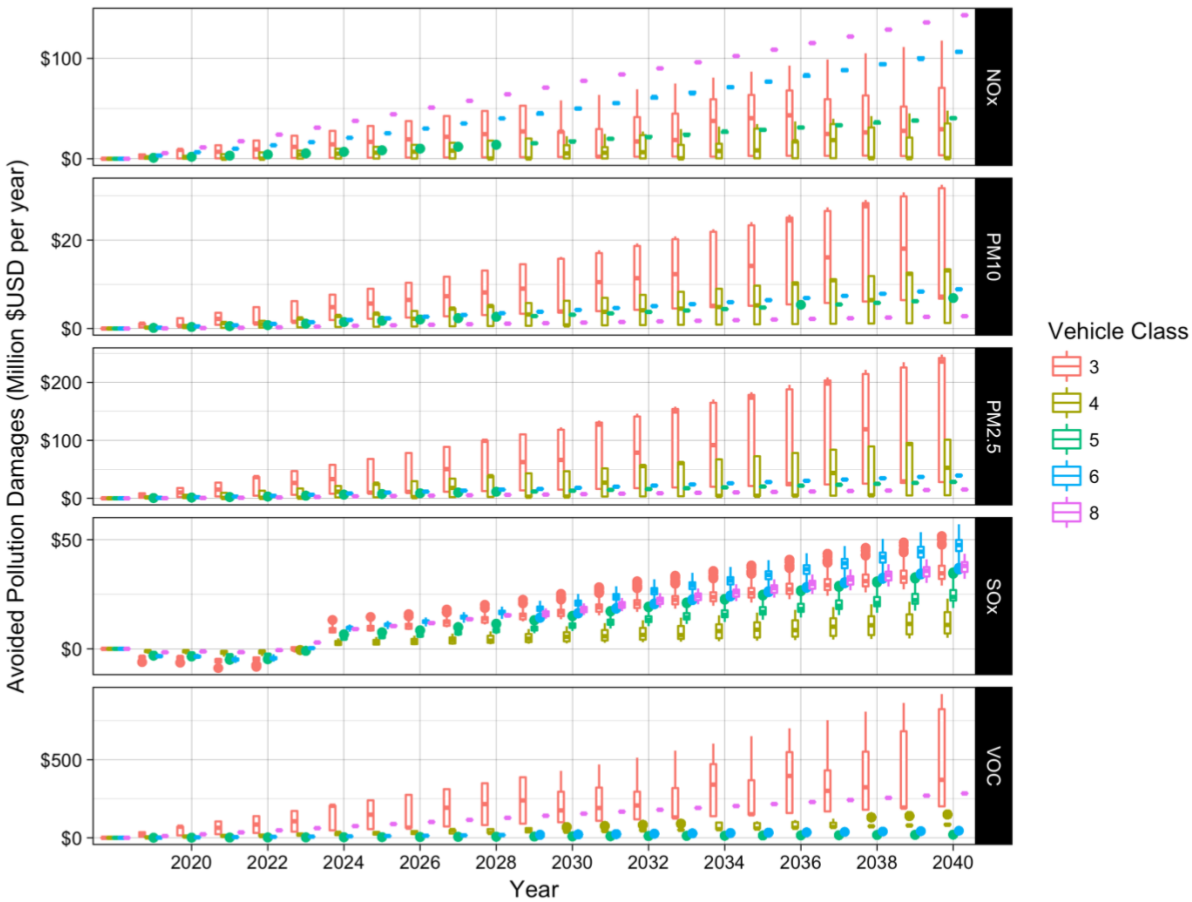

Figure 20. Avoided pollution damages per year in California from Class 3–8 truck electrification

Total pollution related health damages from conventional Class 3–8 vehicles were estimated to range from to $971 million to $2,179 million dollars in 2018. Electrification could reduce pollution related damages by $507 million dollars per year by 2025, and by some $1.6 billion dollars on average by 2040. Electrification of Class 3 and 4 trucks resulted in a wide range of emissions outcomes, but the potential benefits with respect to avoided pollution damages are quite significant (Figure 20).

Discussion

The rapidly falling costs and improving performance of LIBs are enabling an increasingly wide array of plug-in electric light and heavy-duty vehicle technologies (PEVs). Nearly 30 GWh of LIBs have been deployed in U.S. light-duty PEVs since 2012. The most rapid growth in the global market for PEVs is now occurring in China, where over 30 GWh of LIBs for were deployed in truck and bus applications in 2017 [75]. Global manufacturing capacity for LIBs is expected to reach 250 GWh by 2020, and could surpass annual production of lead acid batteries (~*500 GWh/year)* by the year 2040 [64]. As sales of PEVs have increased, the average capacity of batteries in PEVs have also increased by some 32 kWh/vehicle in the U.S. If the trend continues, by 2020 the average vehicle sold would have three times the battery capacity of the comparable passenger PEV a decade earlier.

Vehicle electrification is also a primary strategy for reducing urban pollution and climate-forcing emissions from transportation. Inefficient, fossil-fuel combustion engines are a major driver of pollution and negative health impacts near roadways, and contribute almost a third of CO_2 emissions from developed countries [76]. PEV technologies have matured more rapidly than other alternatives, such as hydrogen fuel cells, while widespread adoption of biofuels have encountered both constraints on supplies [14], as well as cases where emissions intensity were equivalent to conventional diesel and gasoline [11, 13]. Programs to incentivize the deployment of PEVs directly or indirectly subsidize the price and production of large format LIBs [77]. In the U.S., California and nine other states have electric vehicle sales targets through the Zero Emissions Vehicle credit program[1]; California has enacted multiple incentive programs to reach a target of 5 million PEVs sold by 2030, which would exceed 15% of new vehicle sales [7, 78, 79]. The European Union is also seeking to have 30% of new vehicle sales be electric by 2030, while several countries and cities have committed to 100% electric vehicle sales goals or bans on conventional, fossil vehicles. China has taken the lead in PEV deployment, with sales likely to exceed one million vehicles per year by 2020, in addition to deployments of more than 500,000 electric HDVs. The push for passenger PEVs has a direct effect on battery technology improvement and reductions in cost over time.

