Title

Environmental and economic costs, benefits and uncertainties of vehicle electrification: a life cycle approach

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Environmental and economic costs, benefits and uncertainties of vehicle electrification: a life cycle approach

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Abstract

Battery electric vehicles (BEVs) have been proposed as a pathway for reducing the environmental impacts of transportation systems. While BEVs are often referred to as zero-emission vehicles, production and operation consume resources and emit pollutants through the vehicle supply chain and generation of electricity for vehicle charging. Life cycle assessment is a standardized methodology for assessing the environmental impacts of product systems from a system-wide perspective; considering the total supply chain and the product life cycle from cradle-to-grave. However, conventional LCAs are often limited; based off static supply chain analysis, omitting system interactions or indirect effects, and insufficiently reflecting the underlying variability and uncertainty to support robust public policy decisions.

The objective of this dissertation is to develop and refine methods of assessing the life cycle environmental impacts and economic costs of electric vehicle technologies and policies. The chapters of this dissertation make contributions in advancing spatial and temporal dynamics in LCA modelling, integrating vehicle operations with evolutions in technology, background systems, and product development, and offers novel estimates of the costs and emissions abatement potential of light and heavy duty electric vehicles. As shown herein, a systems perspective is required to estimate the environmental benefits and costs of vehicle electrification strategies. Efforts to achieve pollution abatement through technology change must address risks of leakage, substitution, and unintended environmental consequences.

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SUMMARY OF ABBREVIATIONS

EV: Electric Vehicle

BEV: Battery Electric Vehicle

PEV: Plug-in Electric Vehicle

HEV: Hybrid Electric Vehicle

BAU: Business as Usual

CO_2e: Carbon-Dioxide Equivalent

EPA: Environmental Protection Agency

kWh: Kilowatt Hour

LCA: Life Cycle Assessment

LCI: Life Cycle Inventory

LIB: Lithium-ion Battery

mmBTU: Million British Thermal Units

NREL: National Renewable Energy Laboratory

1. INTRODUCTION

1.1 MOTIVATION

The transportation sector is the largest source of greenhouse gas emissions (GHGs) in the U.S., constitutes 80% of domestic petroleum consumption, and by some measures is the largest contributor to health costs from air pollution (Goodkind, Tessum, Coggins, Hill, & Marshall, 2019; Heo, Adams, & Gao, 2016; U.S. Energy Information Administration, 2019). While a multipronged approach is needed to achieve deep reductions in transportation emissions, rapid and extensive deployment of battery electric vehicles (BEVs) is viewed as a crucial part of nearly all strategies (Alexander, 2015; Meszler, Lutsey, & Delgado, 2015; Sperling, 2018). Over the last decade, several national and regional governments have enacted policies to promote the deployment of light and heavy duty electric vehicles, often with the goal of reducing greenhouse gas emissions, and in some cases to reduce local air pollutants as well.

Early life-cycle analyses (LCAs) of conventional vehicles showed that the operation of vehicles overwhelmingly dominated environmental impacts; 75−95% of life cycle GHG emissions for an internal combustion gasoline passenger vehicle is attributable to fuel consumption and combustion (Bauer, Hofer, Althaus, Del Duce, & Simons, In Press; Castro, Remmerswaal, & Reuter, 2003; Geyer, 2008; Kim, Keoleian, Grande, & Bean, 2003). The historic regulatory focus on vehicle fuel economy and tailpipe emissions has reflected this reality. BEVs are typically referred to as zero emissions vehicles because they eliminate tailpipe pollution. However, as with other de-carbonization policies for the transport sector, a life cycle perspective is required to understand the actual mitigation achieved by BEVs. Shifting 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 BEVs, emissions are shifted upstream in the fuel cycle (to the power plant) and potentially to the vehicle production supply chain. In fact, on a percent basis, light-duty or passenger BEVs may have double the emissions from the production phase, and previous studies have shown that battery manufacture alone can be responsible for 35-41% of those production emissions for a 120-160 km range light-duty BEV (~24 kWh battery) (Hawkins, Singh, Majeau-Bettez, & Strømman, 2013).

BEVs have been proposed for both light and heavy-duty applications, but heavy-duty applications have been much less studied with LCA. Heavy-duty vehicles (HDVs) service a variety of diverse and critical vocations, including school and urban mass transit, refuse collection, distribution, and short and long-haul freight goods movements. HDVs are of particular concern as they emit high levels of particulate matter and a complex mixture of pollutants including ozone precursors (Adar & Kaufman, 2007; Heinrich & Wichmann, 2004; Seagrave et al., 2006). While HDVs are less than 5% of the total US vehicle fleet, they account for 18% of transportation energy and well over half of particulate aerosol and nitrogen oxides (NO_X) emissions from highway vehicles (Davis, Williams, & Boundy, 2016). Liquid fuel use from medium and heavy duty vehicles has increased more rapidly in both relative and absolute terms than consumption by other sectors (National Research Council, 2010), and is expected to continue into the near future (Grenzeback et al., 2013). While new developments in renewable transportation fuels and zero emissions vehicle technologies create pathways for mitigating the environmental impacts of HDVs, reduction potentials and costs remain highly uncertain (Durbin, Collins, Norbeck, & Smith, 2000; Lowell, Seamonds, Park, & Turner, 2015; Meszler et al., 2015; Meyer, Green, Corbett, Mas, & Winebrake, 2011; Shi et al., 2006).

This dissertation undertakes a variety of studies, all which apply a systems perspective to estimate the life cycle environmental benefits and costs of vehicle electrification strategies. For BEVs, the interactions between systems of vehicle design, battery production (including the extractive industries on which they rely), driving patterns, charging infrastructure, and electricity generation need to be considered. For example, BEVs can have considerable variability in life cycle operation emissions given the heterogeneity of electricity grids over space and time (Cerdas, Egede, & Herrmann, 2018; Tamayao, Michalek, Hendrickson, & Azevedo, 2015; Yuksel & Michalek, 2015). 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 (Clark, Kern, Atkinson, & Nine, 2002). Studies have established the close links between duty cycle, fuel type, and vehicle energy demands (Simpson, 2005; Sovran & Blaser, 2003), and duty cycle can be the most significant driver of uncertainty in operational emissions estimates from HDVs (Yanowitz, McCormick, & Graboski, 2000). Thus how, where, and when BEVs are produced, operated, and charged could influence the true mitigation potential of vehicle electrification strategies.

1.2 Goals

At the highest level, the central research question answered in this dissertation is simply: *does vehicle electrification make transportation more sustainable?* Given the multifaceted, complex, and interconnected nature of industrial systems and the natural environment, the emerging nature of many electric vehicle technologies, the uncertainty in technical performance and cost of batteries, and barriers to adoption for HDV applications, the answer is not obvious. To build towards this systems perspective on vehicle electrification, this dissertation explores five different areas where the intersection of temporal and spatial dynamics of these systems are poorly understood.

The goal of this research is to develop and refine methods of assessing the life cycle environmental impacts of BEVs, with the ultimate goal of supporting policy decision making and better aligning technological development with more effective movement of goods and people in a low-carbon economy. Therefore, some chapters of the dissertation focus on methodological questions while others seek to directly inform policy. Specific research questions explored include:

1. What are the constraints and environmental impacts of critical materials for future lithium ion batteries?

2. What factors drive the life cycle environmental impacts and costs of lithium batteries for vehicle applications?

3. How will improving battery technology, shifts in vehicle design, and a changing electrical grid impact emissions reductions of light duty electric vehicles?

4. What are the costs and barriers to adoption of battery electric transit buses?

5. What are the life cycle costs, environmental impacts, and avoided health damages from reduced air pollution of electrifying trucks for goods movement applications?

1.3 Methodological Foundations

LCA emerges from the field of industrial ecology. As noted by Frosch (1992), natural ecosystems are both an analogy and framework for understanding the interconnected nature of systems of extraction, production, consumption, and waste. Industrial ecology as a field has traditionally focused on the "influences of economic, political, regulatory, and social, factors on the flow, use, and transformation of resources," (White, 1994), with goals of efficiency, pollution prevention, and waste reduction (Jelinski, Graedel, Laudise, McCall, & Patel, 1992). The 'cradle to grave' framing of product environmental impact also arises from the field of industrial ecology (Patel, 1992). Life cycle assessment studies are often undertaken in support of these core industrial ecology goals: reducing waste, maximizing efficiency, and enhancing the circularity of waste flows (Kendall & Spang, 2019). In this dissertation, LCA is used to quantify emissions, identify key processes (i.e. hotspots), and assess the abatement potential of BEV technologies.

LCA studies of BEVs have consistently shown an increase in vehicle production emissions, and sometimes vehicle disposal emissions as well, and frequently, though not always, shown a reduction in operation emissions relative to conventional, internal combustion vehicles (ICEVs). For example, Hawkins et al. (2013) found that production emissions comprise approximately 40% of an average European BEV's life cycle greenhouse gas emissions. Samaras and Meisterling (2008) found that production emissions increased modestly for hybrid electric vehicles compared to ICEVs, while Notter et al. (2010) found that the proportion of life cycle emissions attributable to production doubled to more than 30% of life cycle emission for BEVs compared to ICEVs.

LCA is intended characterize the full environmental and resource implications of a particular system, which means examining a suite of environmental impact categories and including analysis of some of the uncertainties inherent in such modeling (e.g. standards require the inclusion of sensitivity and scenario analysis). A limitation of many LCA studies of BEVs is a focus solely on carbon footprint. Carbon footprints, or carbon intensity calculations, apply LCA methods only to GHG emissions, reporting the outcome of the study in carbon dioxide equivalents (CO_2e). Given the significant air pollution impacts attributable to medium and heavy duty vehicle operations, this dissertation also examines the air pollutant impacts of heavy duty vehicle electrification.

While LCA is widely used for decision making (Ciroth, Fleischer, & Steinbach, 2004), LCA has historically suffered from several criticisms and methodological limitations (Richard J Plevin, Delucchi, & Creutzig, 2014). Most notably, there is a growing awareness of the need for robust characterization of uncertainty in LCA (Lloyd & Ries, 2007). The uncertainties inherent to an LCA are well characterized and methods for addressing uncertainty have been reviewed in the literature (Ciroth et al., 2004; Heijungs & Huijbregts, 2004). For example, uncertainty in the results of an LCA can arise from a number of sources: variability in assumed values, lack of knowledge, measurement errors, choices related to the model design, value, and specification (Gregory, Noshadravan, Olivetti, & Kirchain, 2016). Where statistical uncertainties can be characterized, they are commonly propagated through Monte Carlo simulation and explored with scenario analysis. This dissertation utilizes a range of scenario and numerical analysis methods.

The scope of LCA is typically limited to environmental impacts, but the life-cycle framework is also used to assess costs and other metrics for sustainability (Finkbeiner, Schau, Lehmann, & Traverso, 2010; Zamagni, 2012). For example, life cycle costing applies life cycle principles to evaluate the economic impacts of decision making (Fuller & Petersen, 1996; Woodward, 1997). Total cost of ownership, which arises from supply chain management and strategic decision making, uses economic discounting to assess the real costs of owning a product over the entire product's life (Ellram, 1995; Ellram & Siferd, 1998). Taken together, these methods provide a robust framework for assessing costs and benefits of decision-making over time, and the potential to capturing spatio-temporal tradeoffs in impacts. In addition to environmental impacts, this dissertation explores the costs of heavy duty electric vehicles systems and the potential public value of pollution abatement from heavy duty vehicle electrification.

1.4 Contributions

This dissertation tackles issues and uncertainties associated with life cycle assessment of light and heavy duty electric vehicles, with a focus on the design, performance, and materials of electric vehicle batteries. Over several chapters, it develops and refines methods of assessing the life cycle environmental impacts of electric vehicles by exploring key inputs, background systems, and applications. It also assess the adoption costs for electric vehicle systems, before finally turning to an examination of the potential private and public costs of key heavy duty vehicle applications.

This dissertation offers contributions in four areas:

1. Advancing spatial and temporal dynamics in LCA modeling, with respect to:
    a. natural resource modelling (e.g. materials demands and production impacts), and
    b. background systems (e.g. electricity grids) and evolutions in technology and product development (e.g. changing technology performance and vehicle design choices).
2. Developing methods for integrated emissions and cost modelling of electric vehicle systems, including vehicle operations (e.g. travel patterns, tractive power), and vehicle and infrastructure design (e.g. battery and charging systems).
3. Providing an estimate of the life cycle costs and benefits of heavy duty vehicle electrification, including public benefit (e.g. avoided marginal pollution health damages).
4. Informing relevant transportation policy (e.g. California's bus and truck electrification programs).

1.5 Dissertation Structure

The format of this dissertation is as follows:

Chapter 1 provides the background and motivation for this research. Chapter 2 discusses the concepts of Life Cycle Assessment, life cycle modelling, as well as issues related to electric vehicle systems and policy analysis.

Chapters 3 and 4 examine issues related to materials for electric vehicle batteries. Chapter 3 discusses the concept of critical materials and examines future demand and production of lithium for batteries. Chapter

4 links this resource model with a LCA model of global lithium production to estimate the global burdens and intensity of global lithium production for batteries between 2020 and 2100.

Chapters 5 and 6 focus on light duty battery electric vehicles. Chapter 5 examines the LCA of batteries for passenger vehicles, and provides a rank ordering of the most important factors for determining BEV GHG emissions. Chapter 6 considers how changing vehicle design, battery performance, and electricity generation will impact near to mid-term GHG mitigation from light duty electrification.

Chapters 7 and 8 focus on heavy duty vehicle applications. Chapter 7 explores the costs and barriers of electrification for transit bus fleets; it examines the form and impact of a mandate in California to transition all public transit fleets to electric buses. Chapter 8 looks at on-road goods movement applications, and estimates the life cycle emissions, costs, and avoided pollution damages of truck electrification in California.

Chapter 9 summarizes and synthesizes the research findings from the previous chapters and proposes potential next steps for advancing this research program.

2. BACKGROUND

While this dissertation undertakes a range of studies, their coherence lies in: one, the application of LCA methods to model the costs and benefits of vehicle electrification; and two, the goal of informing transportation and environmental policy. LCA and cost studies typically rely on some form of life cycle modelling, during which a parametric representation of the product system is developed and characterized. Setting the goals, objectives, and scope of an LCA are critical to informing the proper development of life cycle models, therefore the motivation for the assessment and measures of system performance (i.e. functional unit) must be well defined. This section provides relevant background on LCA standards and modelling methods. It then discusses environmental policy generally, and then provides background on specific policies in California this research seeks to inform.

2.1 LIFE CYCLE MODELLING

LCA is a standardized methodology for assessing the environmental impacts of a product system (ISO, 2006). The name and an initiative to develop guidelines were first formalized in 1989 by the Society for Environmental Toxicology and Chemistry (SETAC), and its methods first codified in international standards in the mid-1990s (International Organization for Standardization, 1997). LCA standards have continued to advance (Guinee et al., 2010; International Organization for Standardization, 2006a). In the context of on-road vehicles, LCA has been used to identify significant drivers of emissions for vehicle and fuel technologies (i.e. hotspots), as well as compare tradeoffs through physical and economic metrics (i.e. allocation), and to assess potential systems and substitution effects (i.e. attributional or consequential) (Ambrose & Kendall, 2016; James Archsmith, 2015; Kendall & Price, 2012; Wardenaar et al., 2012).

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" (Rebitzer et al., 2004). A LCA can be roughly divided into three key stages: goal and scope setting, collecting and/or calculating life cycle inventories (LCIs), and assessing life cycle impacts. The goal and scope of the LCA are critical to describing the product performance requirements and making smart comparisons. To set the scope of an LCA, it is necessary to quantify the performance requirements of the product; the functional unit measures the performance of the product system. It "provides a reference to which the inputs and outputs are related [and] to ensure comparability of LCA results," (International Organization for Standardization, 2006b). "Thus, selecting a functional unit is of prime importance because different functional units could lead to different results for the same product systems" (Reap, Roman, Duncan, & Bras, 2008a).

The life cycle inventory represents a list of environmental flows resulting from an input or output to the product system. The inventory collection and analysis process involves gathering data on and modelling the elemental flows of materials and emissions at each stage of the product's life cycle. Once elemental flows have been inventoried, life cycle impact assessment involves classifying and characterizing the impacts of these flows. Classification involves sorting pollutants and inputs into categories of potential environmental stressors, or impacts. Once emissions have been classified, their impacts are typically quantified using a standardized impact characterization method. Impacts are measured in relation to a standard reference species for each category, such as CO_2-eq for greenhouse gasses, or N-eq equivalents for eutrophication potential. Characterization factors are applied to convert elemental flows into both category indicators (e.g. CO_2-eq for global warming potential), or end-point indicators (e.g. disability adjusted life years - DALYs).

Impact assessment is applied at varying degrees of comprehensiveness in this dissertation, with some chapters focusing only on GWP (or carbon footprinting – a very narrow form of LCA), as well as others that characterize complete LCIs and impact assessment methods such as the analysis of lithium production impacts over time (Chapters 3 and 4). Chapter 8 takes on a hybrid approach, using LCA methods to characterize GWP impacts of truck systems, while relying on marginal health damages to characterize (i.e. valuation), the impacts of key air pollutants on human health (e.g. particulates, NOx, SOx, and reactive and volatile organic gasses).

This research also addresses both practical and methodological issues of quantifying uncertainty in LCA. Uncertainty can arise from several sources: measurement error, parameter variability, data quality, or model structure (Huijbregts et al., 2001). Historically, LC studies have lacked robust characterization of uncertainty, despite use of LCA and LCC for decision making (Ciroth et al., 2004). The preferred method for estimating uncertainty in modern LCA modelling is numerical analysis and sampling methods (Suh & Heijungs, 2007; Suh & Huppes, 2005). Numerical analysis is concerned with the design and analysis of algorithms that approximate physical and societal systems (Stoer & Bulirsch, 2013). Numerical techniques are widely used to optimize underdetermined stochastic systems and estimate statistical models, often relying on Bayesian processes commonly referred to as machine learning.

The most prevalent numerical analysis performed in LCA is correlated random sampling, also called Monte Carlo Simulation (MCS). In the context of LCA, MCS involves estimating a set of probability density functions for parameter values and exploring the posterior probability of an output function.

The process model yields the estimated output function, and describes the necessary relationships between the inputs. Using MCS results, the variance of input parameters is correlated with the variance of response or output, a well-established technique for linear filtering or other prediction problems (Kalman, 1960). Despite the widespread use of numerical analysis to optimize linear and non-linear systems (Kahraman, Cebeci, & Ulukan, 2003; Petrik, Taylor, Parr, & Zilberstein, 2010), its application to LCA has been limited primarily to global sensitivity analysis. Continued developments in computational methods provide new methods for characterization and optimization of scenario uncertainty and parameter estimates (Van den Meersche, Soetaert, & Van Oevelen, 2009).

Uncertainty analysis and probabilistic modeling methods are applied to varying degrees throughout the chapters of this dissertation. MCS is used to provide a rank ordering of correlated variable importance (Chapter 5), and sampling is used to quantify the probable range of outcomes and conduct significance testing (Chapter 7 and 8). Scenario analysis is also used to incorporate parameter variability and discrete design choices for vehicles (Chapter 6 and 8).

Modelling optimal decision making and policy for complex systems is central to engineering, science, and business. The initial step is the formulation of the system as a function of decisions and constraints (i.e. systems dynamics). The formulation of the problem is also key to ensuring the model is amenable to computational techniques for optimization (Stuart 1956). Farias et al. (2003) describes archetypal complex systems familiar to LCA as problems of three: short run allocation, zero-sum competition, and recurring dynamic decision making. In this dissertation, these concepts are applied in the context of expanding production capacity (Chapter 4), and adopting and deploying electric vehicle infrastructure (Chapter 7 and 8).

2.3 Pollution Abatement Through Technology Change

For several decades, theories relating the drivers of environmental impact have focused on technology (Boserup, 1981). The general theory of environmental impact as a function of technology[1] has in turn led to a number of implicit policy models for pollution control through technology change (Bartlett & Kurian, 1999; Boserup, 1981; Jaffe, Newell, & Stavins, 2002). Increasingly, environmental policy interventions affect the process of technology change by directly setting incentives and constraints on technology markets (Jaffe, Newell, & Stavins, 2003). Yet, the efficacy of pollution control through technology change is often poorly understood.

The effects of environmental policies on technology change may, over the long run, be among the most important determinants of success or failure of environmental protection efforts (Schultze,

[1]The concept of the economic transformation function describes the relationship between an available technology and the ability to produce a set of outputs from a given input of capital, labor and materials. The IPAT model and related theories also describes how environmental impact is related to the per capita use of technology and the diffusion of that technology into populations (i.e. affluence).

1975). A key point of comparison for policy actions is the extent to which they encourage the efficient rate and direction of technology change (Jaffe et al., 2002). But there are many methodological and practical challenges to estimating the long-run impacts of policy action on technology change. Challenges include characterizing the innovation or diffusion of new technologies (Carlsson, Jacobsson, Holmén, & Rickne, 2002; Scherer, Harhoff, & Kukies, 2001), quantifying the impacts of research or demonstration project funding (Reinganum, 1989), or addressing the market structure of specific industries (Sutton, 2001). These are challenges for any technology policy, and regardless of the uncertain relationship between policy action and systems of innovation, policy makers are likely to continue to rely on technology change to achieve regulatory objectives.

Efforts to achieve pollution abatement through technology change must also contend with uncertain technologies and methodological issues of estimating impacts. Moreover, in the context on transportation systems, consideration of the entire lifecycle of both vehicle systems and transportation fuel pathways is critical to achieving emissions reductions from technology change. Three primary issues for policies focused on the heavy-duty sector are selecting performance metrics, setting the scope of analysis, and addressing uncertainty (Munn, 1979; Reap et al., 2008a; Reap, Roman, Duncan, & Bras, 2008b). Substitution and other market-mediated effects also complicate prediction of impacts on pollution from technology change. In total, these issues come down to capturing uncertainty and tradeoffs in the effects of technology change or the appropriate direction to incentivize change (O'Hare et al., 2011; Richard Jay Plevin, 2010; Richard J Plevin et al., 2014).

In general, this dissertation does not consider the potential for market substitution effects including model or modal substitution (e.g. switching between technologies), or other economic impacts (e.g. vehicle travel, price and income effects). These are two of the key limitations of the body of studies presented in this dissertation and opportunities for future research, and discussed further in Chapter 9. Given the political and regulatory focus on technology change, this dissertation aims to inform the design and selection of specific, proposed policies. Chapters 7 and 8 of this dissertation focus on characterizing the drivers of electric vehicle costs and emissions, and the value of incentive programs and emissions reductions.

2.4 California and BEV policy

The chapters of this dissertation frequently focus on California policy, particularly in contrast with the US on average. California is recognized as a global leader in policies to support BEV development and deployment. California has a history of critical air quality issues, including persistent non-attainment areas for federal ozone and air borne particulate matter standards. The South Coast Basin, which includes Los Angeles County, represents approximately 10% of the US population, but 34% of the population-weighted national exposure to ozone above the 8-hour limit. Reactive oxides of nitrogen (NOX) are 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 (EMFAC), trucks and buses are expected to remain the largest share of daily NOX emissions, in both the South Coast and neighboring San Joaquin Valley for the near future. California also has 74% of the national population-weighted exposure above limits for ultrafine particulates (PM2.5), more than half of which is concentrated in the South Coast and San Joaquin Basins.

The state's primary strategy for reducing emissions from HDVs 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 80% by 2032. California has also set a target to reduce GHG emissions 40 percent by 2030 under the Global Warming Solutions Act SB32. To achieve these regulatory objectives, California facilitates the deployment of zero-emission and near zero-emission vehicles and equipment. This includes battery electric medium/heavy-duty vehicles (BEV), fuel cell electric vehicles (FCEV), low NO_X engines, and engines and vehicles with greater efficiencies. California initiated several programs designed to spur increased private investment, accelerate heavy-duty vehicle technology advancement, and move technologies through various stages of commercialization. It is expected that these investments and demonstrations of early market successes can launch additional applications, grow the supply chain for similar powertrain and components, and make these technologies more affordable. Policymakers expect that developing capacity in the private sector will achieve the longer-term goals of providing cleaner air for Californians, meeting the State's climate policy commitments, creating green jobs, and building more sustainable communities.

This dissertation primarily informs the state's mitigation strategy by filling needed research gaps in LCA modelling of heavy duty vehicles, and refining methods of forecasting the performance of heavy duty electric vehicle systems. This includes quantifying and comparing the distribution of cost and emissions at the state level, across a range of vehicle classes and technology configurations. To provide an effective counterfactual for comparison, several chapters also undertake parallel LCA or cost modelling of conventional gas and diesel heavy duty vehicle technologies. A probabilistic approach of characterizing uncertainty in large scale fleet operations and transition costs is developed and demonstrated to support transit agencies' assessment of strategic investments in new vehicle technologies (Chapter 7). This approach is then expanded upon by integrating technological development (e.g. learning on battery costs, improving battery energy density), and the economic benefits of pollution reductions (e.g. marginal health damage cost estimation), in Chapter 8.

3. Lithium Batteries and Demand for Critical Materials

3.1 Purpose and Scope

This chapter further examines the key constituent materials used to manufacturer lithium-ion batteries for electric vehicles. This chapter focuses on lithium, a relatively well characterized element that is both the basis and namesake for electric vehicle batteries. Together, this and chapter 4 develop and demonstrate a method for dynamic life cycle assessment of a resource. Key contributions include the paring of a novel model of resource production with a spatially and temporally dynamic life cycle model of lithium production.

This chapter includes some text adapted from Ambrose, H. and Kendall, A. Understanding the Future of Lithium: Part 1 – Resource model., *Journal of Industrial Ecology* (In Press).