Battery Pack Size and Cost

As LIBs have gotten cheaper, the size of LIB systems for vehicles have also increased. In light-duty vehicles, this looks like 20 kWh per vehicle in increasing battery size over the last 5 years. In the HDV sector, battery capacities for some models of electric buses have doubled in just two years, from 300 to 600 kWh [80, 81]. Historically, the prohibitive costs and additional mass of large batteries have been the primary hurdle limiting PEV applications. But reductions in pack costs have been commensurate with increasing pack energy density and specific power. Today, HDV applications are targeting systems between 350 and 600 kWh, such as the much publicized Tesla semi-truck.

[1] Connecticut, Maryland, Massachusetts, New York, Oregon, Rhode Island, Vermont New Jersey, and Maine

Larger LIB systems could also impact vehicle weight. While vehicle light-weighting could be used to offset a portion of the battery weight, material substitution strategies can have the adverse effect, increasing life cycle GHG emissions of vehicles [82, 83]. Increasing vehicle weights is a concern for the maintenance and design of pavement and road infrastructure [84], while potential reductions in cargo capacity is a key issue for freight applications. Few studies have considered the potential impacts of battery systems on vehicle weight and axel loads, and particularly their effects on payload capacity of electrified trucks. The addition of a battery system exceeding 2,000 kg in mass could result in a reduction in the effective payload capacity of the loaded vehicle due to restrictions on axle weights. As battery systems improve, increases in energy and power density at the pack level could enable further applications.

Figure 21 shows a range of estimated battery pack cost, mass, and percentage of vehicle cargo capacity for 2018 in white and 2030 in grey. Currently, battery packs can represent 20% or more of the vehicle cargo capacity. By 2030, both the costs and mass of the equivalent sized battery pack are expected to decrease by almost 50%.

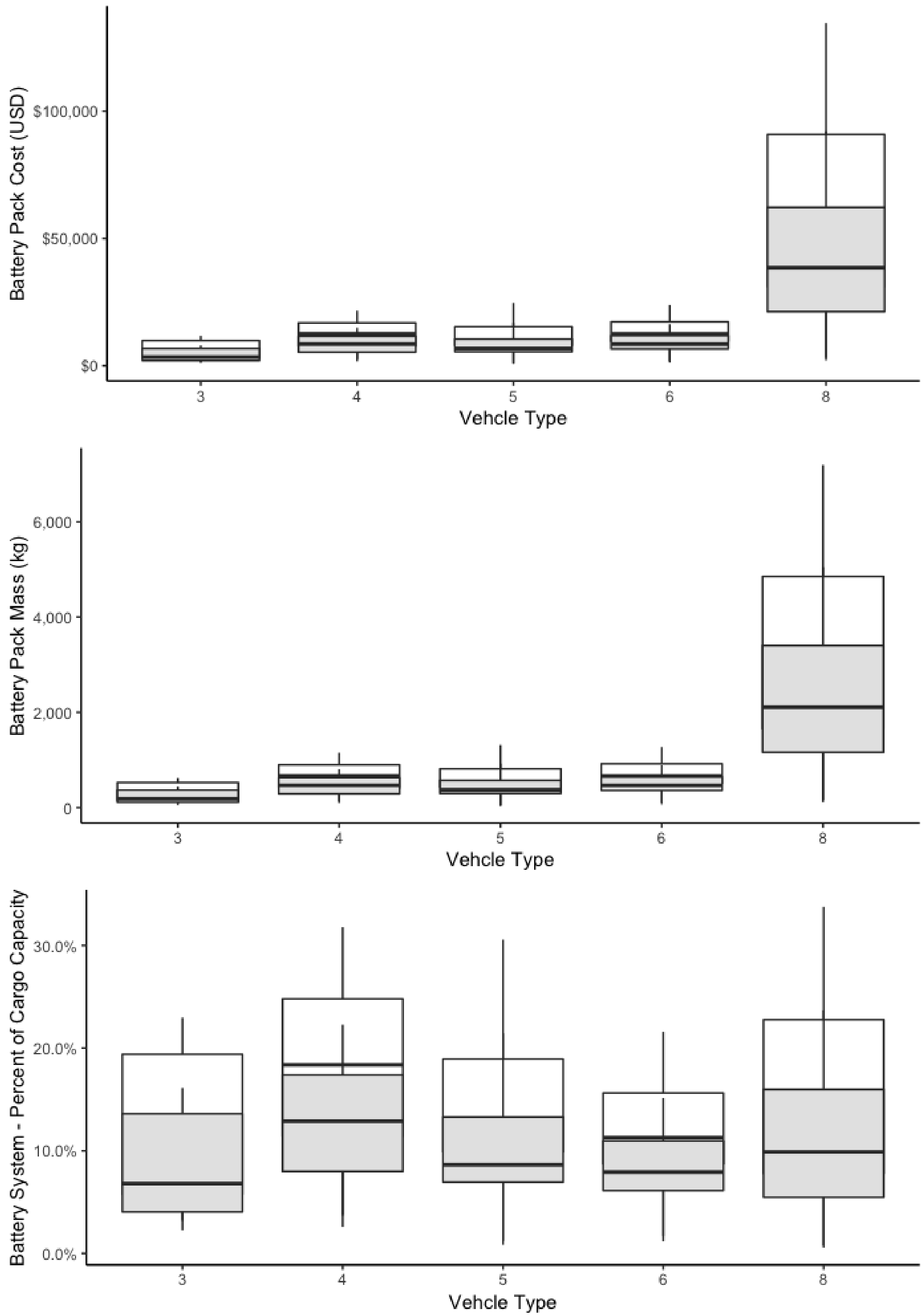

Figure 21. Electric Class 3–8 vehicle battery cost and mass, 2018 (white) vs. 2030 (grey)

There are some potential effects on increasing battery capacity and range that are not analyzed here, but could be important for PEV performance and adoption. First, large battery capacities could lead to significant improvements in battery life and reduced battery capacity fade in future PEVs. Reducing the depth of discharge of LIBs remains one of the most effective methods for improving cycle life, which usually requires oversizing the battery for the duty cycle [85]. Given appropriate storage conditions [86], larger batteries could remain in service longer, thereby reducing demand for battery replacements. Thus, while not immediately obvious, increasing battery material demands initially, could reduce battery material demands over the vehicle life cycle if battery replacement(s) are avoided. There is also the potential for positive feedback loops with respect to improving PEV performance and battery longevity, and more widespread adoption of PEVs (or adoption of PEVs in new vehicle sectors).