3.2 Critical Energy Materials

Many low carbon transportation technologies and enabling technologies for renewable energy generation, from energy storage devices to traction motors, depend on a short list of materials with unique properties and few substitutes (Bauer et al., 2010). Because the supply of these materials is crucial for their performance, but may also be constrained or put at risk due to natural, geopolitical, and economic forces, they are referred to as critical energy materials. The concept of metal criticality arises from the potential mismatch of resource demand and supply. The preferred methodology for evaluating the criticality of metals involves quantifying the supply constraints, risks, and environmental implications over both short and long time horizons (Graedel et al., 2012). In 2018, the U.S. Department of Interior released a report detailing the importance of critical materials to the economic and national security of the United States (Department of Interior, 2018), and, despite its relative abundance in the lithosphere, the report identifies lithium as a critical energy material due to its importance for electrochemical lithium ion batteries (LIBs).

For more than four decades, researchers have considered whether lithium supplies will meet future demand, especially in the context of increasing demands from new technologies and the risks posed by geopolitical factors (Vine, 1976). Lithium is the dominant electrochemical storage material for traction batteries in vehicles and consumer electronics (Goonan, 2012), and recent growth in demand is primarily from increased use in batteries, which became the largest end-use of high-grade lithium products in 2015. Use of lithium for LIBs increased 30% in 2017, exceeding 20 kiloton (kt) and comprising 46% of total lithium use (Figure 3.1.a).

Over the same time, as illustrated in Figure 3.1.b, the price of battery grade lithium carbonate has also increased rapidly, from less than $3,600 per tonne in 2007, to nearly $14,000 in 2017 (Jaskula, 2018). As the value of high-grade lithium products have increased, 12 million metric tons (Mt) have been added to economically recoverable reserves located primarily in China, South America, and Australia.

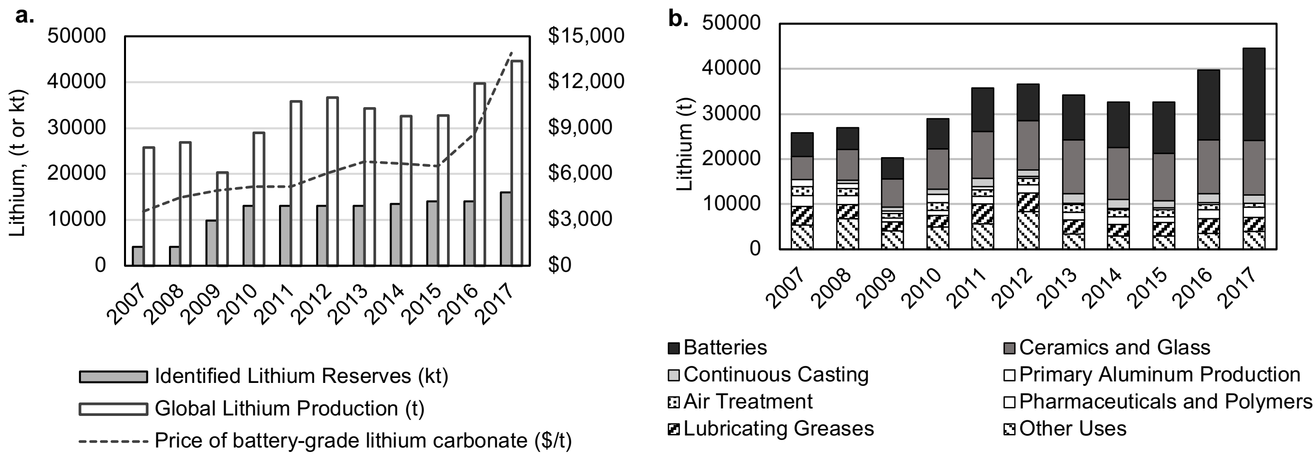

Figure 3.1 (a.) Lithium Reserves and Prices (US dollars), and (b.) Lithium End Uses 2007 - 2017 (Jaskula 2008-2018).

The rapidly increasing demand for large format LIBs in electric vehicles (EVs) and expected use in stationary electricity grid applications to support integration of intermittent renewables like wind and solar has brought renewed attention to issues of lithium supply. At the same time, concerns over the environmental impacts of producing lithium and other resources used in technologies intended to mitigate environmental damages, such as EVs and renewable energy technologies, has also brought focus to the importance of life-cycle based environmental assessments. This article is the first of a two-part article series that respond to the concerns of sustainable lithium supply and its environmental impact. In this first article, a resource model is developed along with an estimate of future lithium demand to evaluate the supply of lithium and expected production from individual lithium deposits between 2018 and 2100. The result of this models provides the basis for part two of this article series, which develops and applies a dynamic life cycle assessment (LCA) model to predict the environmental impacts of lithium production over time, evaluating whether impacts change significantly as demand grows over time.

Many previous research efforts have attempted to estimate the reserves (resources that are economically recoverable today) and the resources (the total amount of a mineral in the earth's crust that may be recoverable at some point now or in the distant future) of lithium, as well as future demand in relation to these estimates. Among relatively recent studies, a wide range of lithium resource estimates have been reported, from 19.2 to 64 Mt of lithium, (Yaksic & Tilton, 2009; Gruber et al, 2011; Wanger, 2011; Vikström, Davidsson, & Höök, 2013).

Studies have also considered a range of vehicle electrification scenarios, and found potential demand for lithium from vehicle LIBs could exceed 4 Mt of lithium carbonate equivalents (LCE) per year. While the majority of studies have not identified a resource constraint related to lithium, some studies have pointed to potential for near-term increases in demand for lithium that exceed available global reserves, thereby necessitating recovery of lithium from recycled sources (Peiró, Méndez, & Ayres, 2013; Wanger, 2011). In addition to considering resource constraints, studies have considered the disposition and quality of deposits. For example, Kesler et al. (2012) evaluated global lithium resources, focusing on the disposition and quality of deposits, finding that even smaller deposits may likely be economically recoverable.

In addition to characterizing reserves and resources, understanding demand for lithium over time is a crucial element for understanding supply risk. Recent growth in demand for lithium is primarily from increased use in batteries, and LIBs are expected to dominate current and future lithium demand (Helbing et al., 2018). Mohr, Mudd, and Giurco et al. (2012) provided historic and literature forecasts of lithium supply and demand, and carefully discussed lithium resources and reserves, as well as the ultimately recoverable resources (URR). A key element of determining demand in Mohr et al. was estimation of lithium demand based on sales assumptions for EV LIBs, assuming each EV required 3 kg of lithium, which falls between estimates in some previous studies that also examined lithium used in EVs (Wanger, 2011; Vikström et al. 2013). Mohr et al. found that the lithium market could expand for several decades with no supply constraints. Further, from 2030 forward, they predicted that growth in supply would be governed by growth in recycling as preferred deposits are exhausted. Though currently not a supply of refined lithium, recycling of LIBs could be an important source of future lithium supply (Gruber et al., 2011; Pehlken, Albach, & Vogt, 2015).

More recent studies have also shown that identified lithium resources are adequate to meet even aggressive demand forecasts (Pehlken et al., 2015). Thus while some studies have identified the potential for near-term supply constraints, many others have concluded that resources are unlikely to be exhausted in the foreseeable future. Lithium is also a relatively small cost component of LIBs and therefore growing demand for batteries may be somewhat unresponsive to even large increases in the price of lithium (Ciez & Whitacre 2016).

This article adds to the growing body of research on lithium and critical materials by developing a novel model of primary lithium production, and providing a review and comparison with past studies. The lithium resource model is used to predict the geographic and technical development of future lithium production capacity given a range of potential demand scenarios and production costs. Another novel feature of this study is the inclusion of battery reuse and repurposing strategies in the assessment of lithium recycling, a gap in some previous studies that could affect the timing and availability of recycling potential. The underlying data, the model approach, and results are transparently reported to provide a basis for part two of this article series, the LCA.

3.3 METHODS

An integrated model of lithium resources is developed to investigate the production and disposition of primary lithium, as well as potential stock of recycled materials. Demand for lithium is estimated from historic, current, and projected market data. The resource production model solves for the optimal or cost minimizing arrangement of annual production and production capacity of each mineral deposit based on the physical and economic properties of the deposit. A recycling model is also developed to understand whether and at what magnitude secondary resources might influence supply and the dispatch of new primary product capacity in the future. Figure 3.2 illustrates the modeling framework undertaken in this research.

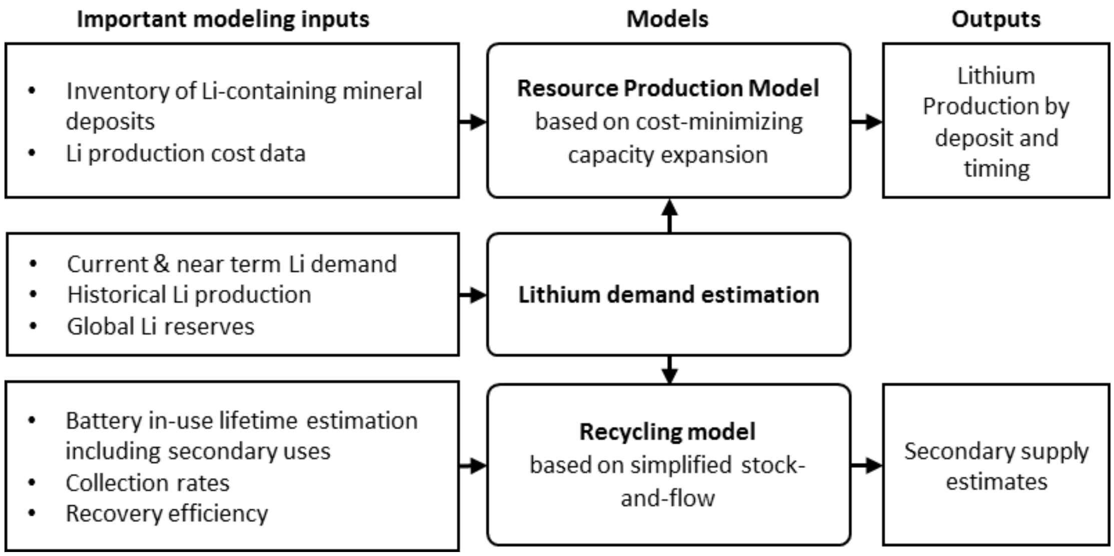

Figure 3.2 Modeling Framework

3.3.1 LITHIUM PRODUCTION AND DEMAND

The economic and technical availability of lithium resources given a particular level of demand govern the production of lithium. Previous studies have examined the production patterns of finite resources; most notably Hubbert (1959) found that the production of petroleum resources closely followed a bell shaped or logistic growth curve (Eq.1). In Equation 1, the cumulative production of a resource in year t is q(t), where URR is the total resource available, t_0 is the year of peak production, and k is the growth factor. Several studies have subsequently shown that production of finite resources, such as petroleum, coal, copper, and phosphorus have experienced predictable logistic growth patterns in production (Bardi, 2005; May et al., 2012; Mohr & Evans 2008). Logistic growth curves have also been used to evaluate and forecast lithium production (Mohr et al., 2012; Vikström et al. 2013). Application of these models are predicated on ex-ante knowledge of the URR. While the URR cannot be precisely predicted, it is typically assumed to range somewhere between what is currently recoverable, and the limits of occurrence within the lithosphere.

$$q(t) = \frac{URR}{1+e^{-k(t-t_0)}} \quad \text{Eq.1}$$

In order to estimate URR, this study relies on identified deposits and prior published estimates of deposit resource base. These data suggest there is a wide range of potential URR, from 55 Mt to 99 Mt of lithium as Li metal, or 293 to 527 Mt of LCE. This span of resource estimates is used to estimate a low-demand, or conservative, scenario and a high-demand, or optimistic, scenario. This study also adopts a logistic growth model of lithium production estimated using historical production data combined with an estimate of near-term lithium demand for LIB production from 2018 to 2030. The near-term demand lithium demand estimate is based not on technology adoption predictions, but instead on three factors, (1) planned and commissioned LIB manufacturing capacity (Curry 2017); (2) improving LIB energy densities (U. S. Department of Energy 2017), and (3) market shares of LIB cathode types (Olivetti et al. 2017). The near-term appraisal is assumed to reflect perceived growth in demand for batteries across multiple sectors, including traction (i.e. EV) and stationary (e.g., grid storage) applications. The growth model was estimated using nonlinear least squares and implemented in R, a statistical computing environment (R Foundation for Statistical Computing 2012).

Figure 3 shows half the last century of global lithium production and the production futures developed for the lithium resource model described above. Global production of lithium was very limited until around 1950, but production then increased by an order of magnitude over the last two decades (note log scale in Figure 3). Under the conservative scenario (the lower bound of the projection shown in Figure 3.3), production increases from 237 thousand t lithium carbonate equivalent (LCE) in 2018, to 4.4 million t LCE/year by 2100. Under the optimistic scenario, demand continues to increase steadily after 2050, to 7.5 million t LCE per year in 2100.

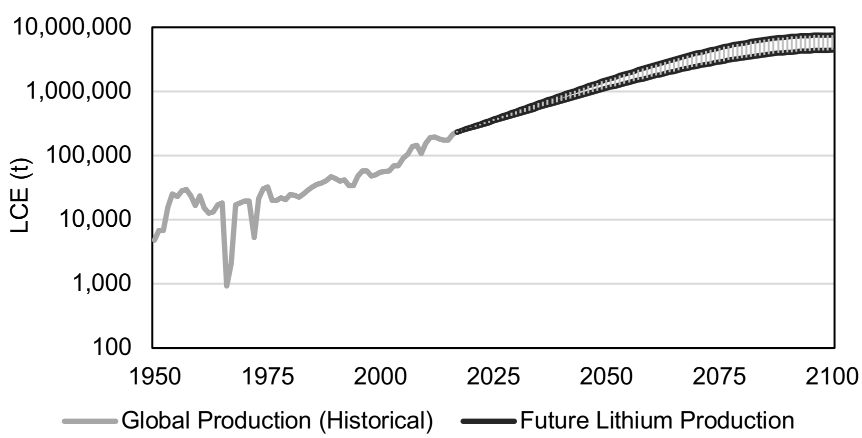

Figure 3.3 Historical Lithium Production 1950 – 2017, and Forecast Global Lithium Production 2018 – 2100 (British Geological Survey 2018, Jaskula 2008-2018)

For comparison, Mohr et al. (2012) estimates lithium production in 2100 to range from 3.2 to 7.45 million t LCE based on a sustained demand of almost 4 million t LCE per year for batteries. Other studies have generally found lower levels of demand for lithium (0.7 to 2 Mt LCE), due to the assumed URR, the estimate of lithium demand, or assumptions about recycling (Vikström et al., 2013; Pehlken et al., 2015).

3.3.2 Characterization of Lithium Resource Deposits

Based on previous studies and publicly available information, 112 deposits of lithium-containing minerals with data on location, mineral type, and/or ore grade were identified. Of these, 32 deposits had available estimates of economically recoverable reserves and mineral samples (Appendix A-S1). Bootstrapping was used to impute ore grades and composition information where feasible, resulting in a final list of 95 individual deposits that were sufficiently characterized for inclusion in the analysis. The study focuses on primary recoverable resources and does not consider unidentified or unconventional resources, although potential implications of these sources are addressed in the discussion section. The upper bound for URR was estimated at 99.5 Mt, with 37.5 Mt Li in current reserves. The majority of current reserves are contained in a few high-grade brine deposits. As evident in Table 3.1, 80% of lithium deposits and 60% of the estimated total maximum resource are contained in low-grade pegmatites and brines.

Deposits were classified by the production pathway required to mine and refine the ore. Six discrete production pathways were identified based on the grade of deposit, the deposit mineral type, the location of the deposit, and ratio of magnesium to lithium content for brines. Two binary variables were used to include location data, the first being the presence of developed reserves in the country (e.g. true or false), and the second established access to international markets (e.g., developing economy or no). A hierarchical tree was used to identify the divisions in resource grade and mineral types.

Table 3.1 Lithium Deposits and Reserves by Production Pathway

Process Model	Deposits	Reserves (Mt)	Resources (Mt)	% Li Content (Avg.)
High-grade Pegmatite	15	0.72	3.75	1.605
Low-grade Pegmatite	37	7.10	24.78	0.761
Low-grade Lithium Minerals	20	0.35	3.69	0.301
High-grade Brine	4	17.30	37.90	0.105
Low-grade Brine	14	9.85	23.92	0.035
Low-Grade Brine/Unfavorable	5	2.20	5.77	0.004

3.3.3 Unit Production Costs

A descriptive model of production costs was derived through regression analysis of published lithium production cost estimates. Production cost data were gathered from a variety of sources, including technical analyses of LCE production facilities (Laferriere et al., 2012), lithium sales data (Shi, Facada, and Radford 2018), and industry and company reports (Johnston, 2016; Staiger, 2017; Roskill, 2017; Roskill, 2015). Cost estimates were adjusted to the current year (2018 USD) from the estimate year using the Producer Price Index (non-seasonally adjusted metals and metal products). As no PPI for Lithium or equivalents is available, this was based on parts for electronics and cathode materials. Specific information identifying the deposit was available for approximately half the cost estimates identified. There was also significant variation in the estimated LCE production cost (+/- 56%) for the same deposit in real dollars. Estimates were disproportionately available for deposits that are currently developed, which is likely also true where the deposit name was not available.

The association of production costs with several explanatory variables were investigated, including, country of origin, grade of deposit, mineral type, lithium content, and years since initial development. Lithium produced from pegmatite sources was generally observed to cost more than brine (Figure 3.4). Lithium production costs vary by country of origin, with production in China being notably more expensive even when controlling for the large amounts of low level deposits. The grade and type of deposit explain the majority of variation between cost estimates and were used as the basis for the production cost model.

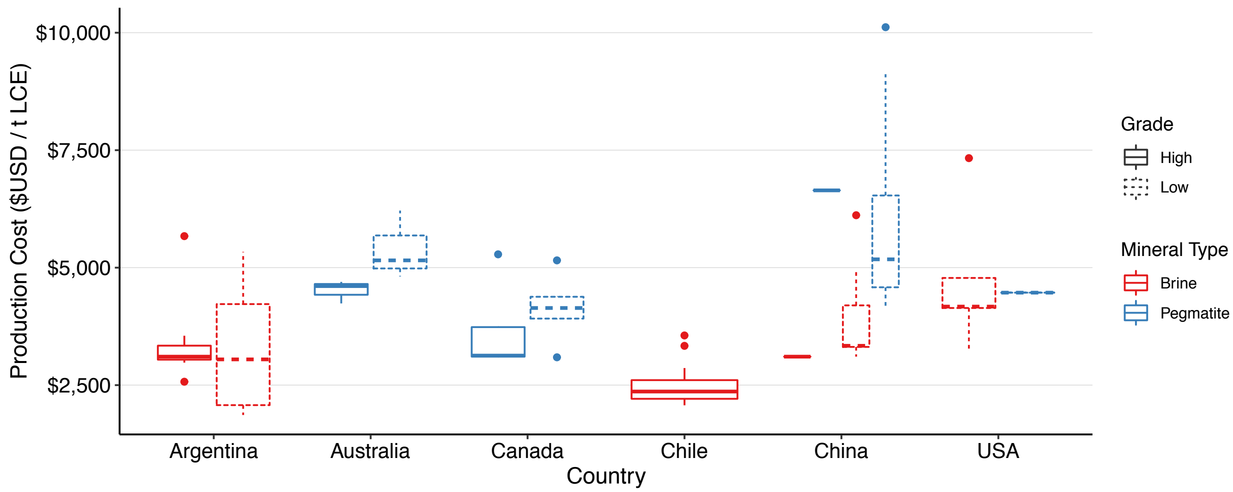

Figure 3.4 Lithium Average Production Cost by Deposit Country, Type, and Grade

A multilevel model was used to estimate the mean (average) production cost for each combination of grade and type, with an error term based on mineral type. The estimated coefficients for production costs for each production pathway are provided in Table 3.2. The summary of the model, coefficient estimates, standard error, and significance test values are also provided in section S2 of Appendix A.

Table 3.2 Estimated Lithium Production Costs (2018 USD)

Deposit/Production Type	$/t	Std. Error
High-grade Brine	$2,869	$292
Low-grade Brine	$3,746	$292
Low-grade Brine/Unfavorable Conditions	$5,434	$923
High-grade Pegmatite	$4,283	$435
Low-grade Pegmatite	$5,080	$326

Low-grade Rock Minerals	$6,517	$533

3.3.4 Resource Production Model

A linear capacity expansion model was used to estimate future lithium production as a function of production capacity expansions. The model solves for the production and capacity at each deposit for each year with a minimum total system cost, where system costs are estimated as the cumulative sum of,

$$\min_{x_{it}^{prod},\, x_{it}^{cap}} \sum_i \sum_t \left(c_i^{cost} x_{it}^{prod} + c_{it}^{cost.cap} x_{it}^{cap}\right) \qquad \text{Eq. 2}$$

Where x^{prod} is the production volume in tons at each deposit (i) in year (t), and x^{cap} is the annual production capacity. The total production cost for each deposit i in year t is the sum of production costs and capacity costs.

The model is subject to the following constraints,

$$\sum_t x_{it}^{prod} \leq URR_i, \forall\, i \qquad \text{Eq. 3}$$

Total production from each deposit does not exceed the deposit URR (Eq.2).

$$x_{it}^{cap} - x_{it}^{prod} \geq 0, \forall\, it \qquad \text{Eq. 4}$$

Production in each year is less than production capacity at that deposit (Eq.3).

$$\sum_i x_{it}^{prod} \geq Demand_t, \forall\, t \qquad \text{Eq. 5}$$

Production in each year exceeds demand based on the logistic growth model (Eq.4).

$$x_{it}^{cap} \leq {}^{URR_i}/_{\beta}, \forall\, it \qquad \text{Eq.6}$$

Production capacity at each deposit cannot exceed the recovery limit (Eq.5), which we define as the URR divided by the minimum design years for a lithium production facility (β). The average minimum design years or service years of a mine is estimated from Mohr et al. (2012) to be 55 years. This constraint also serves to discourage large expansions in capacity that would potentially strand capital investments before the end of their useful life.

Mine capacity costs and ramp rate limits are drawn from Mohr et al. (2012), and modelled after the Beta-Version Peak Lithium Extraction Model used. Capacity costs are estimated as a function of the current deposit reserve and total deposit URR with Eq.7,

$$\alpha_{it} = e^{{}^{URR_i - Reserve_{it}}/_{URR_i}} \qquad \text{Eq.7}$$

The capacity cost factor α is multiplied by the production costs to estimate the capital costs for each deposit. The capacity cost factor decreases to one as the reserve approaches the total URR for the deposit. Reserves are set in the initial year based on current reserve estimates, and relaxed in constant five year increments towards the estimated URR for the deposit. In this way, the resources gradually become reserves, which determines overall production capacity and system costs.

The model estimates the most likely disposition of future lithium supplies (e.g. share of production across deposits) over the study horizon (2018 to 2100). A minimum cost solution for the system was identified using the revised simplex method.

3.3.5 Stock and Flow Model for Recycled Lithium

In addition to the production of primary, the potential for recycled lithium from batteries was investigated via a simplified stock and flow model of the lithium production system (Appendix A-S3). We track four stocks, lithium in primary resources, lithium in batteries, lithium in secondary resources, and lithium in waste stocks awaiting recycling. The flows between these stocks are mitigated by several factors, including,

- Production rate – global production of LCE
- Lithium for batteries– share of total lithium market for large-format LIBs
- Battery material production efficiency – the inverse of material losses during production
- Battery service lifetime – years in primary application
- Battery end-of-life collection rate – the rate which batteries are collected for recycling or second-life when retired
- Battery second-life survival rate – the percentage of retired batteries that can be repurposed to serve economically in a secondary application
- Battery secondary service lifetime – years in secondary application
- Recycling material recovery efficiency – percentage of material recovered from recycled batteries

Given these dynamics, we explored the potential stocks and flows of LCE in both primary recoverable resources and recycled batteries. The projection assumes LCE for batteries increases linearly to 80% of end use by 2040 (Department of Interior, 2018). As a simplifying assumption, we assume batteries serve between 8 to 10 years in a primary application, after which 55% of batteries serve in a secondary application for up to 3-6 years (Jiao & Evans, 2016). As an optimistic projection, we assume collection rates for recycled batteries also increase linearly from 55% in 2018 to 85% in 2100, despite the fact that current collection rates are much lower (Swain, 2017).

The material efficiency (e.g. rates of recovery) are likely to vary by both the type of process used, when in the future the battery is recycled, and chemistry of the cathode. A number of cathode chemistries have been considered for or used in large format lithium batteries. While the current market for cathode materials seems to be coalescing around the Nickel Manganese Cobalt formulation, the mixed chemistry waste stream of disused batteries is likely to confound the economics of recycling processes and makes predicting recovery rates difficult. We draw an assumption for a hypothetical, three-stage recycling system from the critical review of recycling literature by Zheng, Li, and Singh (2014). The net recovery rate for lithium in cathode materials after secondary and deep recovery processes was estimated to be 51%. Further information on the recycling model is provided in the Appendix A.

Currently, lithium recycling is nascent and there are insufficient data on the costs of recycled lithium. Based on available prior studies, the cost of leaching chemicals alone for lithium carbonate from recycled batteries could be more than the $8 per kg or $8000 per metric ton LCE (Gratz et al. 2014). As capital and other operational costs would undoubtedly increase the cost of production, the price of recycled lithium carbonate would be significantly higher than the average cost of production of lithium from primary sources. Thus, the model would not select to expand capacity from recycled stocks based on cost minimization until all other primary resources were exhausted. Instead, impacts of lithium recycling on primary lithium production are examined through a displacement scenario, i.e. where recycled lithium displaces primary production, for the optimistic scenario. The full results of the displacement scenario are available in the Appendix (A-S3.