Resource Constraints

Needed growth in production capacity of LIBs for PEVs may cause unintended environmental consequences throughout the supply chain of raw material acquisition and component manufacturing. A number of studies and recent articles have drawn attention to the potential challenges of rapidly increasing demand for lithium and cobalt. While dramatic increases in the price of lithium may not be immediately impacting the price of batteries today [87, 88], there are notable examples of local environmental and social impacts inflicted on communities in South America from expanding demand for LIB cathode materials [89, 90], and cobalt in Africa [91]. There are also examples of supplies of minor materials disrupting the supply of major technologies [92].

The term critical energy materials is used to refer to a class of materials used in LIBs, permanent magnets, and photovoltaics with considerable risk of supply disruption, constraint, and significant environmental impact [93]. Given expected growth in demand for LIBs to meet low carbon transportation objectives, the low abundance of some LIB material elements in the lithosphere, but perhaps more importantly, the highly concentrated production of particular materials in a single country or region, understanding future demand for LIBs may be crucial for avoiding significant supply disruptions as well as social and environmental impacts for producing communities.

A number of recent studies have sought to examine potential resource constraints for lithium [94–100], but only one study was identified, Olivetti et al. (2017), that included LIBs over 50 kWh [101]. While there is considerable uncertainty in the amount of lithium or cobalt required for a given battery chemistry, the aforementioned studies also use lower assumptions for materials required (<4 kg per vehicle). Resource availability may become an issue with the potential for increasing system sizes in addition to emerging applications for ever larger systems. Further research should consider how the changing costs and performance of LIBs will affect LIB design and system selection for future vehicles.

Conclusions and Next Steps

This research demonstrates a method for estimating the costs, magnitudes, and benefits of emissions reductions from vehicles used for freight goods movements. The key findings include that battery electric trucks could avoid significant emissions of GHG and air quality pollutants, while providing overall cost savings in some applications. The value of avoided pollution health costs and premature mortality from truck electrification were also significantly higher than the estimated increase in private (vehicle) costs. The report also provides emissions inventories for Class 3–8 conventional and electric vehicles by cargo mass (e.g., ton-mile) that reflects the full fuel cycle.

A key next step will be to expand the scope of the cost and LCA models to include the production of vehicle and battery systems. Though fuel cycle environmental impacts tend to dominate the life cycle impacts of all vehicles, the environmental impacts and material requirements of battery and vehicle powertrain systems may also be a source of significant environmental impacts. In addition, as the electricity grid transitions to greater proportions of renewable energy sources, the proportional contributions of batteries in an electric truck's life cycle will grow. LIB manufacturing processes require significant inputs of materials and energy, and are likely to have a significant contribution to emissions associated with vehicle production. In addition, end-of-life management processes for LIBs are not well characterized and could create opportunities for downstream hazards.

A second and equally important next step will be to conduct a global sensitivity analysis of the various parameters affecting costs, emissions, and abatement potential of truck electrification. This study provides an overview of these factors, but it will be increasingly important to identify the key levers and opportunities for leakage to support robust policy design.

Incentives for adoption of zero-emissions truck technologies, like electric trucks, can create co-benefits in the form of criteria pollution abatement. The value of those incentives, with respect to avoided damages, is also regional due to exposure and incidence. Future research will also focus on looking at the spatial distribution of avoided damages and relate those damages back to regional truck activity, as well as statewide and local fuel and purchase incentives.

Selected References

1. Davis, S.C., S.E. Williams, and R.G. Boundy, *Transportation energy data book: Edition 35.* ORNL, 2016. **6974**.

2. Council, N.R., *Technologies and approaches to reducing the fuel consumption of medium- and heavy-duty vehicles*. 2010: National Academies Press.

3. Grenzeback, L.R., et al., *Transportation Energy Futures Series: Freight Transportation Demand: Energy-Efficient Scenarios for a Low-Carbon Future*. 2013, Cambridge Systematics Inc./National Renewable Energy Laboratory.

4. Adar, S. and J. Kaufman, *Cardiovascular disease and air pollutants: evaluating and improving epidemiological data implicating traffic exposure.* Inhalation Toxicology, 2007. **19**(sup1): p. 135–149.

5. Heinrich, J. and H.-E. Wichmann, *Traffic related pollutants in Europe and their effect on allergic disease.* Current opinion in allergy and clinical immunology, 2004. **4**(5): p. 341–348.

6. Seagrave, J., et al., *Lung toxicity of ambient particulate matter from southeastern US sites with different contributing sources: relationships between composition and effects.* Environmental health perspectives, 2006: p. 1387–1393.

7. Witcover, J., et al., *The Low Carbon Fuel Standard." Achieving California's Greenhouse Gas Goals: A Focus on Transportation*, in *Next10*. 2015.

8. Lade, G.E. and C.Y.C. Lin Lawell, *The design and economics of low carbon fuel standards.* Research in Transportation Economics, 2015. **52**: p. 91–99.

9. Yeh, S., et al., *National Low Carbon Fuel Standard: Policy Design Recommendations.* SSRN Electronic Journal, 2012.

10. McCollum, D. and C. Yang, *Achieving deep reductions in US transport greenhouse gas emissions: Scenario analysis and policy implications.* Energy Policy, 2009. **37**(12): p. 5580–5596.

11. Searchinger, T., et al., *Use of US croplands for biofuels increases greenhouse gases through emissions from land-use change.* Science, 2008. **319**(5867): p. 1238–1240.

12. Plevin, R.J., M.A. Delucchi, and F. Creutzig, *Using attributional life cycle assessment to estimate climate-change mitigation benefits misleads policy makers.* Journal of Industrial Ecology, 2014. **18**(1): p. 73–83.

13. O'Hare, M., et al., *Comment on "Indirect land use change for biofuels: Testing predictions and improving analytical methodologies" by Kim and Dale: statistical reliability and the definition of the indirect land use change (iLUC) issue.* biomass and bioenergy, 2011. **35**(10): p. 4485–4487.

14. Janaun, J. and N. Ellis, *Perspectives on biodiesel as a sustainable fuel.* Renewable and Sustainable Energy Reviews, 2010. **14**(4): p. 1312–1320.

15. Delucchi, M.A., *Impacts of biofuels on climate change, water use, and land use.* Annals of the New York Academy of Sciences, 2010. **1195**(1): p. 28–45.