3.4 RESULTS

Results are shown for optimistic and conservative scenarios. Under the optimistic scenario, production increases to 7.5 million t LCE by 2100 (Figure 3.5 a and c). Under the conservative scenario, peak production reaches 3.5 million t LCE in 2100. The results of the analysis show that for the near-term, the majority of demand for lithium is likely to be met by existing production from lithium brines. In fact, given recent expansion in lithium brine production capacity, expansion at new deposits is not required until after 2035.

While the majority of current lithium is supplied from a single brine source (SQM Atacama – Chile), future increases in demand are likely to require the development of new and widely distributed resources (Figure 3.5 – green in c and d). Brines continue to make up the majority of production (67%) through 2100, owing to their lower production costs and significantly larger resources. However, production shifts to include undeveloped, low grade US and Chinese brines after 2050. This shift in lithium sources translates to a significant increase in lithium supplied from low-grade or less favorable deposits. By 2100, pegmatite and mineral sources provide 33% of total production.

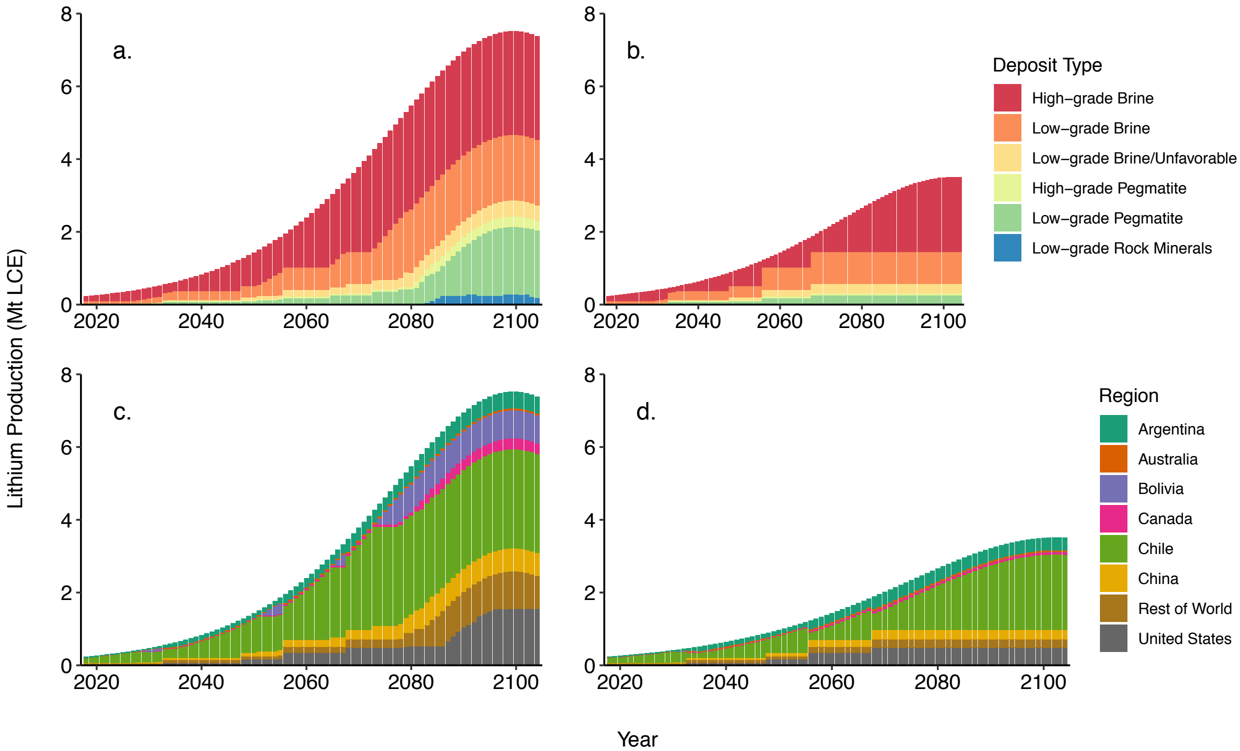

Figure 3.5 Lithium Production by Deposit Type and Country for Optimistic (a and c) and Conservative (b and d) Scenarios

Under the conservative projection, only moderate production from pegmatite resources is required, while brine resources are even more dominant (Figure 3.5b). This suggests that future production from existing high grade brines could be sufficient to sustain a large battery market for the next century.

3.5 Discussion

Compared with previous efforts, this study did not identify a potential resource constraint related to lithium for LIBs. Identified lithium deposits have continued to expand, and this study finds both higher production levels of lithium, and larger potential lithium resources compared to previous studies. While lithium deposits are distributed widely, deposit types are clustered, with identified high-quality brines being far less common geographically. Conversely, a majority of identified pegmatite deposits are less well surveyed and poorly characterized. Deposits often require extensive sampling to reliably estimate the grade of the deposit and how the distribution of minerals might influence ultimate recoverability. One potential limitation of this work is the lack of consideration for short-term supply disruptions (Helbig et al. 2018), or potential knock-on effects from developing near-by or co-located deposits.

We explored the potential stocks and flows of LCE in both primary recoverable resources and recycled batteries to understand the potential effects on resources. If current rates of collection for recycled LIBs persist, stocks and flows of recovered lithium would be very small. Therefore, we consider the potential for recovery of recycled materials given improved collection systems. We assume an optimistic rate of battery collection, increasing linearly from 55% to 85% of batteries by 2100.

Figure 3.6 shows the key lithium stocks and flows between now and 2100; shaded regions reflect flows in t LCE, while lines correspond with the stock of LCE in Mt from primary sources (solid) and recycled sources (dashed). By 2060, batteries retired and collected for recycling each year could represent 320,000 t of LCE; greater than current global production. If current low rates of collection persist, the potential flow of recovered LCE in 2060 decreases by a factor of ten. Assuming lithium recycling infrastructure remains undeveloped, disposed LIBs could accumulate in waste supplies and represent a potential stock of LCE to recover. By 2100, the total stock of LCE in waste batteries awaiting recycling could approach 25% of global primary reserves. A continued lack of development in recycling systems for LIBs over the next century is unlikely given the presence of other high-value materials in battery cathodes, namely cobalt, nickel, and copper (Wang et al., 2014). But in addition to the potential for LCE accumulation in waste stocks over the near to midterm, this analysis demonstrates how LCE might accumulate in in-use supplies through the cascading applications of second-life batteries.

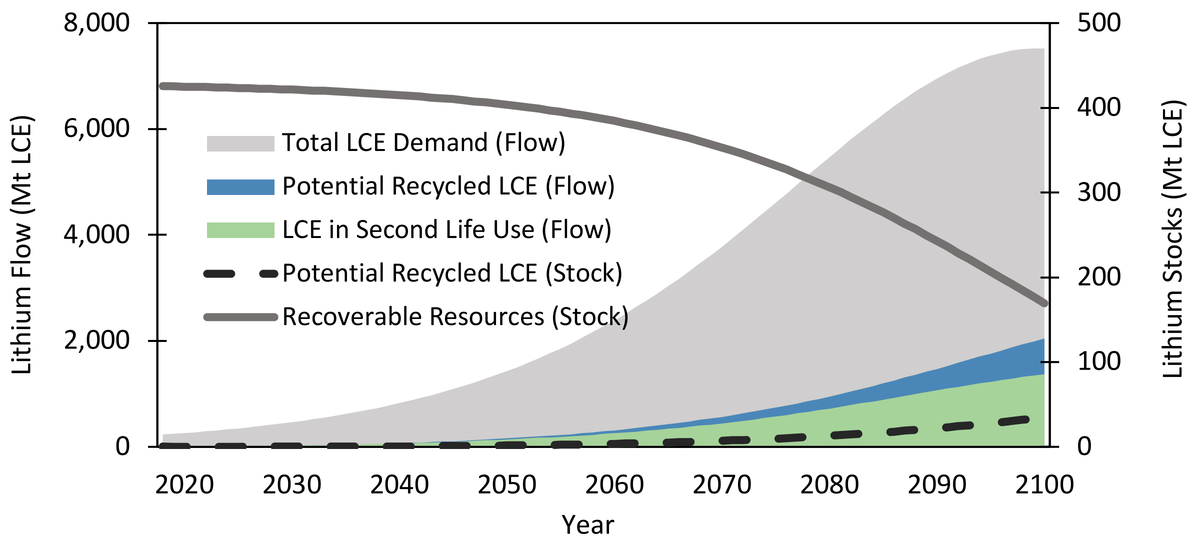

Figure 3.6 Stocks and Flows of Recycled Batteries, Recoverable Resources, and Global Production of Lithium

As noted previously, the costs of recovering LCE from recycled batteries are currently prohibitive. But given policy supports or further technical innovation, it is reasonable to assume that recovered lithium from recycled batteries could be used to displace primary production of LCE. Should recycled lithium displace primary production, it could reduce annual demand for primary lithium by 11% by 2050 and 28% by 2100. Given the system lag in recycled stocks, the potential for recycled lithium would continue to increase after 2100, to over 50% of primary lithium demand by 2020. This indicates the potential long term importance of recycled batteries and recovered lithium to global lithium supplies.

In addition to lithium recovered from spent batteries, the development of unconventional or unidentified resources could also serve to expand the URR available. The most notable and studied unconventional source of lithium is seawater. Previous studies have noted the abundance of lithium in seawater, including the vast resource potential at 20,000 times identified terrestrial deposits (Fasel, 2005; Tahil, 2007). While studies have suggested recovery from seawater is theoretically possible (Kushnir, 2012), the broader literature suggests that costs of extraction from seawater are prohibitive (10-30 times higher than conventional sources), require vast withdrawals of water, significantly increase production energy requirements (Grosjean, 2012; Bardi, 2010), and is therefore unlikely. Perhaps the best discussion of the infeasibility of extracting lithium from seawater is provided by Vikstrom et al. (2013) who note that despite the relatively large abundance of gold in seawater, it is not commercially viable to process the vast quantities of seawater required to produce even a few kilograms of gold. As noted by both Vikstrom et al. (2013) and Tahil (2007), lithium recovery from seawater would require a processing flow of approximately 5,000,000 m^3/t of lithium produced based on an average concentration of 0.17 ppm.

3.6 Conclusions

While some previous studies found resource shortages might occur due to significant increases in LIBs for vehicles, this study did not. Moreover, this study included a novel approach for lithium demand based on projected manufacturing capacity, which reflects more comprehensive demand for lithium for LIBs including other large format LIB users in the heavy duty and stationary power sectors. The findings of this study also indicate that improvements to battery recycling and material recovery systems are critical for recycled batteries to become a significant portion of future lithium supplies. While the effects of increasing lithium demand on global lithium production have been the focus of other studies, little work has considered how production dynamics will affect the average environmental intensity of commodities like lithium for batteries. In part two of this study, a dynamic life cycle inventory model is developed to link with the resource model described in this paper. Taken together, this research describes and refines a method for dynamic life cycle assessment of critical materials.

3.7 References

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4. Dynamic Life Cycle Assessment of Future Lithium Supply

4.1 Purpose and Scope

This chapter considers the life cycle environmental impacts of producing and refining lithium for electric vehicle batteries. This chapter builds directly on the previous chapter. Chapter one developed a forecast of lithium demand and coupled it with a spatially-resolved resource model to predict, at the resolution of identified deposits, the primary lithium resource production over time from 2018 to 2100. This chapter uses the results presented in one to develop a temporally and spatially resolved life cycle assessment (LCA) of lithium that reflects the changing sources of lithium expected to be dispatched over time. The result is a normalized inventory for lithium production for batteries and an estimate of the global burdens of future lithium demand.

This chapter includes some text adapted from Ambrose, H. and Kendall, A. Understanding the Future of Lithium: Part 2 – Dynamic Lifecycle Assessment., *Journal of Industrial Ecology* (In Press).

4.2 Introduction

An array of emerging technologies, from electric vehicles (EVs) to renewable energy systems, rely on large-format lithium ion batteries (LIBs). Improving performance, increased production, and decreasing prices of large format LIBs has enabled remarkable growth in these clean energy applications. In response, global production capacity for LIBs is expected to triple in the next five years, exceeding 300 GWh by 2022 (Curry, 2017). This means that the constituent materials used in LIBs must be produced at increasing rates as well. By 2030, global demand for lithium in LIBs is expected to range from 300-600 thousand tons of lithium per year, comprising more than three-quarters of total lithium demand.

Two key issues for LIBs and emerging technologies that rely on lithium batteries are resource constraints and environmental impacts that occur during production. Growth in demand for LIBs across a number of sectors is already placing strains on current lithium production capabilities, and will likely move production to increasingly low-grade resources over time (Helbig, C., Bradshaw, Wietschel, Thorenz, & Tuma, 2018; Ambrose & Kendall, 2019). It is unclear how the dynamics of supply and demand will affect the life cycle environmental impacts of lithium, and thereby the environmental impacts of technologies that rely on LIBs. Given the role of LIBs as an enabler of technologies associated with mitigating environmental impacts (e.g. electric vehicles and renewable electricity integration), the potential increase in impacts from lithium production are a concern.

LIB demand is fueled in part by the falling price of LIBs; cost targets for LIBs set 10 and 15 years ago have already been met and exceeded; with costs now expected to fall below $80/kWh, enabling economic deployment in an increasing range of applications (U. S. Department of Energy, 2017; Curry, 2017; Nykvist & Nilsson, 2015). Falling prices for LIBs are not a consequence of falling lithium prices. In fact, demand for lithium for use in LIBs is likely insensitive to increases in the price of lithium (Ciez & Whitacre, 2016) because, despite their name, the actual content of lithium in LIBs is low, and relative to other costs in manufacturing, lithium costs are not large. Thus, significant increases in the price of battery grade lithium carbonate may not slow adoption of LIBs and thus demand for LIBs.

Recent growth in the demand for critical energy materials, which includes lithium, is a concern for climate mitigation efforts and local environmental impacts. Previous studies have investigated the effects of increasing demand and decreasing resource quality on the environmental impacts of metal production. For example, production of copper has shifted to increasingly low grade resources with lower yields over the last century (Crowson, 2012; Memary et al., 2012). Studies have indicated the significant decrease in the average copper ore grade, from greater than 12% Cu to less than 1% Cu by mass, has been accompanied by an order of magnitude increase in energy required for mining and beneficiation (Northey et al., 2017). The grade of the deposit affects the design of the mine and processing facilities, as well as overburden, effluent and tailings generated, all of which influence the LCA of metals production (Durucan, S., Korre, A., & Munoz-Melendez, G., 2006). Average ore grade has been proposed as a characterization factor for comparing the life cycle environmental impacts of metal extraction (Vieira et al., 2012). Coupled with continued growth in demand for copper, these trends could result in a doubling of the climate impacts associated with the global copper cycle by 2050 (Kuipers et al., 2018).

While several studies have considered the environmental impacts of lithium used in cathode materials and batteries (Grosjean et al., 2012; Speirs et al., 2014; Swart, Dewulf, & Biernaux, 2014; Notter et al., 2010; Li et al., 2014; Yu et al., 2014), only one study has considered potential variability in impacts resulting from the different resources that can supply lithium. Stamp, Lang, and Wäger (2012) modeled the production of lithium carbonate from generic brine and rock (i.e. pegmatite) sources, and considered potential implications for the environmental impacts of LIBs. They found that carbonate from rock deposits generally have higher impacts than those from brine production, but that heating brines to accelerate the removal of water can quickly increase energy inputs and thus emissions related to lithium production (Stamp et al., 2012).

While previous studies focused on issues and dynamics of lithium supply and demand with respect to the rapidly increasing demand for LIBs, no studies combined this modeling with quantitative assessment of environmental impacts from lithium production at different sites and from different resources. Thus, the relationship between the environmental intensity of lithium production and increasing demand over time has not been previously explored. In addition, the projections of LIB demand for EVs have been highly variable across studies. Here we investigate the temporal dynamics of environmental impacts of lithium carbonate used for LIBs in the context of increasing demand and the need for expansion of production to new sites.

To estimate environmental impacts dynamically we undertook the following research steps (steps one and two were completed in part one of this article series, while step three was completed here in part two):

(1) Provide a novel forecast for demand for battery grade lithium carbonate to 2100 based on capacity for lithium battery manufacturing.

(2) Develop a resource model to link forecasted demand to global lithium resources, development of known reserves, and the relative costs of dispatching new lithium resources to yield estimates of lithium production over time differentiated by the source deposit, which determines location and ore type of source.

(3) Develop LCA models founded on regionalized background data and engineering-based models for mining and refining of different resource types and resource qualities to evaluate the effects of expanding the supply of lithium on the environmental impacts of lithium for the battery market.

Two scenarios for lithium production, an optimistic (high-demand) and a conservative (low-demand) scenario, were developed. Under the optimistic forecast, demand continues to increase steadily after 2050, to 7.5 million t LCE per year in 2100. In the conservative scenario, global production increases from 237 thousand tons LCE in 2018, to 4.4 million tons LCE/year by 2100. The results of the resource model suggest that production from high grade brines could be sufficient to satisfy the majority of demand through 2035, but sustained future demand will require the development of lower grade and unfavorable deposits (Ambrose & Kendall, 2019).

4.3 METHODS

This study undertakes a temporally dynamic (considering an annual time step each year between 2018 and 2100) LCA of battery grade lithium carbonate, tracked in units of lithium carbonate equivalent (LCE). The scope of the LCA includes energy consumption, chemicals, blasting and other site emissions to air and water, but excludes land transformation and some impacts from tailings (e.g. processing wastes). Regional energy inventory data were also used to reflect differences in primary energy sources and conversion technologies. The study provides a novel set of life cycle inventories (LCIs) for lithium carbonate used for large format LIBs (such as those used in EVs). Contributions of this study to the existing body of work include several factors that either are absent in previous studies or have been identified as requiring additional research. These include:

- Inclusion of demand for large format LIBs sectors other than light-duty passenger vehicles (i.e. heavy-duty vehicles and stationary applications).
- Changes in production sources (i.e. expansion of existing sites and development of new deposits) over time.
- Variability in energy requirements and efficiency of lithium carbonate production across lithium deposits.
- Regional availability of primary energy sources and electricity generation technologies.

The methods used to develop the resource model are available in part one of this article series (Ambrose & Kendall 2019); here, we discuss the development of the LCA model.

4.3.1 GOAL AND SCOPE

The goal of the LCA model is to estimate the life cycle impacts for producing LCE from available primary resources. The scope of the LCA is from mine to processor or refining gate and reflects specific resource conditions (e.g. the concentration of lithium in the ore), and differences in background systems (namely national-level energy systems). The functional unit selected is 1 kg of battery grade LCE (>= 99% Li_2CO_3 by content). Figure 1 provides a summary of the key processes and inputs included in the LCA model, and highlights the stages at which dynamic inventory modules have been developed to reflect local environmental conditions, regional availability of primary energy sources, electricity generation technology, and the effects of resource quality on material extraction, transportation, and refining processes. Future technological development in production machinery or electricity generation (e.g. increased renewables deployment) were not included in the scope. Potential implications and limitations of these assumptions are briefly summarized in the discussion section.

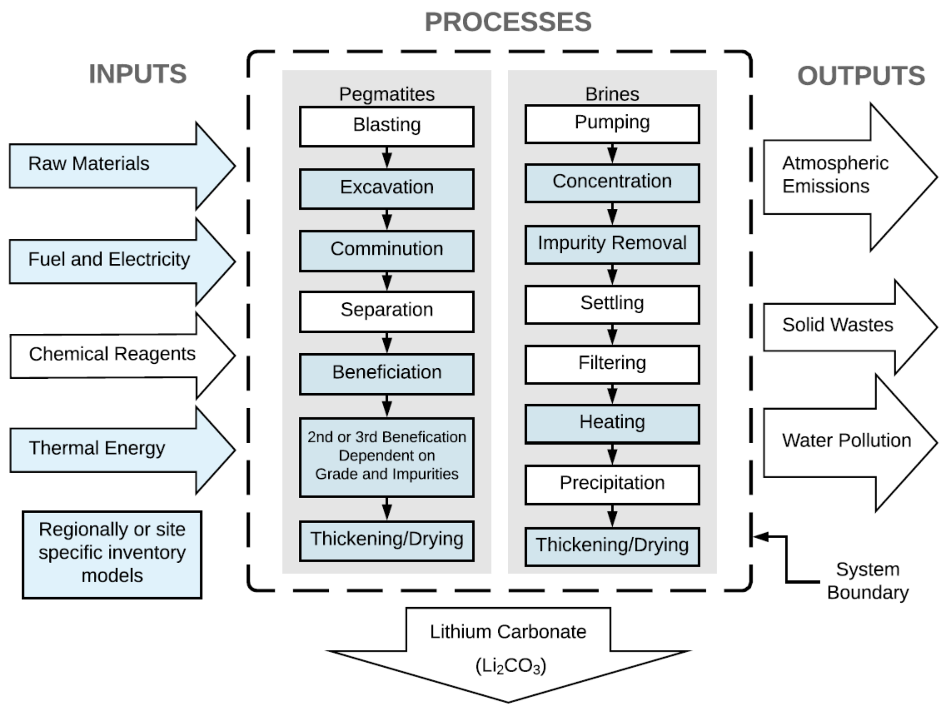

Figure 4.1 Flows and Processes included in the Life Cycle Assessment Model

4.3.2 LIFE CYCLE INVENTORY MODEL

The lithium production process can vary from deposit to deposit, and many of the specifics regarding lithium processing are proprietary. Compounding the potential variability across production sites, many companies use different techniques for lithium processing depending on the desired outputs. Influencing factors include the concentration and distribution of lithium minerals within the deposit, the overall grade of the deposit, the presence of contaminants (such as magnesium), and the location of the deposit (Garrett, 2004). Production system design may also vary by estimated returns on different grades of output, for example low-grade hydroxides versus high-grade carbonate for LIBs, in addition to loss of product (e.g. tailings and slimes). The life cycle inventory (LCI) model differentiates based on resource type and resource quality. Separate production models were developed for each of the two resource types, classified as other minerals (mostly pegmatites) or brines, and then tailored to specific deposit conditions based on ore grade and background systems (namely the fuel source and electricity grid).

For pegmatite resources, the first stage in production includes mining and raw ore recovery, which are affected by ore grade and depth of the deposit. The major processing steps for these hard-rock minerals involve screening, comminution, magnetic separation, froth flotation, and drying (King, 2001). Screening is the initial step to separate inputs based on particle size, followed by crushing. There are many different methods to achieve crushing based on the inputs, desired outputs, and rate of production. Aside from the grinding, power supply for conveyors is also required to transport materials. Magnetic separation is used to remove any magnetized contaminants (such as iron). Although requirements range depending on the field strength needed, low intensity magnets can be used to generate up to a 15-kG field with only 16 kW of energy per pole needed (King, 2001). The largest energy inputs directly associated with pegmatite processing are heating, and comminution (Garret, 2004).

After recovery, raw ore is processed through one or more additional circuits: dry material separation and recovery, heavy liquid material separation including froth flotation (FF), and hydrometallurgical recovery (HMR). Froth flotation is a widely used technique in mineral processing to separate materials based on the ability of air bubbles to attract and remove certain particles while other particles remain behind (Kawatra, 2001). The process is a highly variable step in pegmatite processing, primarily due to the unique physical and chemical properties of processing inputs depending on the location of mineral extraction. Froth flotation involves dewatering, the production of a rougher float and a cleaner float, and thickening with a goal of maximizing a high degree of recovery and meeting market specifications. Froth flotation of lithium spodumene can be achieved through anionic or cationic flotation. Anionic flotation typically provides high recovery rates, but lower purity concentrates, and vice versa for cationic flotation.

In terms of energy inputs, froth flotation does not require a significant amount of direct energy, but that does not account for any energy inputs for producing chemicals used in froth flotation. Additional processing also increases production costs, and energy inputs increase across the three processes. For FF and HMR, reagent inputs are also extensive. Reagent costs can represent 50% or more of average production costs, and additional FF and HMR processing may be required to concentrate and refine lower grade mineral deposits (Staiger, 2017).

For brines, extraction begins with drilling to pump lithium brines to the surface, which are then often collected in solar evaporation pools. Impurities in the final brine include boron, magnesium, and calcium. Unless processing facilities are located on-site or close to the evaporation ponds, the brine must be shipped via truck or rail to a processing plant. The major processes involved in the production of commercial grade lithium products from brine sources are impurity removal, settling, filtering, pressing, heating, precipitation, and thickening/drying (King, 2001).

Impurity removal is done as an initial step to remove contaminants, including but not limited to boron, magnesium, and calcium. Boron is removed through solvent extraction. Magnesium and calcium are removed with lime and soda ash, respectively. The percentage of these contaminants in the brine directly affects the amount of solvents or chemicals and processing needed to remove a given impurity (Garret, 2004). Accordingly, the value of a given brine source will range depending on the percentage of contaminants it contains. After the initial impurity removal the remaining mixture progresses through a settling, filtration, and pressing process. Settling can be achieved via gravitational forces. Filter pressing requires pumps that vary in power use and efficiency depending on the inputs and rates of production. The goal of these processes is to increase the concentration of solid matter in the brine and remove unnecessary water and liquids.

The most energy intensive step to lithium brine processing (not including energy for chemical additives) is the thickening and drying processes. Settling and filtering require very low energy inputs and can rely mostly on gravitational forces. After heating and precipitation of lithium carbonate, the resulting solution must be thickened. Sedimentation uses cycles and vacuum belts for the thickening process. The heating and drying is usually achieved through a rotary steam-tube. These machines typically operate with a combustion chamber to achieve temperatures of approximately 980 °C. Lithium chloride and the concentrate is then made into lithium hydroxide or treated with sodium carbonate to produce lithium carbonate. Additional thermal energy is often required for concentrating brines, which may rely on locally available primary energy sources, such as geothermal resources (Yu et al. 2015).

Though ore grades and geologic conditions are continuous variables, to make engineering model development and LCI model development manageable, all deposits are modeled as one of six hypothetical lithium production routes, three designations in descending order of preference for each of two categories of deposits; brines and other minerals. Brines are grouped as high-grade brine, low-grade brine, and low-grade brine with low solar evaporation potential. Other mineral deposits are grouped as high-grade pegmatite, low-grade pegmatite, and low-grade lithium minerals (i.e. those where the main lithium mineral is not identified, and/or is not a pegmatite or spodumene). Throughput, efficiency, and material and energy inputs are estimated based on company reporting, patents, and prior studies (An et al., 2012; Laferriere et al., 2012; Stamp, Lang, & Wäger, 2012; Garrett 2004). Reference LCI datasets for sub-processes and production inputs were taken from the Ecoinvent Database Version 3.3 (Ecoinvent Centre, 2017). To represent variability in energy generation, inventories for grid electricity were selected based on the region of the deposit. A full list of reference LCI datasets, as well as graphical descriptions of the process models are contained in the Appendix B.

4.3.3 Life Cycle Impact Assessment

The LCA model applies the U.S. Environmental Protection Agency's Tool for the Reduction and Assessment of Chemical and other Environmental Impacts (TRACI) impact assessment model (Bare 2011). The following impact categories were considered: global warming potential (GWP), acidification potential, ozone depletion potential, eutrophication potential, photochemical smog formation potential, human health – particulate, human health – cancer, and ecotoxicity. Additional information on the selected impact categories and the indicators used to represent them is provided in the Appendix B-S2.

4.4 Results

4.4.1 LCA Results by Production Pathway

While there are significant differences in energy inputs and throughput efficiencies across production pathways, impact assessment results do not show dramatic differences in most environmental impact categories (Figure 2). Figure 2 uses the weighted average region for each production pathway to estimate impacts from electricity consumed. In general, high and low grade brines show the most favorable results (i.e. lowest results) for toxicity-related impact categories and human health impacts from air emissions. High and low-grade pegmatites show more favorable results for GWP, smog formation and acidification. These results are primarily explained by differences in the chemical flows between brine and hard-rock mining and extraction processes. We find moderate variation between the most favorable and least favorable potential brine production pathways, with additional fuel use for drying in the "Unfavorable Conditions" brine scenario driving significantly higher toxicity-related air, water, and human health impacts.

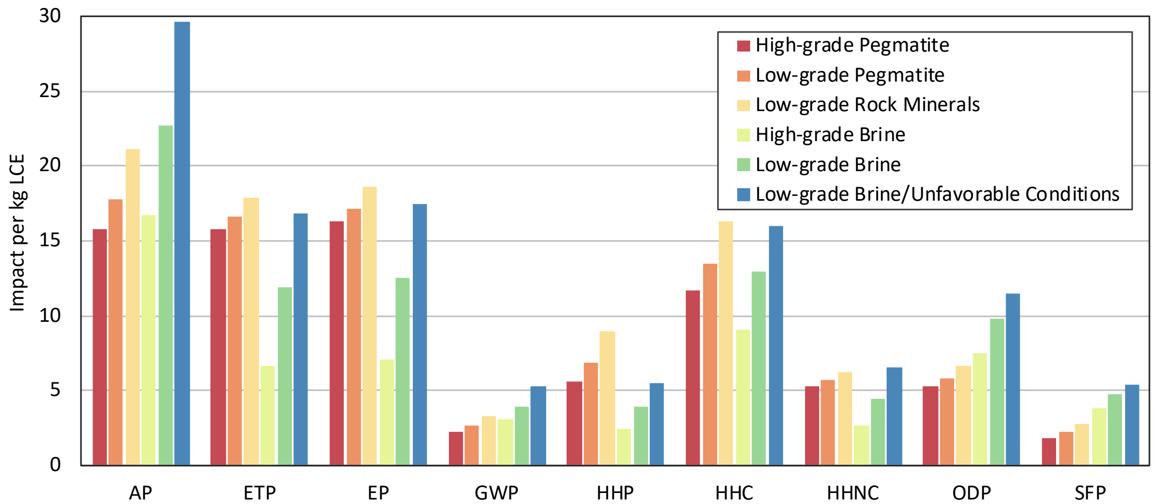

Figure 4.2 Impact Assessment of Lithium Production Pathways

(AP = Acidification Potential in g SO_3-eq; ETP = Ecotoxicity Potential in CTUe; EP = Eutrophication Potential in g N-eq; GWP = Global Warming Potential in kg CO_2-eq; HHP = Human Health Particulate in g $PM_{2.5}$-eq; HHC = Human Health Cancer in CTUh×10^8; HHNC = Human Health Non-Cancer in CTUh×10^7; ODP = Ozone Depletion Potential in mg×10^7 CFC-11-eq; SFP = Smog Formation Potential in kg×10 O_3-eq)

4.4.2 Impacts over time

Combining the impact analysis with the resource projection, we observe the potential changes in impacts over time under the optimistic scenario (Figure 3). Increasing impacts on fresh water, local air quality, and human health are likely to be concentrated around smaller deposits, which are likely to be developed after 2050. Notably, global warming impact intensity from LCE production does not change significantly over time, however given significant growth in LCE production, total CO_2e emissions from the lithium production sector will increase significantly. There can be significant inter-annual variations in production share across lithium resources doe to overall market expansion, production capacity increases, and climate conditions for brine production. These effects are observable in Figure 3 as rapid shifts between years when new deposits are brought online. As the market for lithium continues to grow after 2050, these shifts are less noticeable as fewer new deposits with significant production potential come online. A shift in future supply towards lower grade resources did not translate to significantly higher environmental impacts for lithium carbonate on average.

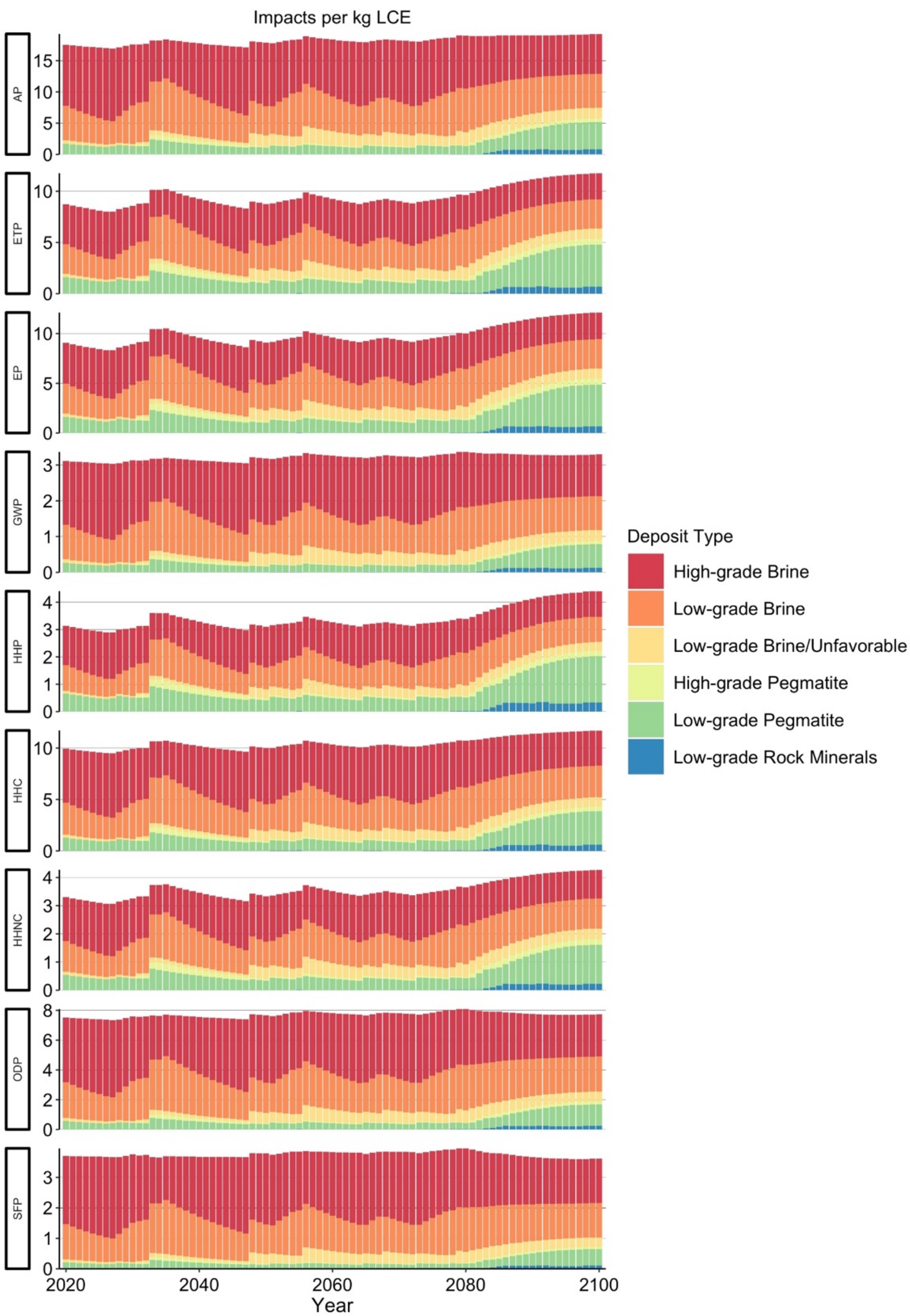

Figure 4.3 Impact Assessment of Production Weighted Lithium Production Over Time

(AP = Acidification Potential in g SO_3-eq; ETP = Ecotoxicity Potential in CTUe; EP = Eutrophication Potential in g N-eq; GWP = Global Warming Potential in kg CO_2-eq; HHP = Human Health Particulate in g $PM_{2.5}$-eq; HHC = Human Health Cancer in CTUh×10^8; HHNC = Human Health Non-Cancer in

$CTUh \times 10^7$; ODP = Ozone Depletion Potential in $mg \times 10^7$ CFC-11-eq; SFP = Smog Formation Potential in $kg \times 10$ O_3-eq)

Under the optimistic scenario, a larger share of production is supplied from lower-grade mineral deposits after 2080, but high and low grade brines continue to be the largest source of supply. This is due to both the increased demand for lithium, as well as the limits on potential production from lower cost brines. Comparing the average impacts per kg LCE over two, ten-year periods, beginning in 2020 and 2080, significant increases in production from low-grade pegmatite and brine resources leads to only small increases in environmental impacts. For example, GWP increases by 3% from 3.2 to 3.3 kg CO_2e/kg LCE. This translates to an increase of 0.14 to 0.16 kg CO_2e/kWh of cathode material, assuming a nickel cobalt aluminum or manganese cathode precursor and a cathode energy density of 0.25 to 0.27 kWh/kg (Ciez & Whitacre, 2019). Changes to water, toxics and particulate matter were larger than GWP, increasing by 11%, 12% and 15%, respectively. While the impact intensity (i.e. impact per kg of LCE) does not change significantly over time, given significant growth in LCE production, total impacts from the lithium production sector will increase significantly. For example, sector-wide CO_2e emissions increased by at least two orders of magnitude between 2020 and 2080 (Appendix B-S3).

Under the conservative demand scenario, there is no significant future development of low grade, hard-rock sources of lithium. This result in a 48% – 64% reduction in sector-wide environmental impacts from global LCE production in 2100 compared with the optimistic demand scenario. In addition, significant increases in the average impacts on ecotoxicity, eutrophication, and human exposure to particulates per kg of LCE after 2080 did not occur. An expanded description of results, including global sector-wide results, and data tables are provided in the Appendix B-S3.

4.5 Discussion

Uncertainty in the results of an LCA can result from a number of sources: variability in assumed values, lack of knowledge, measurement errors, and choices related to model design and specification. We considered the impacts of parametric uncertainty on model findings, specifically discount rate, production costs, reagent use, production energy inputs and sources, and mineral grade/type. Changes to discount rate and production costs did not cause significant changes in the overall production forecast, but did affect year-to-year variation in estimated impacts. This is also due to assumptions around the rate of potential production capacity expansion at existing and new lithium deposits. Estimated production impacts are highly sensitivity to the extent of HMR processing, while the impacts of HMR processing are primarily due to consumption of reagents for collection and dispersion.

For brine production, two primary sources of uncertainty are variability in the effective evaporation rate of solar ponds and the use of external energy sources to dry aqueous brines. Small increases in annual precipitation can cause months-long disruptions in the production of solar evaporated brines, as was experienced in the Atacama region in 2015 (Abad, 2017). The use of natural gas for drying in the worst-case scenario for brine production was the key factor driving increased impacts.

A limitation of this study is the use of temporally static life cycle inventories for regional electricity generation and processing technologies that may not reflect changing energy sources for electricity generation (e.g. decreased consumption of coal and increased use of renewables), or advances in machinery (e.g. improved heat rates for drying machinery). While impacts of regional electricity and natural gas sources were included, this did not result in significant differences across regions under current conditions. Given the large contribution of a single brine deposit to global supply, development of local renewable resources, including geothermal and solar energy, could likely reduce the emissions associated with overall lithium production (Parrado et al., 2015; Lahsen, Muñoz, & Parada, 2010).

The results of this study generally agree with existing estimates of life cycle impacts from LCE production. Figure 4 shows the average results for impacts across rock and brine resources from 2020 to 2100, with error bars indicating the minimum and maximum values observed across production pathways, compared with the inventories for LCE production from Ecoinvent for spodumene and brine respectively.

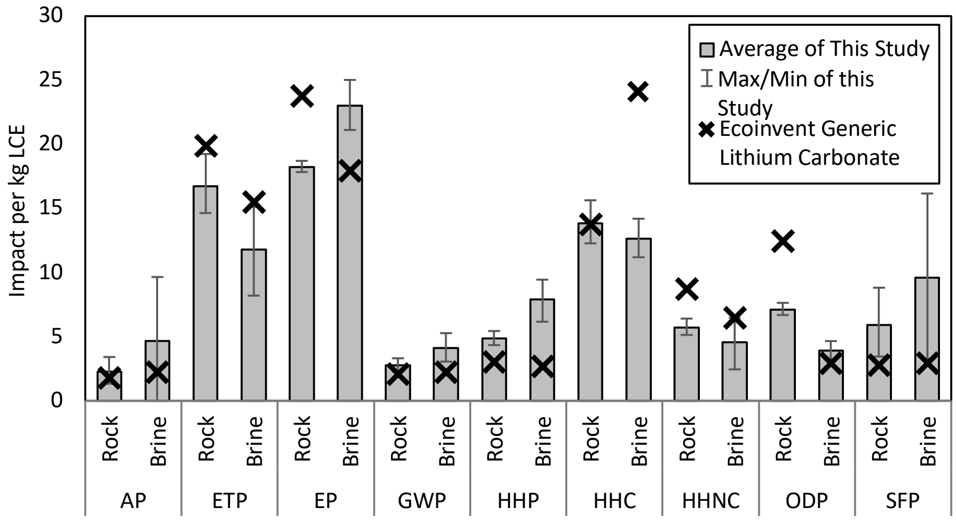

Figure 4.4 Comparison of Findings with Existing Impact Estimates Pathways

(AP = Acidification Potential in g SO_3-eq; ETP = Ecotoxicity Potential in CTUe; EP = Eutrophication Potential in g N-eq; GWP = Global Warming Potential in kg CO_2-eq; HHP = Human Health Particulate in g $PM_{2.5}$-eq; HHC = Human Health Cancer in CTUh$\times 10^8$; HHNC = Human Health Non-Cancer in CTUh$\times 10^7$; ODP = Ozone Depletion Potential in mg$\times 10^7$ CFC-11-eq; SFP = Smog Formation Potential in kg$\times$10 O_3-eq)

Other life-cycle based studies have also reported results that can be compared to findings from this study. Gaines et al. (2010) estimate that 163 MJ are required per kg to process ore into lithium hydroxide at a marketable condition. For the processing of brines into lithium carbonate, they estimated 44.7 MJ per kg were required, with 78% of that energy coming from fuel oils, 4% coming from propane, and the remainder coming from coal. The present study found energy inputs for producing LCE from pegmatites to range from 72 to 230 MJ/kg, while energy inputs from brines ranged 31 MJ/kg to 89 MJ/kg. In comparison to Gaines et al.'s findings, the present study found that energy inputs were lower for high-grade resources, but significantly higher for low-grade resources in unfavorable conditions. The scope of the current environmental assessment is limited in that it did not include site impacts including land transformation for solar evaporation ponds, or site impacts to air and water from the storage/disposal of mining wastes. While energy sources were estimated for deposit regions, these values were treated as static. Changes to the primary energy sources (i.e. a shift from coal to gas or renewables), or improvements in the efficiency of generation technologies could reduce the impacts of producing a kg of LCE. In addition, the reference data used may not accurately reflect the impacts associated with a particular source or supply for reagents or energy sources.

4.5.1 Recycled Batteries, Recovered Lithium, and Unconventional Resources

Though excluded from the resource model in this analysis, recycling of batteries could be an important source of future lithium supply (Gruber, 2011; Pehlken, 2015). Some previous studies have assumed widespread and effective recycling of LIBs as a major source of future lithium; Mohr et al. (2012) estimated recycled lithium could represent 50% or more of lithium demand by 2050. While there has been a proliferation of methods for recovering cathode materials, many developments remain at the laboratory scale which is a challenge for prospective analysis of environmental impacts (Zheng, Li, and Singh, 2014; Zhang et al., 2018). Conventional material recycling processes can generally be divided into two categories: hydrometallurgical and pyrometallurgical. With the exception of some experimental *in situ* recycling processes, conventional pyrometallurgical recovery of high value metal alloys like nickel and copper from spent LIBs does not produce lithium as a coproduct.

The focus of most existing recycling efforts for LIBs has been on recovering cobalt, due to both the quantity of cobalt in the cathode of batteries for consumer electronics (i.e. LCO), and the high value of recovered cobalt (Zhang et al., 2018). Attention has shift to recovering other high value materials, like nickel, copper, and aluminum, as battery systems have increased in size and cobalt content has fallen (Gaines, 2018). For large format LIBs, widely expected to drive demand for lithium in the future, co-precipitation of lithium nickel cathode materials combined with re-lithiation, sometimes called direct cathode recovery, is a promising pathway. Ciez and Whitacre (2019) recently examined the environmental impacts and costs of recycling processes for LIBs, including resynthesis of cathodes through direct cathode recovery at high cathode recovery rates (Ciez & Whitacre, 2019). The authors found limited to insignificant benefits for battery GHG emissions from cathode recycling through hydrometallurgical or pyrometallurgical processes. The limited studies available suggest that recovery of lithium from spent cells provides no clear environmental or economic benefit. Recovery of aluminum, the largest contributor to energy for cell materials and material related GHG emissions, and copper collector foils could reduce energy for cell material production by 70 to 80 MJ/kg of battery cells, or 34% - 69% (Dunn et al, 2015; Gaines, 2018). The cost of leaching chemicals for lithium carbonate from recycled batteries could be more than the $8 per kg or $8000 per metric ton LCE (Gratz et al. 2014). This suggests the price of recycled lithium carbonate would be significantly higher than the average cost of production of lithium from primary sources.

In addition, successful recycling programs for e-wastes are an issue, as current collection rates for LIBs are ~3% (Swain 2017). While collection rates might be significantly improved for large-format LIBs over those in the general e-waste stream, a confounding factor for battery recycling economics is the potential for second-use applications of large-format LIBs in stationary applications. The primary determination of LIB service life in vehicles is power fade, and LIBs employed in high-power vehicle applications are likely to still have considerable capacity when retired. A growing body of research has pointed to the technical and economic feasibility of LIB reuse or second life (Ahmadi et al. 2017, Richa et al. 2017, Martinez et al. 2018). To the extent batteries could be employed in secondary applications, batteries may remain in service longer. The value of recovered materials from recycled batteries may also be too low to motivate sufficient development of recycling infrastructure or to compete economically with second-life applications (Ciez & Whitacre 2019, Ambrose et al. 2014).

Part one of this study assessed the potential for secondary lithium from recycled LIBs using a stock and flow model. Assuming a high rate of LIB collection at end-of-life (85%), and assuming approximately half of all vehicle LIBs find secondary uses, the model showed the total stock of LCE in waste batteries awaiting recycling could approach 25% of global primary reserves by 2100. The potential stock of LIB materials in retired LIBs could also grow as improvements to recycling technologies increase recovery rates. As LIB recycling processes and their technical, economic and environmental performance become clearer, future research could explore the effect of secondary lithium flows on the environmental intensity of average global lithium production.

4.6 Conclusions

Despite differences in impacts by production pathway and a changing mix of resources being dispatched over time, the average impact intensity of a kg of LCE changes very little even out to 2100, though some impact categories (including eutrophication, ecotoxicity, and human health particulate) do show non-trivial increases around 2080 corresponding with new capacity from low-grade mineral ores. Examining results on a per-kg basis can be somewhat misleading, however, because the total quantity of lithium produced is increasing rapidly, meaning that total impacts from the sector will be much larger than today. Moreover, the impacts experienced by the communities that host lithium mining and processing sites may change dramatically when capacity is expanded or a new mine is opened. In addition, the significant variability in environmental protections and enforcement in different regions over the world means that the estimates provided here probably underestimate the variability across production sites. Thus, the industry (or the industries reliant on lithium) should consider focusing on reducing impacts per unit of lithium production to prevent significant increases in the total burden of pollution from lithium production and to protect the communities where lithium is produced.

Given these findings, future work might consider assessments that evaluate local conditions of production on a site-by-site basis to capture the variability in environmental impacts, not to mention the socio-economic impacts, caused by expanding capacity at current sites and exploitation of new deposits. Given the significance of other constituent cathode and electrode materials, future resource analysis could also focus on cobalt (and to a lesser extent nickel). The underlying resource model used to develop this temporally and spatially resolved LCA could facilitate site-specific assessment of impacts likely to be experienced by communities under different demand forecasts, which could be important for understanding which communities may be disproportionately impacted.

4.7 References

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5. Life Cycle Assessment of Batteries for Light Duty Electric Vehicles

5.1 Purpose and Scope

This chapter examines the materials requirements, environmental impacts, and uncertainties related to lithium-ion batteries. Traction battery manufacture can be a significant contributor to vehicle production emissions, and battery performance may have a significant effect on the contribution of battery-related emissions to the vehicle life cycle. However the contribution of batteries to life cycle emissions hinge on a number of factors that are largely absent from previous analyses, most notably battery chemistry alternatives and the number of electric vehicle kilometers of travel (e-VKT) delivered by a battery, which is a function in part of battery sizing, battery service life, and differences in plug-in hybrid electric vehicle versus pure battery electric vehicle applications. This chapter compares life cycle GHG emissions from vehicle operation and battery production using a probabilistic approach based on 24 hypothetical EVs modeled on the current US market.

This chapter includes some text adapted from Ambrose, H. and Kendall, A. Lithium traction battery chemistry and performance: life cycle greenhouse gas emissions implications for electric vehicles. *Transportation Research Part D: Transport and the Environment 10.1016/j.trd.2016.05.009*

5.2 Introduction

Lithium-ion batteries (LIBs) have become the preferred choice for energy storage in PEVs because they offer superior energy density, charge cycle performance, and decreased environmental burdens compared to other electrochemical options such as NiMH and lead acid (Ambrose, Gershenson, Gershenson, & Kammen, 2014). PEVs have been advocated in part because electric powertrain efficiency is significantly greater than conventional internal combustion engines (ICEs), and could lead to deep reductions in operational energy and GHG emissions. As much as 75−95% of life cycle GHG emissions from ICE vehicles are attributable to fuel consumption and combustion for operation (Christian Bauer, Hofer, Althaus, Del Duce, & Simons, In Press; Castro, Remmerswaal, & Reuter, 2003; Geyer, 2008; Kim, Keoleian, Grande, & Bean, 2003). However, increased vehicle production emissions, and decreased operation emissions, means that PEVs may experience a greater proportion of life cycle emissions during production compared to ICEs. In fact, on a percent basis, PEVs may have double the emissions from the production phase, and previous studies have shown that battery manufacture alone can be responsible for 35-41% of those production emissions for a 120-160 km range PEV (~24 kWh battery) (Hawkins, Singh, Majeau-Bettez, & Strømman, 2013).

Despite the potential importance of battery manufacture and replacement, very few life cycle assessment (LCA) based studies of PEVs or PEV traction batteries have considered multiple battery chemistries and differences in battery degradation and service life. Instead, separate bodies of research have developed with different foci: (i) LCA of PEVs and traction batteries; (ii) studies of electricity grids to determine operating emissions for PEVs; and (iii), empirical study, modeling, and performance testing of vehicle traction batteries. Research progress in these three fields has had limited integration, and which, if implemented, could reveal significant sources of uncertainty in emissions estimates for PEVs and important trade-offs for vehicle and climate policies.

This study builds on these bodies of previous research by offering a novel integration of automotive battery cycle-life modeling and life cycle GHG assessment, with the specific goal of assessing how differences between lithium chemistries will affect GHG emissions performance. We apply a probabilistic modeling approach, Monte Carlo simulation, to capture the inherent variability and uncertainty in predictive modeling of a PEV traction battery life cycle. This provides a new framework for comparison of emissions across life cycle stages and technological designs. In addition to considering five possible LIB chemistries, the assessment captures spatial and temporal heterogeneity in electricity grid emissions, variability in battery-to-wheels efficiency including ambient climate impacts, causes and effects of battery aging and health, and uncertainty in lifetime e-VKT delivered by a battery.