16. Shi, X., et al., *Emission reduction potential of using ethanol–biodiesel–diesel fuel blend on a heavy-duty diesel engine.* Atmospheric Environment, 2006. **40**(14): p. 2567–2574.

17. McCormick, R.L., et al., *Impact of biodiesel source material and chemical structure on emissions of criteria pollutants from a heavy-duty engine.* Environmental science & technology, 2001. **35**(9): p. 1742–1747.

18. Durbin, T.D., et al., *Effects of biodiesel, biodiesel blends, and a synthetic diesel on emissions from light heavy-duty diesel vehicles.* Environmental science & technology, 2000. **34**(3): p. 349–355.

19. Whitaker, M., et al., *Life Cycle Greenhouse Gas Emissions of Coal-Fired Electricity Generation.* Journal of Industrial Ecology, 2012. **16**(s1): p. S53–S72.

20. Cai, H., et al., *Updated greenhouse gas and criteria air pollutant emission factors and their probability distribution functions for electricity generating units*. 2012, Argonne National Laboratory (ANL).

21. Venkatesh, A., et al., *Uncertainty in life cycle greenhouse gas emissions from United States natural gas end-uses and its effects on policy.* Environmental science & technology, 2011. **45**(19): p. 8182–8189.

22. Soimakallio, S., J. Kiviluoma, and L. Saikku, *The complexity and challenges of determining GHG (greenhouse gas) emissions from grid electricity consumption and conservation in LCA (life cycle assessment) – A methodological review.* Energy, 2011. **36**(12): p. 6705–6713.

23. Weber, C.L., et al., *Life cycle assessment and grid electricity: what do we know and what can we know?* Environmental science & technology, 2010. **44**(6): p. 1895–1901.

24. Clark, N.N., et al., *Factors affecting heavy-duty diesel vehicle emissions.* Journal of the Air & Waste Management Association, 2002. **52**(1): p. 84–94.

25. Herner, J.D., et al., *Effect of advanced aftertreatment for PM and NO x reduction on heavy-duty diesel engine ultrafine particle emissions.* Environmental science & technology, 2011. **45**(6): p. 2413–2419.

26. Kado, N.Y., et al., *Emissions of toxic pollutants from compressed natural gas and low sulfur diesel-fueled heavy-duty transit buses tested over multiple driving cycles.* Environmental science & technology, 2005. **39**(19): p. 7638–7649.

27. Carlsson, B., et al., *Innovation systems: analytical and methodological issues.* Research policy, 2002. **31**(2): p. 233–245.

28. Scherer, F.M., D. Harhoff, and J. Kukies, *Uncertainty and the size distribution of rewards from innovation*, in *Capitalism and Democracy in the 21st Century*. 2001, Springer. p. 181–206.

29. Reinganum, J.F., *The timing of innovation: Research, development, and diffusion.* Handbook of industrial organization, 1989. **1**: p. 849–908.

30. Sutton, J., *Technology and market structure: theory and history*. 2001: MIT Press.

31. Plevin, R.J., *Life cycle regulation of transportation fuels: Uncertainty and its policy implications.* 2010.

32. ISO, I., *14040: Environmental management–life cycle assessment–principles and framework.* London: British Standards Institution, 2006.

33. Kloepffer, W., *Life cycle sustainability assessment of products.* The International Journal of Life Cycle Assessment, 2008. **13**(2): p. 89–95.

34. Reed, D., *Life cycle Assessment in Government Policy in the United States*. 2012, University of Tennessee, Knoxville.

35. Woodward, D.G., *Life cycle costing—theory, information acquisition and application.* International journal of project management, 1997. **15**(6): p. 335–344.

36. Fuller, S. and S. Petersen, *Life cycle costing manual for the federal energy management program, 1995 Edition.* NIST handbook, 1996. **135**.

37. Rebitzer, G., et al., *Life cycle assessment: Part 1: Framework, goal and scope definition, inventory analysis, and applications.* Environment international, 2004. **30**(5): p. 701–720.

38. Lajunen, A. and T. Lipman, *Lifecycle cost assessment and carbon dioxide emissions of diesel, natural gas, hybrid electric, fuel cell hybrid and electric transit buses.* Energy, 2016. **106**: p. 329–342.

39. Ambrose, H. and A. Kendall, *Effects of battery chemistry and performance on the life cycle greenhouse gas intensity of electric mobility.* Transportation Research Part D: Transport and Environment, 2016. **47**: p. 182–194.

40. Xu, Y., et al., *Assessment of alternative fuel and powertrain transit bus options using real-world operations data: Life cycle fuel and emissions modeling.* Applied Energy, 2015. **154**: p. 143–159.

41. Kim, H.C., et al., *Life Cycle Assessment of Vehicle Lightweighting: Novel Mathematical Methods to Estimate Use-Phase Fuel Consumption.* Environmental science & technology, 2015. **49**(16): p. 10209–10216.

42. USDOT. *FHWA Office of Highway Policy Information*. [cited 2016; Available from: https://www.fhwa.dot.gov/policyinformation/.]

43. DOE. *AFDC Vehicle Weight Classes & Categories*. [cited 2016; Available from: http://www.afdc.energy.gov/data/10380.]

44. Branch, M.S.A., *Mobile Emissions Source Inventory EMFAC Web Database*, C.A.R. Board, Editor. 2017, CARB.

45. Holmberg, K., et al., *Global energy consumption due to friction in trucks and buses.* Tribology International, 2014. **78**: p. 94–114.

46. Simpson, A.G., *Parametric modelling of energy consumption in road vehicles.* 2005.

47. Sovran, G. and D. Blaser, *A contribution to understanding automotive fuel economy and its limits*. 2003, SAE Technical Paper.

48. Yanowitz, J., R.L. McCormick, and M.S. Graboski, *In-use emissions from heavy-duty diesel vehicles.* Environmental Science & Technology, 2000. **34**(5): p. 729–740.

49. Walkowicz, K., et al., *Fleet DNA project data.* J National Renewable Energy Laboratory., 2014.

50. Schwertner, M. and U. Weidmann, *Comparison of Well-to-Wheel Efficiencies for Different Drivetrain Configurations of Transit Buses.* Transportation Research Record: Journal of the Transportation Research Board, 2016(2539): p. 55–64.

51. O'Keefe, M.P., et al., *Duty cycle characterization and evaluation towards heavy hybrid vehicle applications*. 2007, SAE Technical Paper.

52. Burnham, A., *Alternative Fuel Life cycle Environmental and Economic Transportation (AFLEET) Tool*, A.N. Laboratory, Editor. 2016: Lemont, IL.

53. Board, C.A.R., *Assessment of a Zero Emission VehiclevRequirement for Light and Heavy-Duty Vehicle Fleets*. 2018.

54. Neij, L., *Cost development of future technologies for power generation—A study based on experience curves and complementary bottom-up assessments.* Energy policy, 2008. **36**(6): p. 2200–2211.

55. Wright, T.P., *Factors affecting the cost of airplanes.* Journal of the aeronautical sciences, 1936. **3**(4): p. 122–128.

56. de La Tour, A., M. Glachant, and Y. Ménière, *Predicting the costs of photovoltaic solar modules in 2020 using experience curve models.* Energy, 2013. **62**: p. 341–348.

57. Harmon, C., *Experience curves of photovoltaic technology.* 2000.

58. Colpier, U.C. and D. Cornland, *The economics of the combined cycle gas turbine—an experience curve analysis.* Energy Policy, 2002. **30**(4): p. 309–316.

59. Matteson, S. and E. Williams, *Residual learning rates in lead-acid batteries: Effects on emerging technologies.* Energy Policy, 2015. **85**: p. 71–79.

60. Weiss, M., et al., *A review of experience curve analyses for energy demand technologies.* Technological forecasting and social change, 2010. **77**(3): p. 411–428.

61. Nykvist, B. and M. Nilsson, *Rapidly falling costs of battery packs for electric vehicles.* Nature Climate Change, 2015.

62. Kittner, N., F. Lill, and D.M. Kammen, *Energy storage deployment and innovation for the clean energy transition.* Nature Energy, 2017. **2**(9): p. 17125.

63. Chung, D., E. Elgqvist, and S. Santhanagopalan, *Automotive lithium-ion cell manufacturing: Regional cost structures and supply chain considerations.* Contract, 2016. **303**: p. 275–3000.

64. Curry, C., *Lithium-ion battery costs and market.* 2017.

65. Thackeray, M.M., C. Wolverton, and E.D. Isaacs, *Electrical energy storage for transportation—approaching the limits of, and going beyond, lithium-ion batteries.* Energy & Environmental Science, 2012. **5**(7): p. 7854–7863.

66. U. S. Department of Energy, *Advanced Batteries 2016 Annual Progress Report*. 2017: Office of Efficiency and Renewable Energy.

67. Dunn, J.B., et al., *Material and energy flows in the materials production, assembly, and end-of-life stages of the automotive lithium-ion battery life cycle*. 2014, Argonne National Lab (ANL): Argonne, IL.

68. Spath, P.L. and M.K. Mann, *Life cycle assessment of a natural gas combined-cycle power generation system*. 2000: National Renewable Energy Laboratory, Golden, CO.

69. Argonne National Laboratory, *Greenhouse Gasses, Regulated Emissions, and Energy Use in Transportation (GREET) Model 1 - Fuel Cycle Model,*, M. Wang, Editor. 2017: Argonne, IL.

70. US EPA, *Generation Resource Integrated Database (eGRID) 2016*. 2016.

71. Administration, U.S.E.I., *Price Components (Case Reference case Region Pacific)*. 2019.

72. Fann, N., K.R. Baker, and C.M. Fulcher, *Characterizing the PM2. 5-related health benefits of emission reductions for 17 industrial, area and mobile emission sectors across the US.* Environment international, 2012. **49**: p. 141–151.

73. Muller, N.Z. and R. Mendelsohn, *Measuring the damages of air pollution in the United States.* Journal of Environmental Economics and Management, 2007. **54**(1): p. 1–14.

74. March, J.W., *DOT Comprehensive Truck Size and Weight Study.* Public Roads, 2001. **64**(5).

75. Yearbook, C.E.S., *2017 China Statistical Yearbook*. 2017, Beijing: China Energy Press.

76. IEA, *Global Energy & CO2 Status Report 2017*. 2017, International Energy Agency: Paris, France.

77. Prior, T., et al., *Sustainable governance of scarce metals: The case of lithium.* Science of The Total Environment, 2013. **461**: p. 785–791.

78. CARB, *PROPOSED AMENDMENT TO THE ZERO EMISSION VEHICLE REGULATION FAST REFUELING CREDIT PROVISION*, S.R.S.R.I. ASSESSMENT, Editor. 2015.

79. OPR, C., *ZEV Action Plan*, G.s.O.o.P.a. Research, Editor. 2013.

80. Center, A.B.T.a.R., *Proterra, Inc. Catalyst E2*. 2017, University Park: Pennsylvania State University.

81. Center, A.B.T.a.R., *Proterra, Inc. Model BE-35*. 2012, University Park: Pennsylvania State University.

82. Kelly, J.C., et al., *Impacts of Vehicle Weight Reduction via Material Substitution on Life cycle Greenhouse Gas Emissions.* Environmental science & technology, 2015. **49**(20): p. 12535–12542.

83. Kendall, A. and L. Price, *Incorporating time-corrected life cycle greenhouse gas emissions in vehicle regulations.* Environmental science & technology, 2012. **46**(5): p. 2557–2563.

84. Cebon, D., *Vehicle-generated road damage: a review.* Vehicle system dynamics, 1989. **18**(1-3): p. 107–150.

85. Barré, A., et al., *Electric vehicles performance estimation through a patterns extraction and classification methodology.* Journal of Power Sources, 2015. **273**: p. 670–679.

86. Waldmann, T., et al., *Temperature dependent ageing mechanisms in Lithium-ion batteries–A Post-Mortem study.* Journal of Power Sources, 2014. **262**: p. 129–135.

87. Ciez, R.E. and J. Whitacre, *The cost of lithium is unlikely to upend the price of Li-ion storage systems.* Journal of Power Sources, 2016. **320**: p. 310–313.

88. Maxwell, P., *Transparent and opaque pricing: The interesting case of lithium.* Resources Policy, 2015. **45**: p. 92–97.