5.2.1 LITHIUM ION TRACTION BATTERIES

In short-range configurations, traction battery manufacture is likely a small share of overall PEV production emissions due to the small size of the batteries involved (<6 kWh). Early estimates for plug-in hybrid vehicles suggested that potential production emissions for a 10-15 mile all-electric PHEV to be 2-5% of the vehicle's life cycle emissions (Samaras & Meisterling, 2008). In the United States, ranges of PEVs, both pure electric and hybrid, have increased significantly over the last five years as more electric vehicle models have been introduced (see SI: Figure A and Table A for historical data) (U.S. Department of Energy, 2015). A favorable policy landscape for vehicles considered "zero emissions" at federal and state levels (Mock & Yang, 2014), in addition to rapidly falling battery prices (Nykvist & Nilsson, 2015), are helping to increase deployment of long-range PEVs. For long-range PEVs, such as an all-electric vehicle with 25 kWh of on-board storage, battery production likely contributes 12-15% of overall life cycle emissions (Christian Bauer et al., In Press; Hawkins et al., 2013).

A variety of lithium cathode and anode materials are being used in, or considered for, mass market vehicles. These chemistries have significantly different expectations for cycle life, from 1000 to over 5000 cycles in vehicle service, as well as different nominal and maximum voltages (2.4V/2.8V to 3.8V/4.2V) (Burke & Miller, 2009). These differences affect the choice of battery management systems, cooling systems, and other components (Nelson, Bloom, & I Dees, 2011), and may affect cost. Heterogeneity in material composition of the battery also has implications for both the supply of raw materials and the economic value of recovered and recycled materials (Wang, Gaustad, Babbitt, & Richa, 2014).

Samaras and Meisterling (2008) was among the earliest studies to examine the life cycle GHG emissions from a PEV, comparing ICE, hybrid electric, and three PHEV applications (30, 60, and 90 km electric range distances). (Samaras & Meisterling, 2008). The study assumed a lithium nickel-cobalt-manganese (NMC) battery chemistry, and modeled the battery's production-related impacts and performance characteristics using the results of an often-cited study, Rydh and Sandén (2005) (Rydh & Sandén, 2005). Rydh and Sandén examined the NMC battery as one of a number of energy storage options for photovoltaic systems (not vehicle applications). At the time of Samaras and Meisterling's research there were no commercially produced PHEV vehicles, so their study was necessarily conjectural. They found relatively small contributions from the battery to the life cycle impacts of the vehicle.

Notter et al. (2010) was among the earliest and most transparent studies that explicitly examined the contribution of LIB production to the life cycle emissions of a BEV (Notter et al., 2010). They model a lithium manganese-oxide (LMO) battery, developing their own life cycle inventory, and estimate significantly lower production-related impacts compared to those from Rydh and Sandén, and as a consequence those of Samaras and Meisterling. They find the LIB contributes 15% of life cycle impacts, based on the Ecoindicator 99 approach (Hawkins, Gausen, & Strømman, 2012).

Majeau-Bettez et al. (2011) performed an LCA of three PEV battery chemistries, nickel metal-hydride (NiMH), lithium nickel-cobalt-manganese (NMC), and lithium iron-phosphate (LFP), and assume that the LFP battery has twice the cycle life, 6000, compared the NCM and NiMH batteries. Like Samaras and Meisterling, they develop the life cycle inventory and battery performance characteristics for the LIB based on the work of Rydh and Sandén. The authors show larger battery manufacturing impacts compared to the earlier studies of Notter et al. and Samaras and Meisterling.

Hawkins et al. (2013) built upon Majeau-Bettez et al.'s results, taking the results of the two lithium-based battery chemistries, NMC and LFP, and contextualizing them in a full vehicle LCA. While Hawkins et al. account for the different masses required for the batteries, the battery use-phase is treated identically and both are assumed to last the vehicle lifetime. Hawkins et al. compared BEVs with ICE gasoline and diesel vehicles and showed the electricity grid used to charge PEV batteries was the most influential determinant of whether BEVs out-performed ICE vehicles. The publication of this article heralded a shift in the modeling approach for PEVs, by emphasizing the critical role of the electricity grid and the need for all future studies to consider grid heterogeneity.

Several studies have also found that material production can be a significant contributor to the environmental burden of battery manufacture. Notter et al. (2010) finds copper and aluminum have the largest overall impact on the environmental burden for a LMO battery, even fully allocating the impacts of lithium extraction to lithium salts, and with no credit for recycling of materials (Notter et al., 2010). Ellingsen et al. (2014), using primary data on NMC battery manufacture, also finds high impacts from graphite, aluminum and copper (Ellingsen et al., 2014). Dunn et al. (2012) finds much lower impacts for cradle-to-gate battery production, mostly due to significantly lower estimates for cell and pack assembly energies; the authors find that closed loop recycling of key materials (cathode active material, aluminum, and copper) could reduce material production energies by 48% (J. B. Dunn, Gaines, Sullivan, & Wang, 2012).

A largely separate body of work has considered the effect of including temporal and spatial heterogeneity in electricity grids in the context of marginal rather than average electricity used to charge PEV batteries (the most influential being the work of Graff Zivin et al. 2014 (Graff Zivin, Kotchen, & Mansur, 2014)). These studies treat the vehicle rather simply, focusing on new ways of examining the consequences of adding PEV electricity demand to the existing grid. At the same time, additional sources of spatial and temporal heterogeneity that affect battery performance, such as climate effects on batteries have been increasingly studied (K. Kambly & Bradley, 2015; K. R. Kambly & Bradley, 2014; Meyer, Whittal, & Loiselle-Lapointe, 2012). Yuksel and Michalek and Archsmith et al. combine both the spatial heterogeneity of marginal electricity emissions and some climate affects, among other considerations, to provide geography-dependent view of BEV performance (Archsmith, Kendall, & Rapson, 2015; Yuksel

& Michalek, 2015). Both show considerable variability in results by region, but consider only a single battery.

Often absent from EV and LIB life cycle-based studies is research on battery performance testing and cycle life modelling, particularly for lithium cells designed for automotive applications. Despite the common practice of assuming equal battery lifetimes across chemistries and vehicles in LCA studies, Burke et al. (2009, 2013) show 300-500% variation in the expected cycle life of automotive cells with different cathode materials (Burke, 2013; Burke & Miller, 2009). Eddaheck et al. (2015) also finds variation of more than 50% for battery degradation rates across automotive cells of different lithium chemistries depending on thermal and charge conditions during storage. Mathematical models of battery service life derived from accelerated battery testing also point to the potential for significantly shorter cycle lives than assumed in previous LCA studies, as well as differences across battery chemistries (Gu, Sun, Wei, & Dai, 2014b; Omar et al., 2014). The interaction of battery aging and degradation with PEV GHG emissions performance has not been studied, and could present important considerations for original equipment manufacturers (OEMs) and policy stakeholders.

5.2.2 Lithium Chemistries for Electric Vehicle Batteries

The conventional structure for a lithium battery consists of a graphite anode and lithium metal oxide cathode, with a lithium salt electrolyte (e.g. LiPF6) in organic solvent (e.g. ethylene carbonate-dimethyl carbonate). Cathode and anode materials are bound to copper and aluminum collector foils with a resin binder and additional solvent. A generalized common reaction process for $C/LiPF_6$ in EC–DMC/$LiMO_2$ consists of:

$$yC + LiMO_2 \leftrightarrow Li_xC_y + Li_{1-x}MO_2, x{\sim}0.5, y = 6, voltage \sim 3.7\ V \quad (1)$$

Reversible exchange of lithium ions between electrodes results in a significant electrical potential, as shown in Equation (1) (Scrosati & Garche, 2010). Some automakers are now employing batteries with lithium metal oxides in both cathode and anode, such as Toshiba's LTO-NMC cells used in the Honda Fit. With some notable exceptions (e.g. Tesla Model S), the majority of automakers have employed pouch or prismatic lithium cells (20-60 Ah), as opposed to cylindrical cells often found in consumer electronics (<5 Ah) (Anderman, 2014b). While prismatic and pouch cells usually have lower energy density (and specific energy), it is potentially easier to arrange them in modular pack architectures due to their shape. Modules of multiple cell bricks in series can also provide system "balancing," where a differential current is applied to each cell during any charge operation. This limits state of charge (SOC) mismatching, as well as capacity degradation.

To maximize battery lifetimes, SOC is continually balanced across banks of cells by battery management systems (BMS). DOD is limited to 75-85% of the pack's rated capacity, as batteries have exponentially higher cycle life counts at increasingly low DOD. Utilizing a range of discharge less than the cell's rated capacity improves its lifetime charge capacity and voltage degradation. Traction battery lifetimes are usually expected to exceed standard powertrain warranty periods (~60,000 miles), but manufacturers caution against gradual capacity fade during this time. 5-8 year manufacturer warranties are common for traction batteries; although not all manufacturers guarantee for specific levels of capacity fade during the warranty period, 30% reduction in capacity is often considered the cut-off point for removal or replacement (SI: Table D). In addition to manufacturer warranties, California's Zero Emissions Vehicle (ZEV) mandate requires that PEV battery warranties must be extended to 10 years to earn ZEV credits, but this warranty need not specify a level of capacity loss (California Air Resources Board, 2011, 2014).

Continued transformational changes in lithium traction batteries are likely due to strong cost drivers and high performance targets in automotive applications (Amine, Kanno, & Tzeng, 2014; Scrosati, 1989). Lithium metal couples with lower material costs can reduce battery pack prices, but there are a number of tradeoffs to be made, as evidenced in Table 1 and Figure 1. Cost of material is also a critical decision variable for battery chemistry selection, so cathode materials with high levels of cobalt may not be economic choices for continued large-scale roll out of lithium traction batteries (Delucchi et al., 2014). This may explain why no currently mass marketed electric vehicle employs lithium cobalt oxide cells, and the majority of automotive cell suppliers have focused on NCA and LMO configurations (Anderman, 2014b; Committee on the Assessment of Technologies for Improving Fuel Economy of Light-Duty Vehicles, 2015). LFP configurations also have slightly higher costs per kWh because more cells in series are required due to lower cell voltages (Anderman, 2014a). LMO-NMC blends seem to provide very low cost, but require more aggressive cooling. LTO-NMC couples operate at lower voltages than other couples currently employed in automotive applications, and their low energy densities may limit their applications despite lower material costs.

Table 5.1 Lithium chemistries for PEV traction batteries (Burke & Miller, 2009; Gu et al., 2014b; Omar et al., 2014)

Chemistry	**Lithium Nickel Cobalt Aluminum Oxide**	**Lithium Nickel Manganese Cobalt Oxide**	**Lithium Manganese Oxide**	**Lithium Iron Phosphate**	**Lithium Manganese with Titanate Oxide Anode**
Chemistry group	Nickelate		Manganese Spinel	Phosphate	Titanate
Abbreviation	NCA	NMC	LMO	LFP	LMO/LTO
Voltage (Nominal/Max)	3.6/4.2	3.6/4.2	3.6/4.0	3.2/3.6	2.4/2.8
Energy Density (Wh/kg)	100-150	75-170	100-120	80-115	45-100
Estimated Automotive Cycles	2000-3000	1000-2000	300-700	2000-3000	>5000

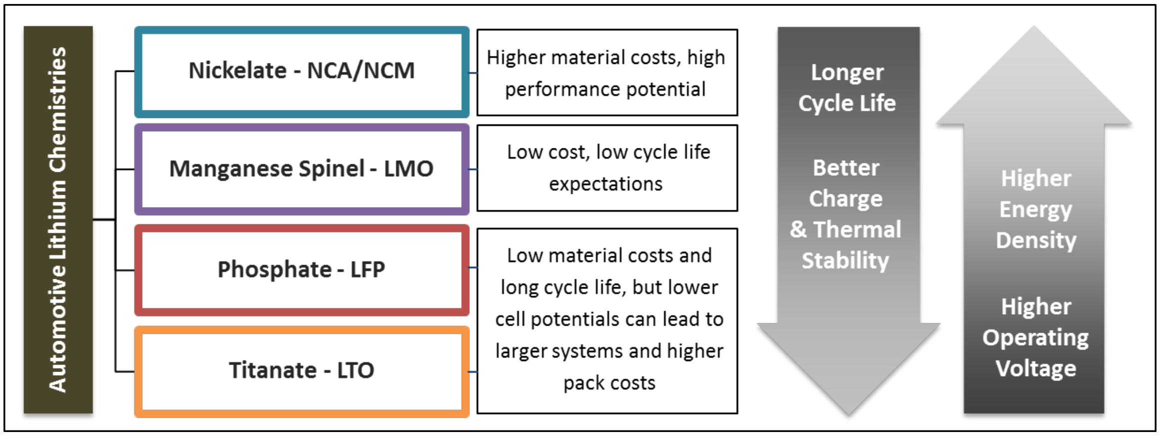

Figure 5.1 Comparing Lithium chemistries for automotive traction batteries

5.2.3 PEV Battery Performance

Decreased material costs could enable wider-scale roll out of PEVs, but battery life cycle performance should be a key concern due to its influence on production-related emissions. This investment in production emissions will generate life cycle emissions reductions only if batteries endure in vehicular service long enough to realize GHG savings from switching away from gasoline, though GHG savings hinges not only on production emissions from PEVs, but on the GHG-intensity of the electricity used for battery charging. Thus battery service life and battery performance over time should be important considerations in life cycle modeling of PEVs.

Battery service life is a function of battery degradation, often referred to as battery aging, and is characterized by gradual capacity fade and impedance growth, eventually resulting in the need for battery replacement or vehicle retirement. Both battery cycling and time cause battery aging, and battery aging is accelerated by the DOD and frequency of cycles, thermal conditions, and SOC/voltage conditions experienced by the battery. Three primary underlying chemical processes occur during lithium battery aging: loss of cyclable lithium; electrode material loss to dissolution; and electrolyte degradation (Barré et al., 2013). While intense charge cycling causes structural degradation of the electrode and active sites, the dominant fade mechanism when stored (i.e. due to time alone) is the growth of a resistive film; both processes also result in a loss of cyclable lithium (Ploehn, Ramadass, & White, 2004). Capacity degradation has clear impacts on vehicle range, but the combination of resistance-induced power fade and diminished capacity will ultimately determine a battery's service life.

Hot ambient temperature conditions have significant impacts on battery performance degradation during charge cycling and storage, which in turn affects automotive cycle life (Eddahech, Briat, & Vinassa, 2015; Song et al., 2013). Aging due to cycles or throughput, and aging due to storage at different SOC, can trade dominance depending on operating conditions. For example, increased charge cycling of battery packs can increase estimated battery lifetime compared to calendar or storage-only estimates, if the battery spends longer periods at lower voltages or more optimal temperatures (Wood, Neubauer, Brooker, Gonder, & Smith, 2012), and active thermal management can mitigate aging caused by extreme thermal conditions, but typically increases vehicle energy requirements.

Premature battery degradation is a significant concern for vehicle manufacturers, especially considering the high price of battery replacement; the cost of a 25 kWh LIB pack at current prices is $7500-12500 USD (Nykvist & Nilsson, 2015). Vehicles have experienced premature battery degradation that resulted in the battery realizing less than 60-70% of the intended cycle life. Idaho National Lab has conducted a long-term road test of four 2012 Nissan Leaf vehicles containing 24 kWh LMO/G battery based on AESC 33Ah cells; after 80467 km (50000 mi) of daily driving (or approximately 700 cycles), vehicles had experienced over a 25% reduction in pack capacity (Shirk & Wishart, 2015). Other empirical studies of LMO cells have obtained cycle lives 15-40% below theoretical estimates when considering automotive operating conditions (Gu, Sun, Wei, & Dai, 2014a; Gu et al., 2014b). LFP lifetimes, potentially greater than 3000 cycles at low charge/discharge rates and low ambient temperatures, can decrease by 50% or more at 40 ^{o}C or with rapid cycling(Omar et al., 2014; Zheng et al., 2015). Long-cycle life lithium couples, such as Toshiba's LTO cells, have begun to emerge into the market, but currently have little market share. LTO-LMO couples are likely very long lived, with 50Ah prismatic pouches losing less than 1% capacity over 1000 cycles during fast charge cycling (6C) (Burke, 2013).

5.3 METHODS

This study uses established life cycle GHG assessment frameworks (British Standards Institute, 2011) to analyze life cycle emissions from PEV traction batteries. Non-CO_2 GHG emissions are characterized in equivalent units of carbon dioxide (CO_2e) using 100-year Global Warming Potentials (GWPs) from the IPCC's 5th Assessment Report (Myhre et al., 2014). Because there is a great deal of uncertainty in this research, the analysis uses a probabilistic rather than deterministic approach, which is increasingly a requirement of life cycle assessment guidance and standards (Finnveden et al., 2009). Probabilistic or stochastic models allow for estimation of parameter values, such as emissions or energy consumption, when individual parameters are not precisely known, a common challenge in life cycle assessment. Fuzzy set theory is frequently used to estimate unknown parameter values and Monte Carlo simulation is well accepted as an uncertainty propagation method in quantitative decision analysis (Livezey & Chen, 1983; Lloyd & Ries, 2007), and both are used in this study to carry out probabilistic life cycle modeling.

Monte Carlo requires probability density functions (PDFs) for expected parameter distributions, which are then used in the context of repeated sampling to estimate results as confidence intervals, rather than point estimates. Probabilistic modeling is also used in this study iteratively to identify key parameters and interrogate underlying assumptions. Comparison of the impacts of parameter uncertainty (caused by a lack of available knowledge/data) and variability (fluctuations inherent to the system) on model outputs is also explored (Hauck, Steinmann, Laurenzi, Karuppiah, & Huijbregts, 2014).

5.3.1 SCOPE OF ANALYSIS

The scope of the life cycle GHG assessment reflects the goal of this study; to estimate the influence of battery service life and battery performance on life cycle GHG emissions. The life cycle stages included in the analysis are: battery material processing, battery manufacturing, and the battery use-phase (including electricity used during charging). The material processing phase encompasses all the production steps prior to assembly for the cell (cathode active material, anode active material, binders, and electrolyte), packaging (plastics, insulation, etc.), and battery management systems (BMSs). Battery material inventories are grouped into four component types: electrodes (cathode/anode active materials, terminals and collector foils), structural (packaging, buss-bars, etc.), electrolyte, and management systems (including BMS and thermal).

We consider five lithium chemistries (cathode-anode couples): NCA-G, NMC-G, LMO-G, LFP-G, and LMO-LTO (as described in Table 1), and estimate the composition and material requirements for seven traction battery design scenarios based on intended range, motor power, glider body energy requirements, cell structure, and thermal management of current on-road vehicles, as described in Table 2. An iterative calculator for battery mass and volume, charge characteristics, and materials is employed based on the BatPaC model (J. Dunn, Gaines, Barnes, Wang, & Sullivan, 2012; Nelson et al., 2011). The model allows for comparison between the material and energy flows for different chemistries based on a set of design scenarios centered on vehicle end-use, power requirements, and thermal considerations. Traction battery design scenarios are constructed to be representative of the PEV market, as well as capture significant differences in battery production and composition across vehicle design (PHEV or BEV) and intended range.

Energy requirements and GHG emissions for these traction battery design scenarios are then used to develop sampling distributions for 24 PEV models representing the current US PEV market. The unit of reporting in this analysis reflects the primary function of the battery; energy storage to provide e-VKT. Thus results of the battery life cycle GHG analysis are normalized by the lifetime e-VKT. This normalized metric is appropriate for comparing the utilization potential of batteries (Majeau-Bettez, Hawkins, & Strømman, 2011; Matheys et al., 2007). Vehicle e-VKT is simulated across vehicle and chemistry combinations based on the expected cycle lives of each battery chemistry.

Table 5.2 Traction battery design scenarios and simulated PEVs (energy requirement is calculated, all other data are from the US Department of Energy's Advanced Fuels Data Center (U.S. Department of Energy, 2015))

Battery Scenario	PEV Type	Vehicle Model	Battery Size (kWh)	Motor Power (kW)	Energy Requirement (Wh/VKT)
Short-range PHEV	PHEV 15	Toyota Prius Plug-in Hybrid	4.5	18.0	251.4
		Honda Accord Plug-in Hybrid	6.7	124.0	318.1
		BMW I8	7.1	125.0	294.1
		McLaren Automotive Limited P1	4.7	132.0	154.0
		Ford Fusion Energi Plug-in Hybrid	7.6	68.0	234.4
		Ford C-Max Energi Plug-In Hybrid	7.6	68.0	234.4
Mid-range PHEV	PHEV 40	Chevrolet ELR	16.9	126.0	283.5
		Cadillac Volt	15.7	111.0	256.1
Long-range PHEV	PHEV 80	BMW i3 (REX)	21.6	96.0	175.5
Short-range BEV	EV 40	Scion iQ EV	12.0	110.0	195.5
		Mitsubishi Motors Corporation i-MiEV	17.0	49.0	165.3
		Mercedes-Benz Smart fortwo EV	17.6	55.0	161.1
Mid-range BEV (Low Power)	EV 80	Nissan Leaf	23.8	80.0	175.8
		Kia Soul Electric	27.0	81.0	180.4
		FIAT 500e	24.0	82.0	171.7
		Volkswagen e-Golf	27.1	85.0	202.7
		Honda FIT	20.0	92.0	50.0
Mid-range BEV (High Power)	EV 80	Chevrolet SPARK EV	22.2	104.0	168.2
		Ford Focus Electric FWD	26.3	107.0	214.6
		Mercedes-Benz B-Class Electric	44.0	132.0	314.5
Long-range BEV	EV 100	Toyota RAV4 EV	50.2	126.0	302.7
		Tesla Motors Model S	86.0	164 and 350	222.6

5.3.2 Battery System Design and Production Emissions

Battery design is considered through seven scenarios constructed around common PEV vehicle classes (PHEV15, PHEV40, PHEV80, BEV80, BEV200, BEV250). Battery scenarios are modeled based on intended vehicle type (PHEV or BEV), intended vehicle electric range, battery pack configuration, electric motor power, and the thermal management system. Data for material composition per kWh, emissions per kWh, energy requirements per kWh, as well as pack energy density and mass were developed and used to generate sampling distributions. These distributions were then applied to several vehicle designs within the PEV vehicle class.

While battery packs are usually designed for a specific vehicle, real-world performance of a particular battery system will vary based on different vehicle types. To assess variation in vehicle performance within battery design scenarios, we look at several specific vehicle models for each PEV class; for instance, the Ford C-max and Fusion Energi, as well as the Honda Accord Plug-in, are all simulated from the same underlying distribution of material composition and energy requirements, but adjusted for the specific vehicle design by the kWh capacity.

All batteries are simulated as a prismatic cell type and a blend of steel and aluminum structural elements, and with only one exception, all scenarios utilize active liquid cooling systems. Battery cycle life is used to simulate energy throughput and calculate lifetime e-VKT. Lifetime e-VKT for each simulated vehicle and chemistry combination is based on initial estimated all-electric vehicle range, expected gradual capacity fade during vehicle service life, and estimated cycle life by chemistry. Gradual capacity fade is estimated for small charge cycle intervals (<100 cycles), and the full electric range delivered by the charge cycle is used to estimate e-VKT. The distributions of key parameters are detailed in Table 3.

End of LIB vehicular service life is assumed to occur after a 30% reduction in rated energy storage capacity from when the battery was new. Battery cycle life is estimated for each lithium couple based on a meta-analysis of published sources and other publicly available data. Table B in the Supplementary Information (SI) summarizes the key parameters from the studies included in the meta-analysis. Empirical test data of prismatic or pouch cells are used when available; the most likely cycle life outcome is assumed to occur at or near ambient temperatures with relatively low (~2C) charge/discharge rates (Marano, Onori, Guezennec, Rizzoni, & Madella, 2009). Lower-bound cycle life is assumed to occur due to calendar aging or cycling at elevated temperatures, as opposed to increased high c-rate cycling. Aging effects and cycling effects are considered to be additive (Smith, Earleywine, Wood, Neubauer, & Pesaran, 2012), and differences between vehicle duty cycles are simulated by way of thermal impacts (e.g. increased accessory load and increased battery degradation). Upper-bound cycle life is estimated for optimal DOD cycling patterns and calendar storage limits, indicating the maximum expected cycles to be delivered by the battery before capacity fade thresholds are reached. Extrapolated estimates are used where no complete cycle life data is available.

Material production emissions estimates were calculated from life cycle material inventories in the 2014 Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation Model (GREET) (Argonne National Laboratory, 2014). The material life cycle inventories (LCIs) are consistent across chemistries.

A distribution of emissions factors for electricity consumed during cell and pack assembly and vehicle use-phase is estimated from regional US emissions factors (Archsmith et al., 2015) (SI: Figure B).

Energy consumed directly in cell and pack assembly is simulated stochastically based on existing inventories in published studies. Energy requirements for cell and pack assembly are assumed to be the same across battery chemistries. Fuel-cycle energy consumption is based on vehicle specific energy requirements (Wh/km), charger efficiency, and accessory load. Charger efficiency varies based on the system and charging rate, but is typically between 85-95%. Climate impacts on accessory load factor are estimated to increase per mile energy consumption by 0-15% (Yuksel & Michalek, 2015).

Production of the BMS is modeled based on results from Dunn et al. (2012) for a 5 kWh $LiFePO_4$ battery. Data from general electronics manufacture is used where specific data for process burdens of circuit boards and semiconductors in BMS systems was unavailable. Recycling is not considered in this data (meaning no recycling credit is assigned to the BMS), however materials preserved in the manufacturing process (such as binders), are considered in the inventory.

5.3.3 Electricity Grid Emissions

GHG emissions from electricity consumption are influential in determining the GHG intensity of battery operation, but also affect manufacturing because some processes are electricity-intensive such as cell and pack assembly. Understandably, much of the detailed modeling of use-phase impacts for PEVs has focused on variability in generation source, such as regional or temporal variations in electrical grids (Faria et al., 2013), and whether PEV charging demand should be modeled as marginal demand (e.g. as an additional unit of demand on the grid), or should be considered part of existing demand (Graff Zivin et al., 2014).

Future electric vehicle charging at high penetration rates would represent significant demand for electricity, which could have modest to severe impacts on local utility grid emissions factors based on penetration of renewables, energy storage systems, electric vehicle range, level of public charging deployment, charging schedules, and charging rates (Hadley, 2006; Hadley & Tsvetkova, 2009; Jansen, Brown, & Samuelsen, 2010; Kintner-Meyer, Schneider, & Pratt, 2007; Weiller, 2011). Current and future changes to the electricity generation system in the US will undoubtedly affect PEV emissions performance, and disparate carbon and climate policies at the state level are potentially exacerbating variation across regional emissions factors (Carley, 2011a, 2011b). Though these issues are important, this analysis does not include a prediction of *future* electricity grid emissions, but rather looks to recent history to estimate emissions from U.S. electricity and treats PEV charging as marginal demand.

There appears to be a trend towards representing PEV charging demand as marginal, a paradigm shift initiated by the work of Graff-Zivin et al. and the successive studies that have built upon it (Graff Zivin et al., 2014). In accordance with this trend we use the results of Archsmith et al., which report estimates of life cycle GHG emissions for marginal demand across the North American Electric Reliability Corporation regions in the lower 48 states (James Archsmith, (Accepted)). We chose this study because, unlike other available marginal emissions estimates, it includes total fuel cycle GHG emissions (rather than combustion-only emissions from power plants) and includes the contribution of marginal electricity supply generated from renewables.

5.3.4 Summary of Parameter Distributions

To implement a probability based life cycle model, parameter values must be represented as PDFs rather than point estimates. Table 3 summarizes the parameter PDFs developed and used in this analysis.

Table 5.3 Summary of parameter distributions

Parameter	**Minimum**	**Likeliest**	**Maximum**	**Distribution**
Production Emissions				
Cell Production Energy (MJ/kWh)	316	960	2318	triangle
Pack Assembly Energy (MJ/kWh)	~N(0.014,0.01)			normal
Grid Emissions Factor (kg/kWh)	~LogN(μ=0.81,σ=0.13,k=-0.14)			Log-normal
Battery Cycle Life by Chemistry				
NCA Battery Cycles	400	1000	3000	triangle
NMC Battery Cycles	1000	1700	3000	triangle
LMO Battery Cycles	305	685	1000	triangle
LFP Battery Cycles	1600	3200	5039	triangle
LTO Battery Cycles	2000	5000	6800	triangle
Material Production Emissions (kg CO_2e/kWh) by Battery Type				
NCA BEV	39.86	42.87	45.54	triangle
NCA PHEV	44.94	53.3	61.14	triangle
NMC BEV	33.36	34.78	36.22	triangle
NMC PHEV	38.78	48.32	53.85	triangle
LMO BEV	36.29	39.83	42.98	triangle
LMO PHEV	43.07	522.84	58.65	triangle
LFP BEV	30.77	33.9	36.68	triangle
LFP PHEV	35.89	43.21	49.56	triangle
LTO BEV	28.17	31.79	34.98	triangle
LTO PHEV	35.15	46.85	53.26	triangle
Battery Charge and Discharge and Battery Aging				

Charger Efficiency	85%	--	95%	uniform
Climate Induced Degradation	0%	--	20%	uniform
Climate Accessory Load	0%		15%	uniform

5.3.5 Limitations

This study does not consider potential interactions of vehicle design, range, and battery chemistry on cycle life; it is possible that cycle life for certain chemistries is longer in particular vehicle designs due to correlation between vehicle type and frequency of certain drive cycles. The effects of different thermal management strategies on average pack temperatures and impacts on battery aging are also not considered. Regional levels of PEV deployment could also impact the probability of the occurrence of specific climate impacts or emissions from electricity. Changes in future production systems, raw material provision, or operating grid efficiency could have significant impacts on emissions estimates and are not addressed in this study.

Despite the widespread use of probabilistic modeling approaches in quantitative analysis, they suffer from several criticisms. Inappropriate or arbitrary parameter distributions gives false confidence in unreliable results, lack of uncertainty incorporated into scenario analysis yields little information on key factors, and independent sampling of correlated parameters reduces comparability between modeled product stages or systems. Dependent sampling has been used to facilitate comparisons between product stages (Henriksson et al., 2015); to that end, the same distribution of electricity emissions factors is used for production and use-phase energy consumption. Fuzzy set quantitative analysis is used in this study to derive parameter distributions from empirical data, with the goal of limiting arbitrary application of density functions to parameters (Kala, 2005).

5.4 Results

While battery composition varies considerably across chemistries (Figure 5.2a), GHG emissions impacts are predominately due to a few materials. Including the battery management system (BMS), GHG emissions from material production were on average 20% of total battery production emissions (Figure 5.2b). Aluminum was responsible for approximately 40% of material production GWP for all five chemistries. Emissions attributable to energy directly consumed in cell and pack assembly was ~80% of total production emissions, or 157-475 kg CO_2e/kWh.

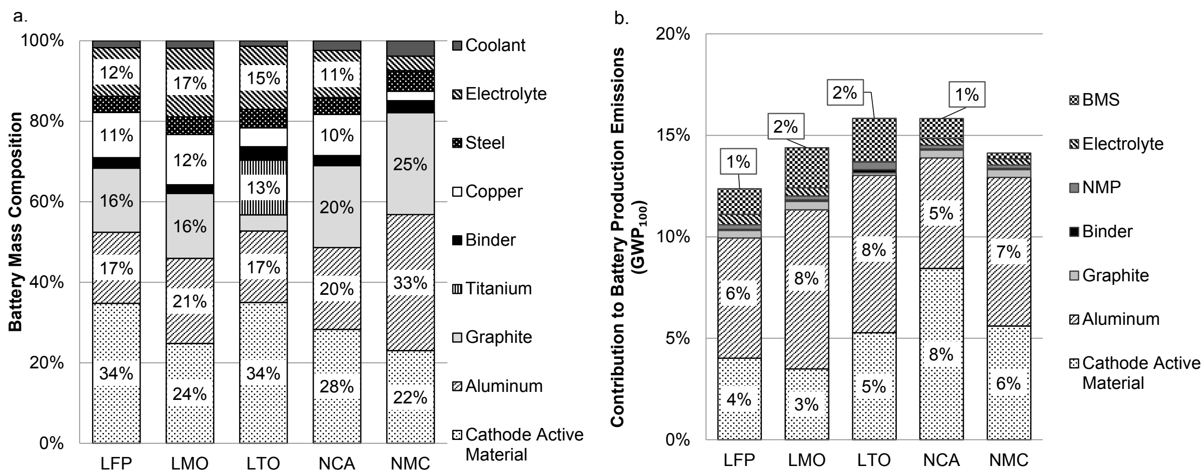

Figure 5.2 Composition of lithium batteries and material GHG emissions by chemistry: (a) mean composition of traction batteries by components (% of total mass) (b) mean GHG emissions from materials by chemistry (% of total battery production emissions)

As shown in Figure 5.3, mean cradle-to-gate GWP intensity for LIB chemistries is 256-261 kg/kWh, with only LFP and LTO showing statistically significant differences in production GWP between chemistries (Tukey-Kramer, $\alpha = 0.05$). Production emissions are log normally distributed, ranging widely from 194-494 kg/kWh; upper bound estimates were predictably correlated with more carbon intensive electricity for cell assembly.

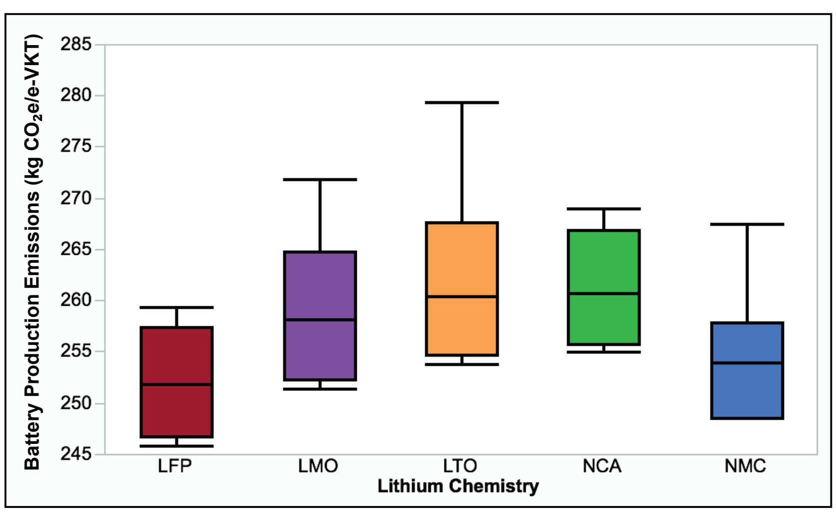

Figure 5.3 Mean battery production emissions estimates for LIB chemistries

Significant differences are also observed across vehicle configurations and vehicle electric range (Figure 5.4). Battery production emissions intensity (e.g. per kWh of capacity) is 4% higher for PHEVs on average compared to BEV batteries. Small batteries (~5 kWh) had higher production emissions per kWh of capacity because many battery components or systems did not scale completely with pack size. Estimated lifetime e-VKT for traction batteries was 26000-86000 e-VKT, with significantly shorter estimates for PHEVs compared to BEVs. Lifetime e-VKT for BEV vehicles was ~95,000 kilometers across all chemistries; long range vehicles, such as the Tesla model S, could reach well in excess of 241,000 kilometers considering charge cycle degradation only. PHEV lifetime was 13000-53000 e-VKT across chemistries and vehicles.

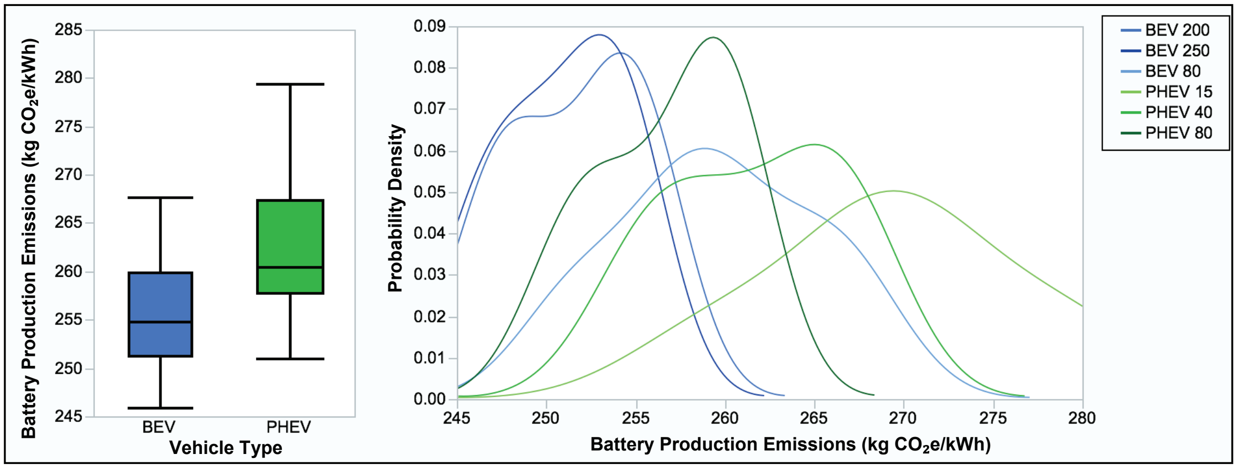

Figure 5.4 Battery production emissions by PEV vehicle type and all-electric range

Considering a likely electricity emissions factor range of 660-970 g CO_2e/kWh, fuel cycle emissions rates for the US were estimated at 140-244 g CO_2e/e-VKT. The range of this estimate is likely more reflective of regional variability than temporal or seasonal variability within regions. However, if the climate effects on batteries and grid emissions intensity were varied in a geospatially explicit manner, this would likely change (see Archsmith et al. for a discussion of this) (Archsmith et al., 2015). Battery production emissions of 4-17 g CO_2e/e-VKT were ~7% on average of comparable fuel cycle emissions (Figure 5.5). The combined emissions rate (production and fuel cycle) was 148-261 g CO_2e/e-VKT.

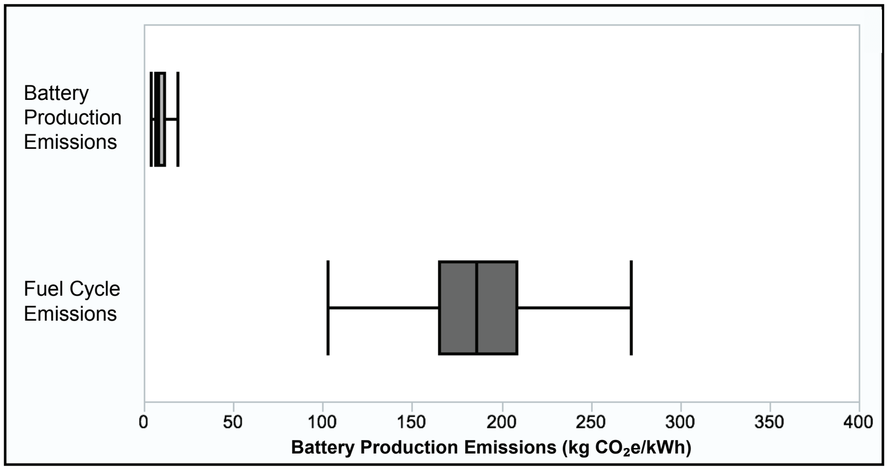

Figure 5.5 Battery and fuel cycle emissions rates

Uncertainty in total life cycle emissions rates was predominately driven by emissions from the operating grid (Figure 5.6). Climate and cycle-life were also key factors for overall emissions rates. Larger uncertainties in the life-time of NCA batteries, combined with slightly higher material production emissions estimates, led to stronger affects from NCA lifetime estimates. Climate and charging efficiency assumptions also varied total emissions estimates by +/- 5%.

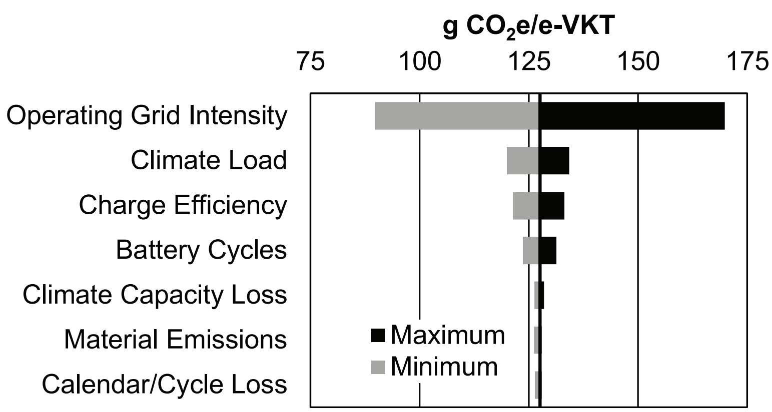

Figure 5.6 Sensitivity to key parameters

5.5 DISCUSSION

Lithium ion cell manufacture can be highly energy intensive. For example, high temperatures and sterile conditions, which are energy-intensive and thus emissions-intensive processes, are required for binding cathode and anode active materials to collector foils, trimming and filling pouches with electrolyte, as well as sealing and testing of cells (J. Dunn et al., 2012). Recent studies have illustrated that estimates of energy consumption during cell manufacture can drive estimates of overall battery production emissions (C Bauer; Zackrisson, Avellán, & Orlenius, 2010) Estimates for cradle to gate emissions for early Japanese cells were approximately 70 kg CO_2e/kWh (Ishihara, Kihira, Terada, Iwahori, & Nishimura, 2002), with direct energy in cell manufacture of 0-28.3 MJ/kWh (Amarakoon, Smith, & Segal, 2013). More recent studies have found much higher impacts: 133-338 kg CO_2e/kWh based on energy consumption of 326-2318 MJ/kWh for cell manufacture (C Bauer; Ellingsen et al., 2014; Majeau-Bettez et al., 2011). While earlier estimates are based primarily on laboratory test data, both Bauer et al. (2010) and Ellingsen et al. (2014), with the highest published estimates for cell manufacture energies, rely on inventories and other primary data from of existing cell manufacturers.

Previous studies report a wide range of estimates for traction battery life cycle GHG emissions: 38-487 kg CO_2e/kWh. This study's estimates fall within that range, 193−494 kg CO_2e/kWh (Figure 5.7). Despite very different findings for emissions per kWh of capacity, Notter (2010) and Zackrisson (2012) find similar production impacts of 6−8 g CO_2e/km, with fuel cycle impacts of 62−109 g CO_2e/km. Both Notter (2010) and Dunn (2012) stand out with very low estimates for battery production in comparison to other studies. While previous research also point towards high-energy requirements (and emissions potential) from cell assembly, the significance of battery production emissions on a per VKT basis is strongly affected by battery cycle life. This is due to the large uncertainties in current lithium battery performance, as well as the wide variability in cycle life expectations across chemistries.

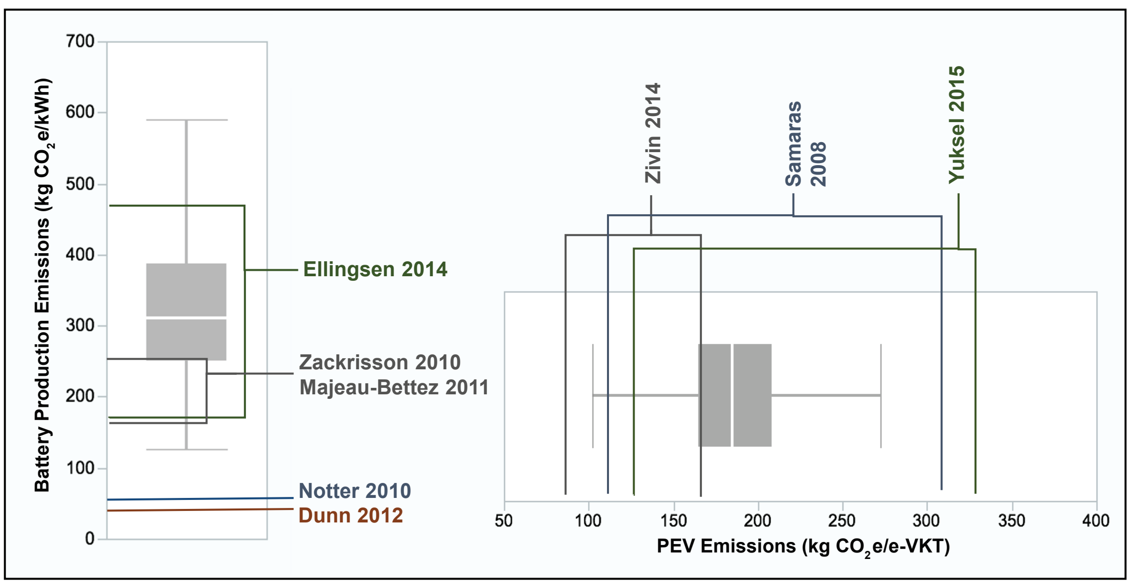

Figure 5.7 GHG emissions comparison for to other studies for PEV LIB Battery Production and PEV Operation

Early estimates for battery production of approximately 70 kg CO_2e/kWh or less suggested GHG emissions reduction potential from electric vehicles after only ~200 cycles (compared to a comparable conventional gasoline ICE vehicle), when charged from a typical electricity grid dominated by fossil fuels coal and natural gas(Armand & Tarascon, 2008). Comparing to a conventional vehicle producing 220 g CO_2e/VKT, GHG payback periods for battery production (2-8 metric tons CO_2e on average), are approximately 400-1150 cycles. This estimate, while not taking into account battery aging, is already close to or exceeding battery cycle life for LMO configurations. A push towards longer-range vehicles and larger capacity batteries could exacerbate uncertainties about life cycle performance by further extending carbon payback periods. This underscores the need for life cycle GHG accounting; estimates of emissions performance based solely on the fuel cycle or tail pipe emissions could miss structural shifts in emissions between production and use-phase.

Dependent sampling is used in this study to emphasize comparability within the life cycle GHG assessment framework and reveal non-intuitive trade PEV LIB Batteries offs between use-phase and production emissions. Some additional scenarios highlight this point. Consider a scenario where battery production and vehicle operation occur with different underlying distributions for electricity emissions factors. This is a reasonable scenario to consider as the majority of automotive battery cells, including those used in the US, are currently manufactured in China and other Asian countries (SI: Table C). In addition, over 50% of the US PEV market is in a single state: California. The state's reported utility emissions factors are also much lower than national averages. Using a production grid intensity closer to some Asian manufacturing hubs (around 1 kg CO_2e/kWh), and an average operating grid intensity for California (approximately 0.23 kgCO_2e/kWh), production emissions increase to 214-687 kg/kWh, but the life cycle emissions rate decreases to 94-135 g CO_2e/e-VKT. Doubling the expected range of production energy emissions intensities has little to modest impacts on per kilometer emissions rates, as exhibited by these results. Cycle life (including climate impacts), and operating grid emissions intensity are likely the key factors affecting traction battery emissions performance.

Effective throughput of the traction battery over expected cycles has been used to estimate the total kilometers travelled by the vehicle. Lifetime e-VKT generation for long-range traction batteries is currently highly uncertain due to a number of factors; some, including driver behavior, mechanical failure, and vehicle accidents, are not assessed in this study. Regional variations in travel patterns and travel demands could also impact lifetime e-VKT. Further research is required to assess how these factors will impact traction battery carbon payback period. High mileage vehicles may come up against calendar aging considerations or accident/mechanical failure before maximum mileages are reached. As more data on PEV usage and real-world battery cycle performance becomes available, estimates of effective lifetime e-VKT for PEVs is also likely to improve.

5.6 CONCLUSION

This research highlights a number of factors that influence the performance of PEVs from a GHG emissions standpoint; these findings can be used to inform the regulatory landscape for deployment of PEVs in the U.S. and globally, as well as shape engineering decisions for vehicle OEMs. This probabilistic approach to considering life cycle battery performance as a function of chemistry and based on a meta-analysis of battery performance data, shows that the exclusion of production-related emissions for PEVs and realistic operating performance may ignore tradeoffs in production and operation emissions of PEVs. This means a life cycle approach for regulating emissions intensity (g CO_2e/VKT) may be required to ensure that policies intended to reduce GHG emissions and preferentially encourage low emissions vehicles are successful. This conclusion supports the findings of previous work on other production-related emissions, even for non PEVs, such as those from lightweight materials, which can overwhelm the emissions reduction achieved during vehicle operation (Kendall & Price, 2012). Projections of future grid CO_2e emissions intensity, which suggest significant reductions over time, and increasingly efficient ICE vehicle operation, serve to increase the contribution of production emissions to life cycle emissions for light-duty vehicles, and suggest that the need for a life cycle perspective in regulatory frameworks.

Acknowledgements

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6. Life Cycle Assessment of Future Light Duty Electric Vehicles

6.1 Purpose and Scope

The majority of previous studies examining life cycle greenhouse gas (LCGHG) emissions of battery electric vehicles (BEVs) have focused on efficiency-oriented vehicle designs with limited battery capacities. However, two dominant trends in the U.S. BEV market make these studies increasingly obsolete: sales show significant increases in battery capacity and attendant range, and are increasingly dominated by large luxury or high-performance vehicles. In addition, an era of new use and ownership models may mean significant changes to vehicle utilization. At the same time, the carbon intensity of electricity is expected to decrease. Thus, the question is whether these trends significantly alter our expectations of future BEV LCGHG emissions. To answer this question, this chapter considers the possible evolution of three archetypal vehicle designs for the year 2018 and 2025; a high performance luxury sedan; and a luxury sport utility vehicle. A LCGHG models developed and used to compare emissions for vehicles with longer range, different battery capacity, different use models, or operating grids.

This chapter includes some text adapted from **Ambrose, H.**, Wachche, S., Lozano, M., & Kendall, A. (Under Review) Life Cycle Assessment of Current and Future Electric Vehicles. *Transportation Research Part D: Transport and the Environment.*

6.2 Introduction

Transportation comprises 28% of U.S. greenhouse gas (GHG) emissions, 60% of which come from light-duty vehicles (LDVs) (US Environmental Protection Agency, 2018). While a multipronged approach is needed to achieve deep reductions in transportation GHG emissions, rapid and extensive deployment of battery electric vehicles (BEVs) is viewed as a crucial part of nearly all strategies (Alexander, 2015a; Meszler et al., 2015; Sperling, 2018). BEVs are typically referred to as zero emissions vehicles (ZEVs) because they eliminate tailpipe pollution. However, as with other de-carbonization policies for the transport sector, such as those that promote biofuels, a life cycle perspective is required to understand the actual mitigation achieved by ZEVs, since emissions are not eliminated, but rather shifted upstream in the fuel cycle (to the power plant) and potentially increased in the vehicle production supply chain. BEVs can also have considerable variability in life cycle operation emissions given the heterogeneity of electricity grids over space and time (Cerdas et al., 2018; Tamayao et al., 2015; Yuksel and Michalek, 2015).