89. Jaffe, S., *Vulnerable Links in the Lithium-Ion Battery Supply Chain.* Joule, 2017. **1**(2): p. 225–228.

90. *Clean energy—an increasingly precious metal*, in *The Economist*. 2016.

91. Frankel, T.C., *The Cobalt Pipline*, in *Washington Post*. 2016.

92. Eichstaedt, P., *Consuming the Congo: War and conflict minerals in the world's deadliest place*. 2011: Chicago Review Press.

93. Erdmann, L. and T.E. Graedel, *Criticality of non-fuel minerals: a review of major approaches and analyses.* Environmental science & technology, 2011. **45**(18): p. 7620–7630.

94. Speirs, J., et al., *The future of lithium availability for electric vehicle batteries.* Renewable and Sustainable Energy Reviews, 2014. **35**: p. 183–193.

95. Ziemann, S., et al., *The future of mobility and its critical raw materials.* Revue de Métallurgie, 2013. **110**(01): p. 47–54.

96. Swart, P., J. Dewulf, and A. Biernaux, *Resource demand for the production of different cathode materials for lithium ion batteries.* Journal of Cleaner Production, 2014.

97. Gruber, P.W., et al., *Global Lithium Availability.* Journal of Industrial Ecology, 2011. **15**: p. 760–775.

98. Mohr, S.H., G. Mudd, and D. Giurco, *Lithium resources and production: Critical assessment and global projections.* Minerals, 2012. **2**(1): p. 65–84.

99. Vikström, H., S. Davidsson, and M. Höök, *Lithium availability and future production outlooks.* Applied Energy, 2013. **110**: p. 252–266.

100. Pehlken, A., S. Albach, and T. Vogt, *Is there a resource constraint related to lithium ion batteries in cars?* The International Journal of Life Cycle Assessment, 2015: p. 1–14.

101. Olivetti, E.A., et al., *Lithium-ion battery supply chain considerations: analysis of potential bottlenecks in critical metals.* Joule, 2017. **1**(2): p. 229–243.

Data Management

Products of Research

The data used for this research was collected from a range of public sources, including government and agency databases, reports, white-papers, and peer-reviewed publications. The data collected included vehicle population, routing, activity, emissions rates, costs, fuel production, electricity generation, and general market data. The data gathered is described in greater detail throughout the research report.

Data Format and Content

The data files are organized into several comma separated value (CSV) files, while the emissions and cost model is contained in a single R file also included in the data depository. A read-me file is also provided describing the data files:

- ***"Freight LCA-TEA Model.R"*** – The complete model as an R script.
- ***"allfreightFleetNDA.csv"*** – The aggregated composite duty cycle data taken from Walkowicz, K., et al., *Fleet DNA project data.* J National Renewable Energy Laboratory, 2014.
- ***"vehicle_scenarios.csv"*** – Descriptions of the vehicle scenarios and conventional vehicle costs data.
- ***"charging_infrastructure.csv"*** – Charging infrastructure costs and electricity costs (see Table 4 in the main report).
- ***"EMFAC2017_vehicle_pop_baseline.csv"*** – Number of in-state, registered Class 3–8 vehicles as reflected in *Mobile Emissions Source Inventory EMFAC Web Database 2017, California Air Resources Board.*
- ***"EMFAC2017_emissions_rates.csv"*** – Combustion and operations emissions rates for conventional vehicles by model year for Class 3–8 vehicles from the *Mobile Emissions Source Inventory EMFAC Web Database 2017, California Air Resources Board*.
- ***"conventional_GREET_WTP_LCIs.csv"*** – Life cycle emissions for production and refining of conventional liquid fuels from *Greenhouse Gasses, Regulated Emissions, and Energy Use in Transportation (GREET) Model 1 - Fuel Cycle Model by Argonne National Laboratory.*
- ***"batter-cost-energy.csv"*** – Forecast of battery costs in $/kWh (see Figure 4 in the main report).
- ***"fuel_prices.csv"*** – Costs of conventional fuels from the U.S. Energy Information Administration, *Price Components (Case Reference case Region Pacific)*.
- ***"electricity_emissions_perkwh.csv"*** – Forecast of emissions rates for delivered electricity based on generation model described in the main text ("Generation of Electricity" section).
- ***"CAstate_avg_dmg.csv"*** – Estimate of pollution related health damages based on the Air Pollution Emission Experiments and Policy analysis (AP2) described in Muller, N.Z.

and R. Mendelsohn, *Measuring the damages of air pollution in the United States.* Journal of Environmental Economics and Management, 2007. **54**(1): p. 1–14.

Data Access and Sharing

All data files and the main modelling script are made available publicly via the Dryad Digital Repository: https://datadryad.org/stash/. The DOI for the dataset is https://doi.org/10.25338/B8NS4T.

Reuse and Redistribution

All data used for this project is public and available for unrestricted use, unless otherwise specified in the data citation. If the data are used, our work should be properly cited:

Ambrose, Hanjiro; Kendall, Alissa (2019), Life Cycle Modeling of Tech & Strategies for a Sustainable Freight System in California, v2, UC Davis, Dataset, https://doi.org/10.25338/B8NS4T

Appendix 1 – Emissions Rate of Conventional Vehicles, All Units are grams per mile

Year	Vehicle Fuel Type	Flow	Class 3	Class 4	Class 5	Class 6	Class 8
2018	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2019	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2020	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2021	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2022	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2023	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2024	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2025	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2026	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2027	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2028	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2029	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2030	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2031	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2032	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2033	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2034	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2035	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2036	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2037	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2038	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2039	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2040	DSL	CH_4	0.61	0.72	0.81	1.08	2.39
2018	DSL	CO	0.24	0.24	0.21	0.25	0.97
2019	DSL	CO	0.28	0.27	0.21	0.25	0.97
2020	DSL	CO	0.31	0.30	0.22	0.26	0.98
2021	DSL	CO	0.34	0.34	0.22	0.26	0.98
2022	DSL	CO	0.37	0.37	0.22	0.26	0.99
2023	DSL	CO	0.40	0.40	0.22	0.26	0.99
2024	DSL	CO	0.43	0.42	0.23	0.27	1.00
2025	DSL	CO	0.46	0.45	0.23	0.27	1.00
2026	DSL	CO	0.48	0.48	0.23	0.27	1.00
2027	DSL	CO	0.51	0.50	0.23	0.27	1.00
2028	DSL	CO	0.53	0.52	0.24	0.28	1.01

Year	Vehicle Fuel Type	Flow	Class 3	Class 4	Class 5	Class 6	Class 8
2029	DSL	CO	0.55	0.54	0.22	0.26	0.99
2030	DSL	CO	0.41	0.40	0.23	0.26	0.99
2031	DSL	CO	0.43	0.43	0.23	0.27	1.00
2032	DSL	CO	0.46	0.45	0.23	0.27	1.00
2033	DSL	CO	0.48	0.47	0.23	0.27	1.00
2034	DSL	CO	0.50	0.50	0.23	0.27	1.01
2035	DSL	CO	0.53	0.52	0.24	0.28	1.01
2036	DSL	CO	0.54	0.54	0.24	0.28	1.01
2037	DSL	CO	0.56	0.55	0.24	0.28	1.01
2038	DSL	CO	0.58	0.57	0.24	0.28	1.02
2039	DSL	CO	0.59	0.58	0.24	0.28	1.02
2040	DSL	CO	0.61	0.60	0.25	0.28	1.02
2018	DSL	GHGs (CO_2e)	570.82	637.55	1019.94	1112.58	1742.48
2019	DSL	GHGs (CO_2e)	570.96	637.59	1017.39	1110.03	1739.64
2020	DSL	GHGs (CO_2e)	571.04	637.67	1016.43	1109.16	1738.73
2021	DSL	GHGs (CO_2e)	571.19	637.87	1016.17	1108.86	1738.90
2022	DSL	GHGs (CO_2e)	571.25	637.93	1015.39	1107.97	1738.28
2023	DSL	GHGs (CO_2e)	571.30	637.99	1014.61	1107.29	1737.74
2024	DSL	GHGs (CO_2e)	571.84	638.62	1015.15	1107.94	1738.34
2025	DSL	GHGs (CO_2e)	571.88	638.67	1014.42	1107.24	1737.82
2026	DSL	GHGs (CO_2e)	571.93	638.71	1013.75	1106.59	1737.34
2027	DSL	GHGs (CO_2e)	571.97	638.76	1013.13	1105.98	1736.91
2028	DSL	GHGs (CO_2e)	572.01	638.80	1012.53	1105.39	1736.50
2029	DSL	GHGs (CO_2e)	572.05	638.84	907.24	1012.25	1572.98
2030	DSL	GHGs (CO_2e)	532.14	594.55	906.54	1011.57	1572.31
2031	DSL	GHGs (CO_2e)	532.14	594.67	905.40	1010.42	1570.81
2032	DSL	GHGs (CO_2e)	532.20	594.74	904.76	1009.78	1570.24
2033	DSL	GHGs (CO_2e)	532.26	594.80	904.15	1009.18	1569.72
2034	DSL	GHGs (CO_2e)	532.32	594.85	903.57	1008.59	1569.21
2035	DSL	GHGs (CO_2e)	532.37	594.91	903.00	1008.03	1568.71
2036	DSL	GHGs (CO_2e)	532.42	594.95	902.47	1007.48	1568.24
2037	DSL	GHGs (CO_2e)	532.46	595.00	901.95	1006.96	1567.79
2038	DSL	GHGs (CO_2e)	532.50	595.04	901.47	1006.46	1567.36
2039	DSL	GHGs (CO_2e)	532.54	595.08	901.00	1005.98	1566.95
2040	DSL	GHGs (CO_2e)	532.57	595.12	900.56	1005.53	1566.56
2018	DSL	N_2O	0.09	0.10	0.16	0.17	0.26
2019	DSL	N_2O	0.09	0.10	0.16	0.17	0.26

Year	Vehicle Fuel Type	Flow	Class 3	Class 4	Class 5	Class 6	Class 8
2020	DSL	N_2O	0.09	0.10	0.16	0.17	0.26
2021	DSL	N_2O	0.09	0.10	0.16	0.17	0.26
2022	DSL	N_2O	0.09	0.10	0.16	0.17	0.26
2023	DSL	N_2O	0.09	0.10	0.16	0.17	0.26
2024	DSL	N_2O	0.09	0.10	0.16	0.17	0.26
2025	DSL	N_2O	0.09	0.10	0.16	0.17	0.26
2026	DSL	N_2O	0.09	0.10	0.16	0.17	0.26
2027	DSL	N_2O	0.09	0.10	0.16	0.17	0.26
2028	DSL	N_2O	0.09	0.10	0.16	0.17	0.26
2029	DSL	N_2O	0.09	0.10	0.14	0.15	0.24
2030	DSL	N_2O	0.08	0.09	0.14	0.15	0.24
2031	DSL	N_2O	0.08	0.09	0.14	0.15	0.24
2032	DSL	N_2O	0.08	0.09	0.14	0.15	0.24
2033	DSL	N_2O	0.08	0.09	0.14	0.15	0.24
2034	DSL	N_2O	0.08	0.09	0.14	0.15	0.24
2035	DSL	N_2O	0.08	0.09	0.14	0.15	0.24
2036	DSL	N_2O	0.08	0.09	0.14	0.15	0.24
2037	DSL	N_2O	0.08	0.09	0.14	0.15	0.24
2038	DSL	N_2O	0.08	0.09	0.14	0.15	0.24
2039	DSL	N_2O	0.08	0.09	0.14	0.15	0.24
2040	DSL	N_2O	0.08	0.09	0.14	0.15	0.24
2018	DSL	NO_X	0.28	0.27	2.06	1.75	2.92
2019	DSL	NO_X	0.29	0.28	2.13	1.82	2.99
2020	DSL	NO_X	0.30	0.29	2.21	1.90	3.06
2021	DSL	NO_X	0.30	0.29	2.29	1.98	3.13
2022	DSL	NO_X	0.31	0.30	2.37	2.06	3.19
2023	DSL	NO_X	0.31	0.30	2.44	2.13	3.25
2024	DSL	NO_X	0.32	0.31	2.51	2.20	3.31
2025	DSL	NO_X	0.32	0.31	2.58	2.27	3.36
2026	DSL	NO_X	0.33	0.32	2.64	2.33	3.41
2027	DSL	NO_X	0.33	0.32	2.69	2.38	3.46
2028	DSL	NO_X	0.34	0.33	2.75	2.44	3.50
2029	DSL	NO_X	0.34	0.33	2.39	2.08	3.20
2030	DSL	NO_X	0.27	0.27	2.45	2.14	3.26
2031	DSL	NO_X	0.28	0.28	2.51	2.21	3.32
2032	DSL	NO_X	0.28	0.28	2.57	2.27	3.37
2033	DSL	NO_X	0.28	0.28	2.63	2.32	3.42