Numerous life cycle-based studies have been conducted with the goal of verifying if BEVs achieve real reductions in emissions relative to internal combustion engine vehicles (ICEVs). These studies suggest that GHG emissions associated with energy for BEV operation (i.e. production of electricity) can be 44% - 80% of BEV LCGHG emissions. For non-operation GHG emissions, energy required for manufacturing of lithium-ion batteries is the primary driver of increased GHG emissions relative to ICEVs (Peters et al., 2017). Uncertainty about battery manufacturing and a lack of primary data have contributed to a wide range of results for GHG emissions associated with battery production (Ambrose and Kendall, 2016; Ellingsen et al., 2014). Moreover, given the growth in BEV sales, the evolution of BEV designs and model availability, and declining prices for traction batteries (Nykvist and Nilsson, 2015), previous life cycle assessments (LCAs) may not be representative of current and future BEV performance, vehicle specifications, or patterns of use.

6.2.1 Review of Literature and Relevant Data

A review of previous LCAs (here we use the term LCA to refer both to comprehensive LCAs that track a suite of environmental impacts as well as those that narrowly assess GHG emissions), summarized in Table 1, shows that most studies used the early generations of the Nissan Leaf as the exemplar BEV (Archsmith et al., 2015; Ellingsen et al., 2014; Graff Zivin et al., 2014; Hawkins et al., 2013; Majeau-Bettez et al., 2011; Samaras and Meisterling, 2008; Tamayao et al., 2015). Because of this, most previous LCAs have used similar assumptions, including the ~24 kWh battery capacity and efficiency-oriented compact vehicle design. Many of the earliest LCA studies of electric vehicles found that emissions from the electricity grid used to charge EVs were the most significant contributor to life cycle CO_2e emissions from BEVs (Hawkins et al., 2012). Justifiably, more recent studies have focused on interactions of BEVs and the electricity system, examining the consequential effects of replacing ICEVs with BEVs, and the intersection of charging strategies with the marginal dispatch decisions of electric utilities (Archsmith et al., 2015; Jenn et al., 2016; Yuksel and Michalek, 2015). At least one study has considered the effect of battery range and vehicle size on BEV performance (Ellingsen et al., 2016). They found commensurate increases in LCGHG with increasing battery and vehicle size and, similar to previous studies, found that electricity grid carbon intensity determined the preference of BEV vehicles over their conventional fossil fuel counterparts.

While previous studies provided valuable insights about the life cycle performance of vehicles and the importance of electricity grid emissions (whether modeled as marginal or average emissions), the majority of these studies reflect outmoded assumptions about BEV vehicle designs and did not reflect trends in the BEV market. A review of U.S. BEV sales between 2012 and 2018 shows a marked shift towards significantly higher capacity batteries, longer vehicle ranges, and an increasing preference for high performance and luxury BEVs. The combined effect of these two trends is evident in Figure 1, which shows the U.S. sales-weighted average annual increase in BEV battery capacity of 6.5 kWh per year between the first quarter of 2012 and the second quarter of 2018, reaching 74 kWh by the second quarter of 2018. As the market for BEVs has grown, so too have the number of BEV models available. Instead of the efficiency-oriented compact passenger vehicle, the fastest selling BEV in the U.S. has become the leader in the luxury sedan segment (Alternative Fuel Data Center, 2018). Sport-utility BEVs have emerged as an important market segment with several major vehicle manufacturers launching cross-over style BEVs (Gale, 2018).

Two important trends in personal mobility are also changing the use-cases for BEVs: one, the increased use of and participation in on-demand ride sharing services; and two, increased reliance on automated and connected vehicle technologies to replace human driving activities (Greenblatt and Shaheen, 2015). While the net effects of these trends on vehicle travel is still unknown, the emergence of ride-hailing services like Uber and Lyft are having significant impacts on traditional modes (e.g. transit) and historical patterns of mobility (Clewlow and Mishra, 2017; Hall et al., 2018). Based on early research, individual shared or automated vehicles could generate three to four times the comparable annual VMT of a conventional (private) passenger vehicle (Fagnant and Kockelman, 2014; Gurumurthy and Kockelman, 2018; Loeb et al., 2018). Vehicles participating in ride-hailing services can also experience significant mileage from return links, also known as dead-heading (Henao, 2017). While induced VMT has important implications for climate and environmental policy, use of shared, automated vehicle technologies (SAVs) could increase access to mobility, particular for vulnerable, disadvantaged, or mobility challenged populations (Harper et al., 2016).

Table 6.1 Review of Selected Vehicle and Performance Characteristics from Life Cycle Studies of BEVs and Gasoline Vehicles (ICEV and HEV)

Study	Vehicle Type	Battery Capacity (kWh)	Vehicle Production Emissions (kg CO_2e)	Battery Production Emissions (kg CO_2e)	Vehicle Operation Emissions (g CO_2e/km)
Samaras and Meisterling (2008)	PHEV	20.1	7800	2420	40.0
Notter et al. (2010)	BEV	34.2	6200	1800	101
Majeau-Bettez et al. (2011)	BEV	24	7200	4704	
Dunn et al. (2012)	BEV	28	7000	1092	
Hawkins et al. (2013)	BEV	24	7813	4620	
Ellingsen et al. (2014)	BEV	26.6		6400	
Zivin et al. (2014)	BEV	24			69 – 293
Miotti et al. (2015)	BEV	19 – 60	7360	1090	120 – 185
Tamayao et al. (2015)	BEV	24	2444	4124	41 – 144
Kim et al. (2016)	BEV	24	7500	3400	
Archsmith et al. (2016)	BEV	28	7710	1542	124 – 194
Ellingsen et al. (2017)	BEV	60		6390	
Average ICEV (N=8 Studies, see table S1.1 for details)	ICEV		8294		191.5
Average HEV (traction battery included in vehicle production; N=6 Studies, see table S1.1 for details)	HEV		9420		195

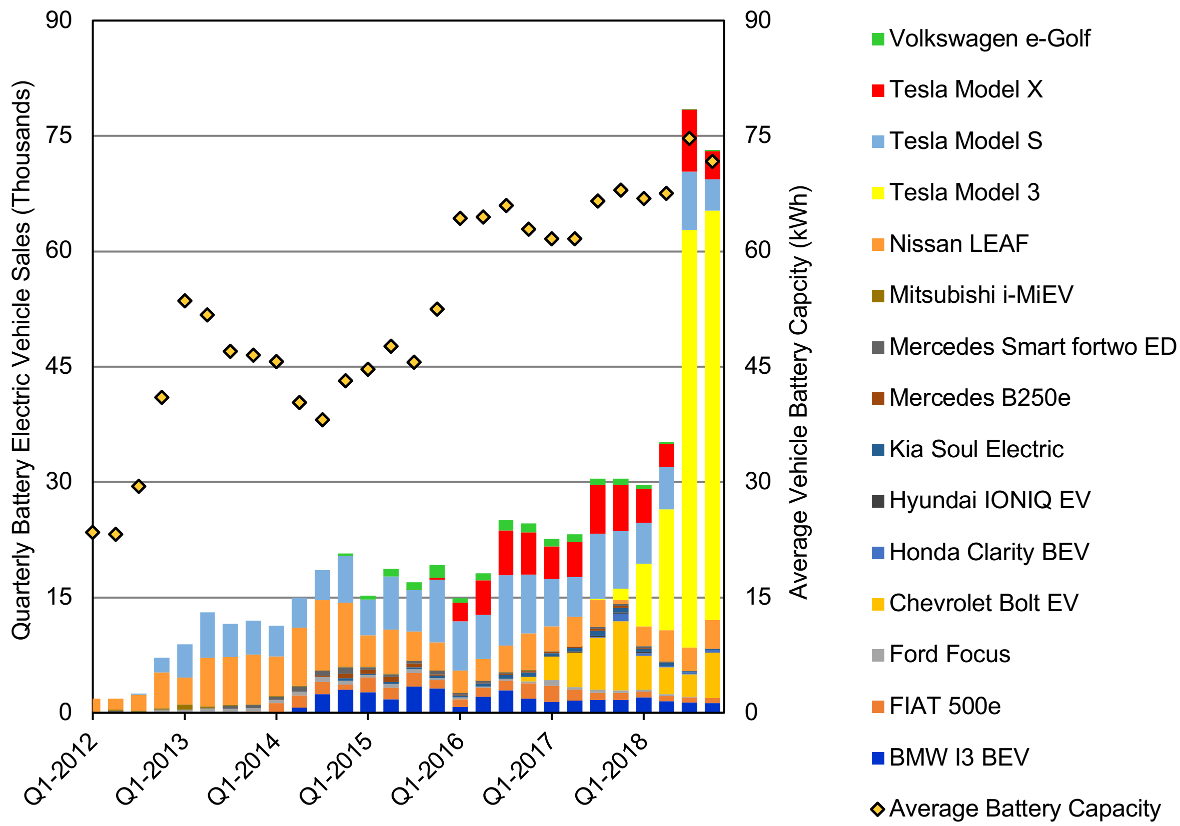

Figure 6.1 BEV sales and battery capacities in the U.S.

The combined effects of larger battery capacity; a shift towards large, high-performance BEV models; and the increased use of BEVs in high-mileage applications may challenge some of the widely accepted conclusions of earlier BEV LCAs, namely the small contribution of vehicle production-related emissions to life cycle emissions and that in many parts of the U.S. (and in regions throughout the world) BEVs provide GHG mitigation benefits (albeit sometimes small) relative to internal combustion engine vehicles (ICEVs). This observation led to the following research questions explored in this study:

- How do current trends in BEV vehicle design, including increased battery capacity and high performance and luxury vehicles, affect LCGHG intensity of vehicle?
- What is the combined effect of vehicle design trends and technology and electricity grid evolution on the LCGHG emissions intensity of BEVs?
- How will these trends effect future emissions rates of BEVs, particularly in high-mileage applications like shared ride fleets?

6.3 Methodology

6.3.1 Goal and Scope

This study aimed to quantify the LCGHG emissions of three archetypal future BEVs that reflect the changing BEV market, as described below:

- Archetype 1 - An efficiency-oriented compact vehicle (EOV), based on the Chevrolet Bolt.
- Archetype 2 - A high performance luxury sedan (PLS), based on the Tesla Model S P100D.
- Archetype 3 - A high performance SUV (PSUV), based on the Tesla Model X P100D.

For each vehicle archetype, the study considers how future changes in vehicle design, battery performance, changing electricity grid, and annual mileage will affect the total LCGHG emissions of the vehicle. Results are presented in a functional unit of vehicle mile travelled (VMT), where total emissions are divided by the lifetime miles of the vehicle. This facilitates comparisons with ICEVs.

For each vehicle scenario, we evaluate a set of 2025 models with improved battery systems (Table 2). We then compare this to both current market BEVs, as well as a set of 2025 models with increased battery capacity and travel range (Long Range or LR).

The model includes both the operation and non-operation stages of the vehicle life cycle. The operations phase requires that differences in travel behavior and potential utilization strategies be considered. These differences are captured by modeling two sets of travel scenarios, which are applicable to the different vehicle models shown in Table 2:

- A privately-owned vehicle in an average U.S. Household (referred to as the AVE scenario)
- A service vehicle deployed in an urban, ride-hailing fleet (referred to as the SAV scenario)

The vehicle life cycle is divided in two phases; the vehicle phase, which includes vehicle production and disposal, and the operation phase. The vehicle phase is broken down into the battery system and the rest of the vehicle, referred to as the glider. The end-of-life (EOL) stage includes disposal and recycling of the glider. Disposal and/or recycling of the traction battery is not included because of uncertainty in how batteries will be managed in the future, particularly as many more batteries are retired and either recycling networks or second life uses emerge.

Use-phase emissions for BEVs are then estimated as a function of vehicle energy efficiency and the emissions associated with electricity production and delivery. Electricity emissions rates were modelled for both California and the U.S. national average based on the grid fuel mix from 2017 to 2025. To capture regional variability, changing fuel sources, and generation technologies in the electricity system, we also considered a range of electricity generation forecasts through sensitivity analysis as discussed in the next section.

6.3.2 LCI Inventory Model

The life cycle inventory (LCI) model tracks only energy consumption and GHG emissions. A three part LCI model was developed to estimate the required inputs of energy and raw materials and resulting emissions: part one evaluated the production of the vehicle glider body and balance of systems (the glider model); part two evaluated the production of the battery system; and part three evaluated the generation of electricity supplied to charge the vehicle.

Table 6.2: Overview of Scenarios Included in this Study

	ICE car	ICE SUV	HEV car	2012 MY Leaf	2018 EOV	2018 PLS	2018 PSUV	2025 EOV	2025 PLS	2025 PSUV	2025 LR EOV	2025 LR PLS	2025 LR PSUV
Fuel Economy (kWh/100 mi)	116	160	80	28.6	28.6	33.5	39.4	28.1	31.4	35.5	32.1	34.4	39.5
Battery Capacity (kWh)	–	–	–	24	60	100	100	60	100	100	100	125	175
Utilization (VMT) Scenarios (annual VMT in year 1 shown*)													
AVE	13467	14026	13467	12135	12135	12135	14026	12135	12135	14026	13467	13467	14026
SAV-High	-	-	-	-	-	-	-	-	-	-	69350	69350	69350
Electricity Generation Mix Scenarios													
California Average (BAU)	-	-	-	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑
California Average (carbon tax)	-	-	-	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑
U.S Average (BAU)	-	-	-	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑
U.S. Average with (carbon tax)	-	-	-	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑

*VMT changes every year with a decreasing trend (NHTS, 2017)

6.3.2.1 GLIDER MODEL

The glider model examined the life cycle emissions of the vehicle without the battery, which included raw material acquisition and refining, processing, assembly and disposal. The reference LCI data for this model was acquired from the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) 2 Model developed by Argonne National Laboratory (Argonne National Laboratory, 2017b). This data source provides the per-mass life cycle embodied energy and air pollutants, including GHGs, for materials used in vehicles. The data were combined with estimates of the material composition of vehicle gliders and their masses. The mass used for each modelled glider was the curb weight of the reference vehicle for each archetype (EOV/Chevy Bolt, PLS/Tesla Model S, PSUV/Tesla Model X) reduced by the mass of the battery. The impacts of material transformation were calculated for each material. The per-vehicle assembly and disposal impacts were assumed to be identical across all modelled BEVs. Other assumptions included the mass and number of replacements for fluids and tires, also acquired from the GREET 2 model. Further, because electricity use does not constitute a large portion of total energy use and resulting emissions in this phase, time dependence of the electric grid was not considered in the glider model–meaning that a vehicle produced in the future is modeled using the same electricity grid LCI as those produced today. For both 2018 and 2025 scenarios, glider material composition as well as per-mass emissions are assumed to be the same. And since no light-weighing was assumed, glider masses also remain the same. The baseline ICEV car, SUV, and HEV scenarios presented for comparison are taken from the default vehicle set in GREET2. The resulting estimates for the material balance of the vehicles, the average energy input for assembly processes, and further details on the vehicle model can be found in the.

6.3.2.2 BATTERY PRODUCTION
Battery production LCIs were developed using the model described in Ambrose and Kendall (2016), which combines the Battery Performance and Cost (BatPAC) model and underlying research from Argonne National Labs (Dunn et al.); Nelson et al. (2011) with life cycle inventories from GREET 2 to examine the GHG emissions and material composition of lithium-ion batteries (LIBs) for light-duty applications. The methods used to develop this model are described in Ambrose and Kendall (2016). All vehicle scenarios are assumed to use a lithium nickel manganese cobalt (NMC) battery chemistry. Variations of NMC have emerged as the dominate cathode chemistry for most light duty applications owing to its high specific power (Olivetti et al., 2017). The composition of lithium ion battery (LIB) packs can vary due to the type of cells used, thermal management systems, and structural elements. There is also considerable uncertainty in estimating the energy required for assembling LIB cells owing to limited, poor quality data (Peters et al., 2017). We considered several futures for battery design, production processes, and key inputs through a scenario based sensitivity analysis. These results, the normalized average material composition for each battery pack, assembly emissions estimates, as well as more discussion on the battery production model is included in the (Appendix D-S4).

The baseline assumption is that no battery replacements are required over the course of a vehicle's lifetime. This assumption and the conditions where battery replacement is likely to be needed is discussed in Section 3.1.

6.3.3 USE-PHASE MODEL

A use phase model was developed to estimate GHG emissions resulting from EV operation summarized in Equation 1, where the total emissions in kg CO_2-equivalent (CO_2e) for each technology (*i*) is the sum of, from 0 to the expected vehicle life (*n*), the annual miles travelled (*VMT*) in year (*t*), the average vehicle energy demands per mile (ρ_i), the LCGHG emissions rate for electricity generation in each year (*EF*), and the efficiency of the charger system (φ).

$$OperationsGHG_i = \sum_0^n VMT_{it} * \rho_i * {}^{EF_t}/_{\varphi} \qquad \text{Eq. (1)}$$

6.3.3.1 VEHICLE ENERGY DEMANDS
An existing vehicle dynamics model, the Future Automotive Systems Technology Simulator (FASTSim) tool developed and maintained by the National Renewable Energy Lab (NREL), was used to estimate the

average vehicle energy demand (ρ_i). FASTSim simulates vehicle energy demands as a function of primary physical forces including: drag, acceleration, ascent, rolling resistance, powertrain component efficiency and power limits, and regenerative braking (Brooker et al., 2015). Since FASTSim models vehicle performance at the powertrain component level, it allows users to modify the parameters of vehicle powertrain, such as battery capacity, energy density, motor power, glider dimensions, and weight to examine how powertrain design impacts fuel economy. The model was used to simulate vehicle energy demand. To ensure that this model represents vehicle performance appropriately, the model was parameterized for the 2012 and 2018 model years of the three archetypal vehicles and simulated results were validated against fuel economy values reported by the EPA (Environmental Protection Agency (EPA), 2018). FASTSim results were found to be within 7% range of the EPA reported fuel economy values for all models.

Table 6.3: Vehicle mass and key parameters by scenario

	Leaf (2012)	**EOV**	**PLS**	**PSUV**	**2025 EOV**	**2025 PLS**	**2025 PSUV**	**2025 LR EOV**	**2025 LR PLS**	**2025 LR EOV**
Drag coefficient	0.32	0.31	0.24	0.25	0.31	0.24	0.25	0.31	0.24	0.25
Frontal area (m^2)	2.76	2.82	2.34	2.59	2.82	2.34	2.59	2.82	2.34	2.59
Curb Weight (kg)	1557	1619	2215	2459	1448	1929	2173	1640	2050	2543
Battery mass (kg)	290	460	766	766	288	481	481	481	601	841

Table 6.3 shows the assumed curb weight and key vehicle specification inputs by vehicle scenario. The aerodynamic and motor specifications are held constant across each class of vehicle modeled. As explained in the section on Glider model, curb weights vary according to battery systems improvements and battery sizing. Hence in the 2025 vehicle models, the expected increase in future battery density brings down the curb weights when battery capacities remain the same as 2018 vehicle models. But as battery capacities are increased in the long range scenarios, the curb weights increase accordingly. Additional review of the vehicle assumptions and discussion is provided in the (Appendix D).

6.3.3.2 VEHICLE MILES TRAVELLED (VMT)

Two sets of scenarios for vehicle travel were developed: one representing primary use in a personal passenger vehicle application and another representing use in a shared on-demand or potentially automated ride-hailing fleet. The 2017 National Household Transportation Survey (NHTS) was used to estimate passenger vehicle travel. The 2017 NHTS collected information on the type (e.g. car, van, SUV, or truck), fuel, hybrid or electric powertrain, and annual mileage of vehicles present in the household. These data suggest: one, a strong decline in mileage generation over the life of the vehicle, with older vehicles generally less likely to experience high annual mileage; and two, significant differences in mileage generation across vehicle types and fuel types, particularly for HEVs and BEVs. U.S. vehicle scrappage rates from 1999 – 2009 were used to estimate the average lifetime of vehicles for all scenarios (Jacobsen and Van Benthem, 2015). The average annual vehicles miles travelled for gasoline cars (i.e. automobiles and station wagons), hybrid cars, and gasoline SUVs (e.g. Santa Fe, Tahoe, Jeep, etc.) were used. There are relatively few BEVs reflected in the 2017 NHTS sample (n=545 out of n=252,042 vehicles). While BEVs reported approximately 10% fewer annual miles travelled compared to conventional gas vehicles, it was not possible to estimate the annual mileage by vehicle age. Therefore, the annual mileage for gasoline cars and SUVs were scaled linearly by the average difference to estimate annual miles for BEV scenarios.

The SAV scenario was modelled based on secondary empirical data from ride hailing vehicles (Henao, 2017), and simulations of potential future automated vehicle fleets (Fagnant and Kockelman, 2014; Gurumurthy and Kockelman, 2018; Loeb et al., 2018). In the SAV scenario, vehicles are assumed to travel 200 miles per day in service, and to have a declining utilization factor (i.e. days in service per year) averaging 80% over the vehicle lifetime. The assumed annual vehicle travel for both the passenger vehicle and SAV scenarios are provided in the (Appendix D).

6.3.3.3 CHARGING

BEVs are likely to utilize a range of private or public charging infrastructures with different power levels for charging events, which could impact the efficiency of refueling the vehicle (Smart and Schey, 2012; Tal et al., 2014). Sears et al. (2014) collected data on charger efficiency for a range of charging power levels and climate conditions from a small sample of Nissan Leaf and Chevy Bolt drivers; the authors found efficiency ranged 83.8% to 89.4% for Level 1 vs 2 charging events. There are much more limited data is available for the efficiency of high power chargers. It is likely that any variability in BEV emissions rate attributable to variation across charging infrastructures is less than that due to climate, driving distance, and other factors (Taggart, 2017). In this study, an average efficiency of $\varphi = 86\%$ is used for all scenarios, and the sensitivity of results to this assumption is explored in the discussion.

6.3.3.4 ELECTRICITY GENERATION

LCAs of EVs have long struggled to determine how best to model electricity used in vehicle charging. The alternatives from a modeling perspective are typically framed as either a consequential perspective (how the additional or new demand from a BEV charging event is met) or an attributional perspective, where BEVs are treated as requiring an average unit of electricity. The average emissions or attributional approach assumes all electricity as a shared resource for all end uses, while the consequential emissions approach recognizes the role of certain generators in meeting marginal demand, thereby scaling in response to the incremental load of vehicle charging (Alexander, 2015b). Researchers have taken different approaches for estimating marginal emissions. Some studies try to identify the marginal electricity supply based on what will be or has been dispatched amongst the current mix of sources in response to an extra load, while other studies have looked at long term change in the grid mix in response to the additional demand from EVs (Archsmith et al.; Siler-Evans et al., 2012). While there is a strong argument for consequential approaches to estimating electricity emissions, the focus of this study is not to capture the short term consequences of deploying electric vehicles. Instead, the goal is to estimate how trends in the foreground system (i.e. vehicle production and use) and background system (e.g. electricity grid mix) are likely to change the LCGHG performance of future vehicles. As such, the average fuel mix and associated GHG emission factors are used to estimate vehicle operation emissions for each year of vehicle operation.

The projected electricity generation by fuel source was obtained from the U.S. Energy Information Administration (2018). Two regions were considered, the California sub region of the Western Electricity Coordinating Council region (CAMX), and the U.S, national average. For both regions, emissions were evaluated under a reference case or business as usual scenario(BAU), and a carbon tax scenario assuming a $25 allowance fee on CO_2 emissions from utility-scale electricity generators beginning at $25 (in 2017 dollars) in 2020 and increasing at 5% per year in real dollar terms (U.S. Energy Information Administration, 2018). The average emissions rate (EF_t) is estimated as the mass of GHG equivalent emissions per unit of delivered energy with Equation 2, 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 (*m):*

$$EF_t = \frac{Fuel_{tx}}{\sum_x Fuel_{tx}} * LCI_{xe} * m_e \qquad \text{Eq. (2)}$$

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 2018 GREET 1 model (Argonne National Laboratory, 2017a), and a representative LCI was estimated for each fuel source based on the net generation by generator type for each regional scenario (US Environmental Protection Agency, 2016). The renewables were treated as zero emission fuels here. The resulting carbon intensity forecasts for each electricity generation mix are shown in Figure 6.3(B), and the full results are available in Appendix D.