Year	Vehicle Fuel Type	Flow	Class 3	Class 4	Class 5	Class 6	Class 8
2034	DSL	NO_X	0.28	0.28	2.68	2.38	3.47
2035	DSL	NO_X	0.29	0.29	2.74	2.43	3.52
2036	DSL	NO_X	0.29	0.29	2.79	2.48	3.56
2037	DSL	NO_X	0.29	0.29	2.84	2.53	3.61
2038	DSL	NO_X	0.29	0.29	2.88	2.58	3.65
2039	DSL	NO_X	0.29	0.29	2.93	2.62	3.69
2040	DSL	NO_X	0.29	0.29	2.97	2.66	3.72
2018	DSL	PM_{10}	0.11	0.12	0.16	0.17	0.16
2019	DSL	PM_{10}	0.11	0.12	0.16	0.17	0.16
2020	DSL	PM_{10}	0.11	0.12	0.16	0.17	0.16
2021	DSL	PM_{10}	0.11	0.13	0.16	0.17	0.16
2022	DSL	PM_{10}	0.11	0.13	0.17	0.17	0.16
2023	DSL	PM_{10}	0.11	0.13	0.17	0.17	0.16
2024	DSL	PM_{10}	0.11	0.13	0.17	0.17	0.16
2025	DSL	PM_{10}	0.12	0.13	0.17	0.17	0.16
2026	DSL	PM_{10}	0.12	0.13	0.17	0.17	0.16
2027	DSL	PM_{10}	0.12	0.13	0.17	0.17	0.16
2028	DSL	PM_{10}	0.12	0.13	0.17	0.17	0.16
2029	DSL	PM_{10}	0.12	0.13	0.17	0.17	0.16
2030	DSL	PM_{10}	0.11	0.13	0.17	0.17	0.16
2031	DSL	PM_{10}	0.11	0.13	0.17	0.17	0.16
2032	DSL	PM_{10}	0.11	0.13	0.17	0.17	0.16
2033	DSL	PM_{10}	0.11	0.13	0.17	0.17	0.16
2034	DSL	PM_{10}	0.11	0.13	0.17	0.17	0.16
2035	DSL	PM_{10}	0.11	0.13	0.17	0.17	0.16
2036	DSL	PM_{10}	0.12	0.13	0.17	0.17	0.16
2037	DSL	PM_{10}	0.12	0.14	0.17	0.17	0.16
2038	DSL	PM_{10}	0.12	0.14	0.17	0.17	0.16
2039	DSL	PM_{10}	0.12	0.14	0.17	0.17	0.16
2040	DSL	PM_{10}	0.12	0.14	0.17	0.18	0.16
2018	DSL	PM_{10}	0.05	0.06	0.07	0.08	0.08
2019	DSL	PM_{10}	0.05	0.06	0.07	0.08	0.08
2020	DSL	PM_{10}	0.05	0.06	0.07	0.08	0.08
2021	DSL	PM_{10}	0.05	0.06	0.08	0.08	0.08
2022	DSL	PM_{10}	0.06	0.06	0.08	0.08	0.08
2023	DSL	PM_{10}	0.06	0.06	0.08	0.08	0.08
2024	DSL	PM_{10}	0.06	0.06	0.08	0.08	0.08

Year	Vehicle Fuel Type	Flow	Class 3	Class 4	Class 5	Class 6	Class 8
2025	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2026	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2027	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2028	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2029	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2030	DSL	PM_{10}	0.05	0.06	0.08	0.08	0.08
2031	DSL	PM_{10}	0.06	0.06	0.08	0.08	0.08
2032	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2033	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2034	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2035	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2036	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2037	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2038	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2039	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2040	DSL	PM_{10}	0.06	0.07	0.08	0.08	0.08
2018	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2019	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2020	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2021	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2022	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2023	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2024	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2025	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2026	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2027	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2028	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2029	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2030	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2031	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2032	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2033	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2034	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2035	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2036	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2037	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2038	DSL	SO_X	0.09	0.10	0.12	0.16	0.34

Year	Vehicle Fuel Type	Flow	Class 3	Class 4	Class 5	Class 6	Class 8
2039	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2040	DSL	SO_X	0.09	0.10	0.12	0.16	0.34
2018	DSL	VOC	0.25	0.27	0.16	0.20	0.53
2019	DSL	VOC	0.26	0.27	0.16	0.21	0.53
2020	DSL	VOC	0.26	0.27	0.16	0.21	0.53
2021	DSL	VOC	0.27	0.28	0.16	0.21	0.53
2022	DSL	VOC	0.27	0.28	0.16	0.21	0.53
2023	DSL	VOC	0.27	0.29	0.16	0.21	0.53
2024	DSL	VOC	0.28	0.29	0.16	0.21	0.53
2025	DSL	VOC	0.28	0.29	0.16	0.21	0.53
2026	DSL	VOC	0.28	0.30	0.16	0.21	0.53
2027	DSL	VOC	0.29	0.30	0.16	0.21	0.53
2028	DSL	VOC	0.29	0.30	0.16	0.21	0.53
2029	DSL	VOC	0.29	0.31	0.16	0.21	0.53
2030	DSL	VOC	0.27	0.29	0.16	0.21	0.53
2031	DSL	VOC	0.28	0.29	0.16	0.21	0.53
2032	DSL	VOC	0.28	0.30	0.16	0.21	0.53
2033	DSL	VOC	0.28	0.30	0.16	0.21	0.53
2034	DSL	VOC	0.29	0.30	0.16	0.21	0.53
2035	DSL	VOC	0.29	0.30	0.16	0.21	0.53
2036	DSL	VOC	0.29	0.31	0.16	0.21	0.53
2037	DSL	VOC	0.29	0.31	0.16	0.21	0.54
2038	DSL	VOC	0.30	0.31	0.16	0.21	0.54
2039	DSL	VOC	0.30	0.31	0.16	0.21	0.54
2040	DSL	VOC	0.30	0.31	0.16	0.21	0.54