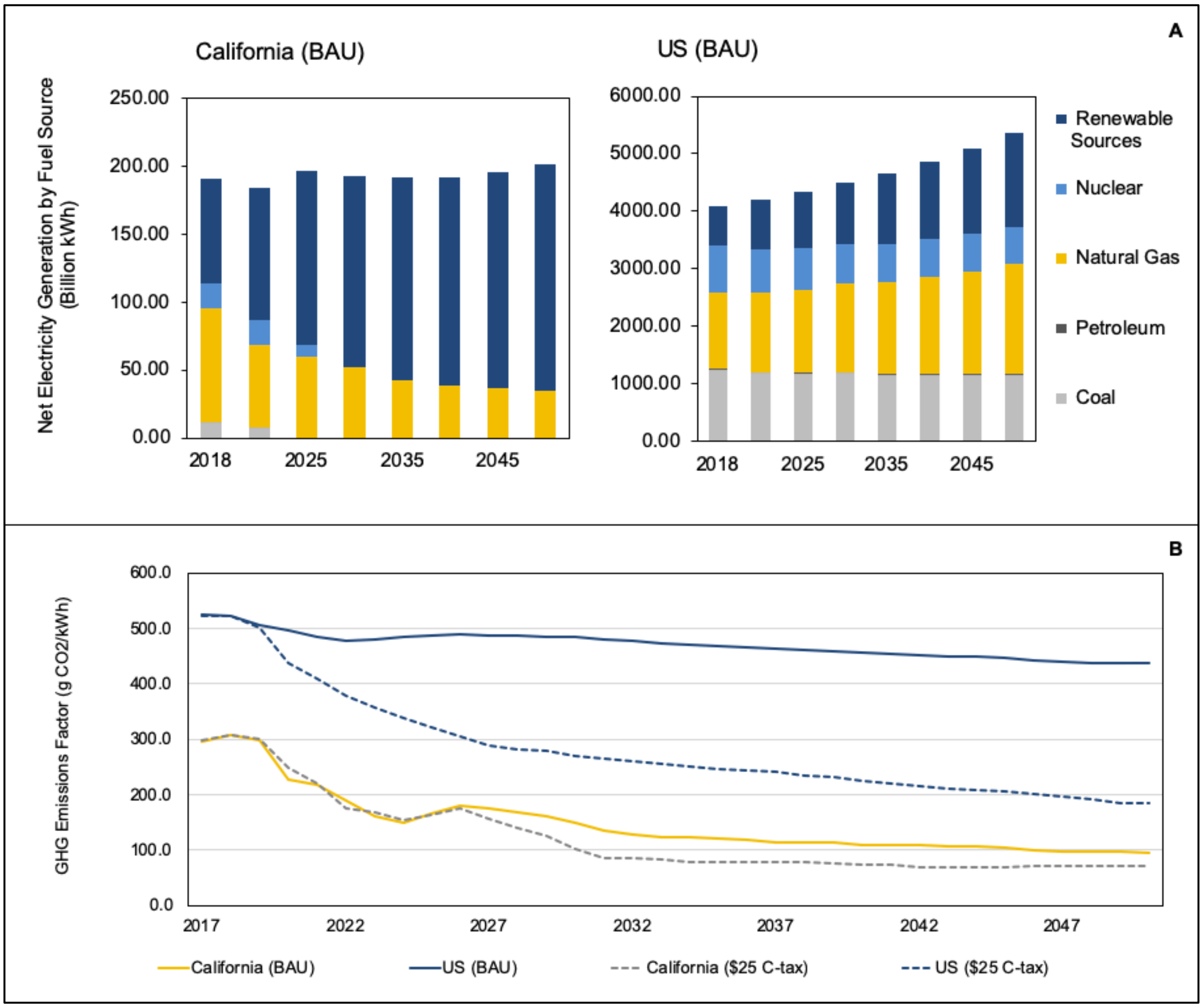

Figure 6.3 (A) Total Electricity Generation by Fuel Source in California and the US and (B) Average GHG Emissions per kWh for Residential and Commercial End-Uses for BAU and $25 carbon tax ($25 C-tax) scenarios in California and the US (2017 – 2050)

6.4 Results

LCGHG emissions for BEVs were found to range from 108 gCO_2e/mile for an efficiency-oriented compact BEV in California up to 370 gCO_2e/mile for the larger PSUV in the U.S. average scenario. This compares to conventional gasoline vehicle life cycle emissions of 460 to 503 gCO_2e/mile and to hybrid electric vehicle life cycle emissions of 336 gCO_2e/mile. Figure 4 summarizes the average contribution of vehicle and battery production, vehicle end of life, and vehicle operation to life cycle GHG emissions for each vehicle and utilization scenario. Life cycle emissions from BEVs under the California scenarios (105 - 204 gCO_2e/mile - black diamonds in Figure 6.4), were 37% - 50% lower than under the U.S. average scenario (210 – 342 gCO_2e/mile). Across all the three vehicle archetypes, emissions for the long range (LR) vehicles increased by 7% - 13% for 2025 models. Like conventional ICEVs and HEVs, the main driver of LCGHG emissions for BEVs is the operation phase. But while only 8% to 15% of LCGHG emissions for ICEVs are attributable to vehicle production, production of electric vehicle and battery systems were estimated to contribute 20% - 55% of per mile emissions for BEVs. Production of the battery system contributed 37% - 40% of production emissions for BEVs, and 8% to 21% of overall per mile emissions.

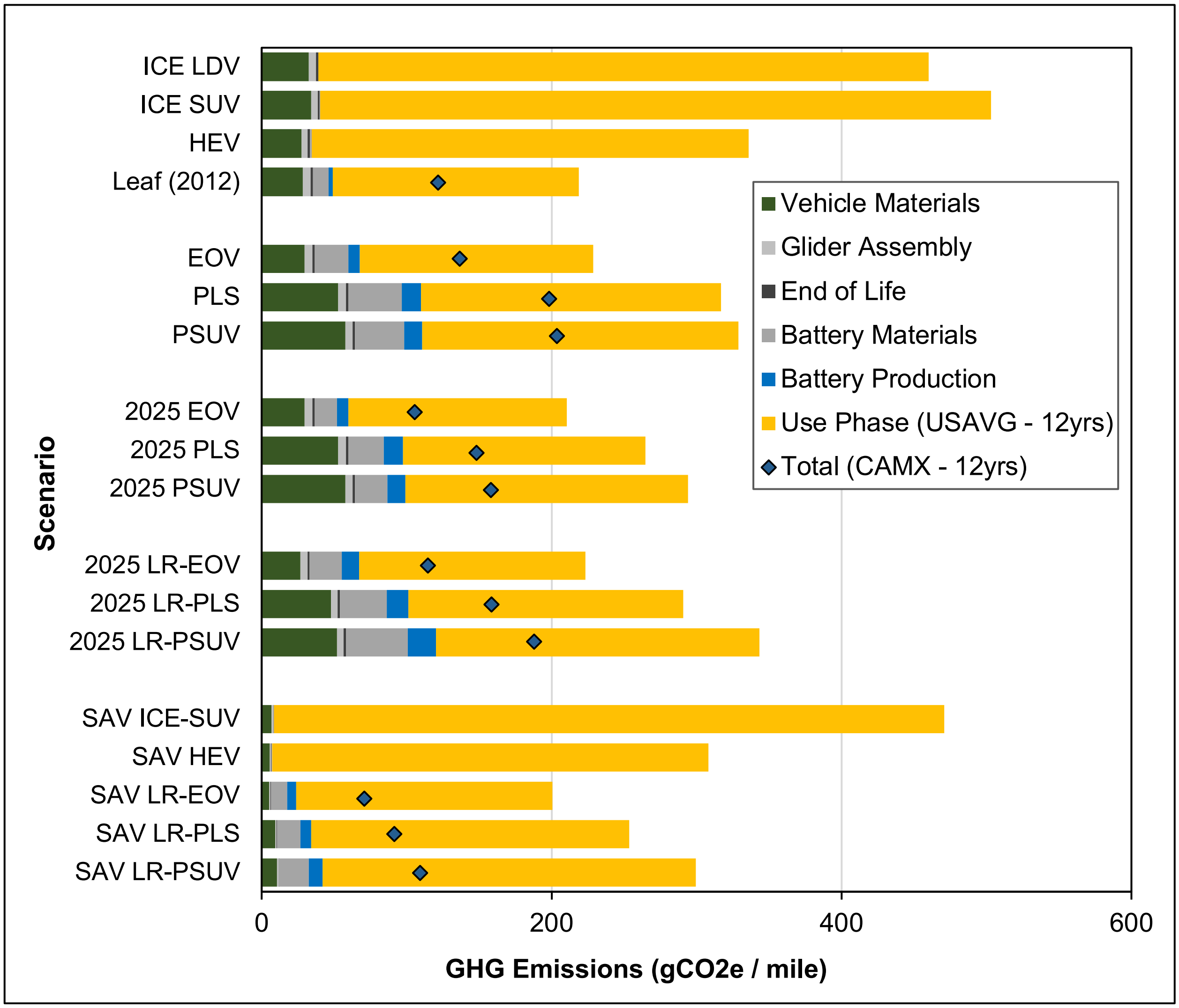

Figure 6.4 LCGHG Emissions by vehicle, grid, and utilization scenario

While BEV emissions were lower under the carbon tax scenarios, the difference was significantly larger for the U.S. case. The $25 US carbon tax scenario reduced life cycle emissions of current (2018) BEVs by 14% - 17% compared to the USAVG over an average 12 year vehicle life; emissions reductions grew to 27% - 30% for 2025 BEV models. The carbon tax scenarios reveal the importance of assumptions about electricity generation over time in estimating use phase emissions rates and the significance of use-phase emissions in life cycle emissions rates. This includes both the types of generation technologies and fuel sources associated with electricity for vehicle charging.

The SAV scenarios assume the 2025 LR vehicle archetypes and grid mix, and these vehicles are assumed travel approximately 200 miles per day, for an average of 5.45 times the annual mileage of the personal SUV scenario. The SAV scenarios resulted in lower LCGHG emissions for BEVs on a per mile basis compared to the private average personal vehicle scenarios when compared over equivalent service periods. The use of BEVs could reduce LCGHG emissions of service vehicles by over 44% when switching from a comparable ICEV PSUV and 42% when switching from a comparable HEV to a 2025 LR-EOV. These reductions become more significant under the carbon tax scenarios, with the BEV SAVs averaging 57 – 86 gCO_2e/mile under the California with $25 carbon tax scenario.

In these high mileage applications, it is also expected that key vehicle systems will require additional replacement due to excessive wear. The results reported for the SAV scenarios assume replacement of vehicle battery based on expected lifetimes. Battery systems are assumed to be replaced after delivering a fixed number of equivalent charge and discharge cycles, and the estimates in Figure 6.4 for BEV SAVs assume an average 1 to 1.5 battery replacements over the average 12 year vehicle life. Vehicle powertrain, chassis, and other systems were not assumed to experience additional replacements as a function of mileage. The service life of the battery is discussed further in the next section.

6.4.1 Battery Replacement and Service Lifetimes

Battery cycle life is generally defined by the total number of times a battery can deliver its energy storage potential in a particular discharge program (Barré et al., 2014; Fortenbacher et al., 2014; Han et al., 2014), thus the service life will vary under different duty cycles and operating conditions. The effective cycle life is highly dependent on the utilization of storage potential and the rate of discharge. A common metric or measurement of battery performance is cycles to 80% depth of discharge (DOD), or 80% of the battery energy storage potential. Cycles to 80% DOD is also convenient as utilization of the battery near the maximum and minimum of the battery potential are associated with accelerated battery degradation. Many battery systems are managed to prevent discharge below or charging above a certain threshold to prevent damage to the battery system. While early lithium ion vehicle cells might only deliver several hundred cycles before experiencing noticeable capacity degredation (>20%), current and future batteries are expected to exceed 1000 cycles and may reach 5000 to 6000 cycles at 80% DOD (Burke, 2014; Howell et al., 2018).

Given the average vehicle miles traveled (VMT) of personal vehicles and the range of vehicles included in the study, batteries would not necessarily exceed 1000 equivalent cycles over the average vehicle lifetime (12 years). Figure 6 shows the cumulative average battery cycles to 80% DOD for each scenario considered in this study. In ride hailing applications, recent literature suggest vehicles could travel more than 2 to 5 times the average daily vehicle miles of a comparable personal vehicle (Fagnant and Kockelman, 2014; Gurumurthy and Kockelman, 2018; Henao, 2017). In the SAV scenarios, where vehicles travelled 200 miles per day on average, battery replacement could be required over the vehicle lifetime to ensure that older vehicles continue to meet range requirements. In the SAV scenario, battery systems are discharged completely on most days and experience 277 - 323 equivalent cycles per year

(Figure 6.6). Assuming a limit of 1500 cycles to 80% DOD, the average vehicle would require one battery replacement on average (0.8 to 1.5 replacements in 12 years depending on battery size).

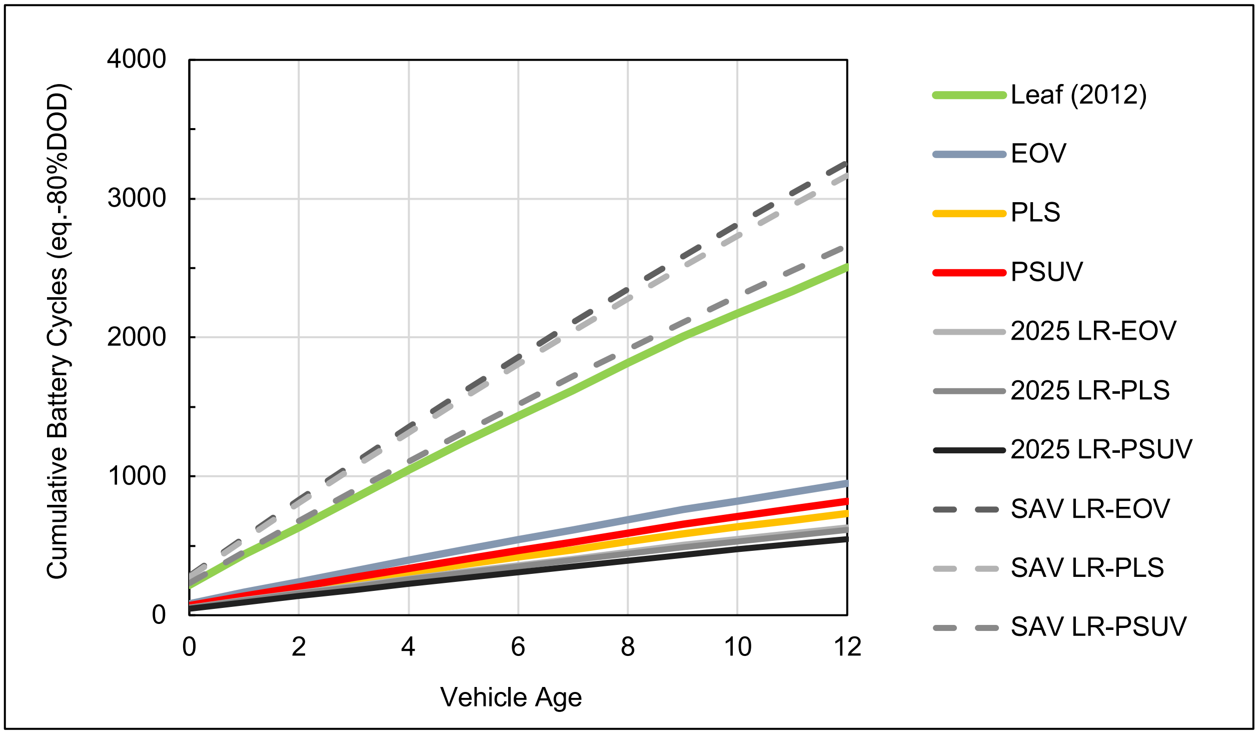

Figure 6.6 Battery Cycles by VMT Scenario

6.4.2 Electricity

Emissions generated during the vehicle use-phase from producing electricity to charge the vehicle are on average more than 50% of LCGHG emissions. A key uncertainty in estimating use-phase emissions for BEVs stems from variability in the emissions rate for delivered electricity. The effects of BEV efficiency on per mile emissions have also been poorly addressed in many previous studies due to the limited types of vehicles evaluated. Figure 7 shows the relationship between vehicle efficiency (kWh/100 miles) vs. the GHG emissions per kWh of energy for vehicle charging. The labelled lines are constant emissions rates delimitating ranges of emissions from 100 to 500 gCO_2e/mile. The average life cycle emissions rate for current and 2025 LR vehicle archetypes are also indicated in the California and U.S. reference case (BAU) grid scenarios in the left and right panels respectively.

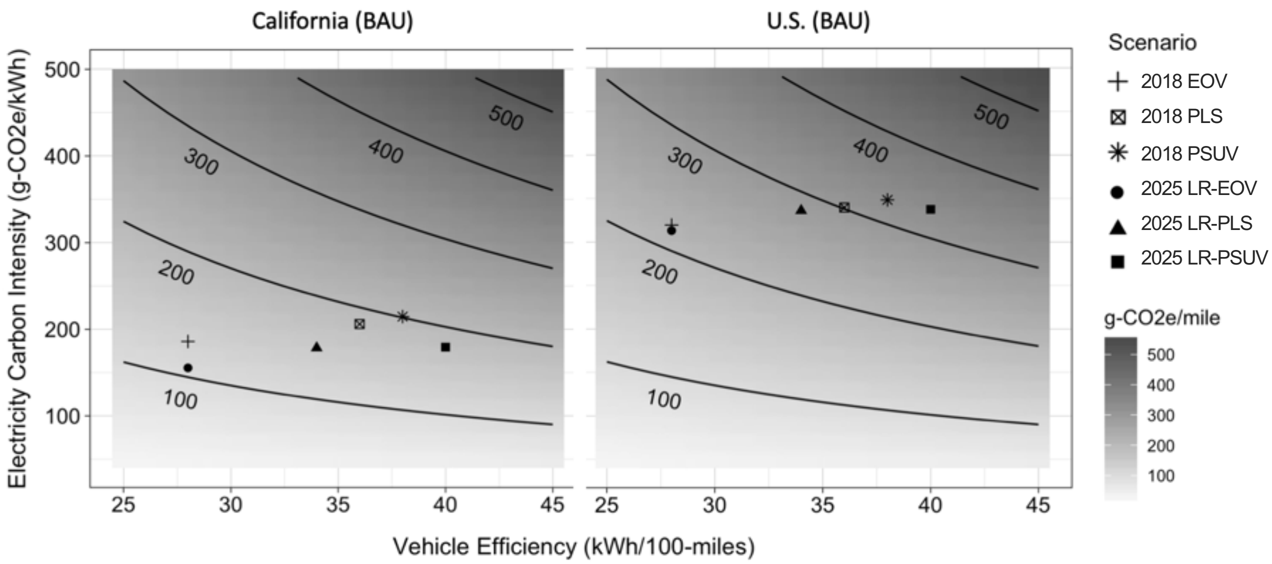

Figure 6.7 EV LCGHG Emissions per Mile with Sensitivity to Grid Emissions and Vehicle Efficiency

6.5 DISCUSSION

Increasing BEV battery capacities could have mixed impacts on the life cycle emissions rate of grid-tied BEVs and the GHG abatement from a transition away from gasoline powered vehicles. Longer range BEVs could reduce barriers to adopting electric vehicles and enable more electric vehicle travel where charging infrastructure is undeveloped. But the materials and energy required to manufacture batteries could have a significant contribution to per-mile emissions rates, particularly when vehicles have low utilization. In the absence of other measures to de-carbonization electricity for charging vehicles, future longer range BEVs may have higher life cycle emissions rates than current BEVs.

A shift towards larger, less efficient vehicles can offset current transportation emissions abatement measures, but would only increase the importance of vehicle electrification to goals for de-carbonization. The 2017 NHTS data used in this study suggest SUVs and larger passenger vehicles travel 8% more miles per year on average, but this discrepancy is skewed towards older vehicles. Older SUVs can travel 20% more miles than the comparable age US passenger car. Prior assessment by the EPA for the mid-term evaluation for the Corporate Average Fuel Economy Standard found a similar pattern of vehicle aging on annual vehicle miles travelled for cars and light trucks (US Department of Transportation, 2017). While larger BEVs could have twice the emissions rate of efficiency-oriented compact designs, the total reduction in emissions of switching from an ICE SUV to a BEV SUV is equivalent or greater to that for cars. This highlights the need for more development of the BEV SUV and large vehicle market.

Extending the vehicle life of BEVs and increasing vehicle utilization can lower the LCGHG emission intensity (i.e. gCO_2e/km) rate of BEVs. BEVs in high-mileage applications such as ride-hailing were found to have lower LCGHG emissions despite the potential for additional battery replacement. This was attributable to increased utilization of battery and vehicle systems (vehicles are usually idle), and the decreasing carbon intensity of electricity emissions.

6.6 Conclusions

This study examined trends in BEV design choices and use models including battery pack size, vehicle archetype, and vehicle utilization (annual VMT assumptions), as well as changing electricity emissions to examine the potential effects on LCGHG emissions of BEVs. While BEVs can reduce emissions relative to conventional ICEVs, trends in vehicle choice, utilization of increasing battery capacity, and considerations of future ownership and utilization models all influence their relative performance. In particular, the trend towards larger vehicles with larger battery packs leads to a deterioration in BEV GHG mitigation potential compared to ICEVs as a result of both vehicle production and operation emissions. At the same time, the decreasing carbon intensity of electricity grids over time, not to mention current and future differences over space (i.e. California versus U.S. average grid emissions), are largely countervailing trends that lead to improving GHG mitigation potential for BEVs over time. Increasing battery capacity (i.e. larger batteries), can reduce the per-mile life cycle emissions for vehicles, however, if they enable high-mileage use models, such as vehicles used in ride-hailing applications.

These results suggest three important conclusions: (1) like all vehicle types (whether ICEVs or BEVs) larger high-performance vehicle choices are likely to decrease energy efficiency and thus increase emissions; (2) the most benefit for investing in large-capacity batteries and BEVs more generally are in high-mileage applications; and (3) including trends in BEV design choices, temporal and spatial heterogeneity of electricity grids, and new vehicle use and ownership models lead to non-negligible differences in estimates of the LCGHG emissions (and mitigation potential relative to ICEVs) of BEVs. The results highlight predictable opportunities to increase the abatement potential of BEVs, such as de-carbonization of the electricity grid and a focus on vehicle energy economy. Slightly less obvious opportunities include right sizing batteries based on expected vehicle use, or put differently, higher utilization rates for BEVs (especially those with larger battery capacity).

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7. LIFE CYCLE COSTS AND BARRIERS FOR ELECTRIFICATION OF TRANSIT BUSES

7.1 PURPOSE AND SCOPE

In 2018, the California Air Resources Board (CARB) adopted regulatory changes that will require all new transit buses in the state to be zero-emissions by 2040. Battery electric buses (E-bus) are expected to be the primary technology adopted to achieve this policy goal. While a transition to E-buses may support emissions reductions targets and provide other benefits for urban areas, a transition to electricity from conventional liquid and natural gas fuel buses could also create new costs and uncertainties for transit agencies. Resource-constrained transit agencies must consider tradeoffs between service coverage, frequency, and operating expenses against investments in new technologies. This chapter explores how bus electrification will impact these costs by assessing the total cost of ownership (TCO) of transit buses using a probabilistic approach.

This chapter contains text from Ambrose, H., Pappas, N., Kendall, A. (2017). *Exploring the Costs of Electrification for California's Transit Agencies. Institute of Transportation Studies*, University of California, Davis, Research Report UCD-ITS-RR-17-16.

7.2 INTRODUCTION

The California Air Resources Board (CARB) is considering regulatory changes that would require an increasing share of transit buses to be zero-emissions by 2040 to mitigate transit's contribution to local air pollution and greenhouse gas (GHG) emissions. Transit operators serve multiple goals, including providing low-cost mobility to underserved populations and reducing pollution in urban communities. The proposed regulation will lead transit operators to purchase an increasing number of battery electric and fuel cell buses, which qualify as zero-emission buses (ZEBs). Battery electric buses (E-buses) are expected to be the primary zero-emission technology that will be adopted in the coming decades due to the high capital costs and limited availability of fuel cell buses. While a transition to ZEBs is aligned with the state's larger emissions reductions targets and has other benefits for urban areas, a transition to electricity from conventional liquid and natural gas fuel buses could create new costs and uncertainties for transit agencies. Resource-constrained transit agencies must consider tradeoffs between service coverage, frequency, and operating expenses against investments in new technologies; this research explores how electrification will impact these costs.

ZEBs combined with renewable transportation fuel pathways are likely critical to meeting demand for mobility in a low carbon future. The last fifteen years has witnessed a dramatic decline in the costs of vehicle hybridization, biofuels, renewable electricity generation, and vehicle light-weighting with advanced materials, which are enabling technologies for all zero-emission vehicles (ZEVs), and key to increasing the efficiency of vehicles while shifting them away from direct fossil energy combustion. Rapidly improving economics of battery storage, in particular, enable new ZEV applications, such as transit buses (Nykvist & Nilsson, 2015). Today, there are a growing number of commercial offerings of ZEBs for transit agencies to consider, as well as demonstration data to draw upon (Center, 2014, 2015a, 2015b; Cooney, Hawkins, & Marriott, 2013; Eudy, Prohaska, Kelly, & Post, 2016).

Transit agencies considering fleet technology upgrades need to consider the costs of vehicle ownership and operation when weighing vehicle purchase decisions. ZEB vehicle and fuel technology adoption offer new trade-offs between purchase and operation costs, uncertain vehicle and component system lifetimes, and the potential to consider environmental performance improvements. The lifetime cost of electric buses include not only the purchase cost of the vehicles, but also of charging equipment, maintenance costs, the cost of energy, and potential battery replacement costs (Ellram & Siferd, 1998). Lifetime cost of ownership models are often used to compare vehicle purchase options or fleet operations scenarios, and take into account both the fixed costs of vehicle acquisition and operation (Jørgensen, Pedersen, & Solvoll, 1995). Total cost, life cycle cost, product life cycle cost, and total cost of ownership are all related concepts that consider purchases in the context of longer term decision making (Ferrin & Plank, 2002).

Previous studies have found that the total cost for a transit bus over its lifetime is determined mostly by purchase price and fuel costs, when labor is excluded (Ahluwalia, Wang, & Kumar, 2012; Lajunen, 2014; Lowell, Seamonds, Park, & Turner, 2015). This has also been true for ZEBs, although limited purchase price data or demonstration costs have often been available for study (Bubna, Brunner, Gangloff, Advani, & Prasad, 2010; Karlaftis & McCarthy, 2002). Battery replacement costs for E-buses, and fuel cell stack replacements, have also been raised as potentially significant cost drivers. E-bus charging equipment and other infrastructure upgrades can also have a significant impact on overall vehicle cost (Ambrose & Jaller, 2016). Another potential confounding factor for estimating the costs of ZEBs for agencies is the presence of other enabling technologies that can affect operating performance. For example, on-route charging infrastructure for E-buses could both increase the costs of a system upgrade, but also allow for greater utilization and storage system size reductions (Cooney et al., 2013; Jang, Ko, & Jeong, 2012; Shirazi, Carr, & Knapp, 2015).

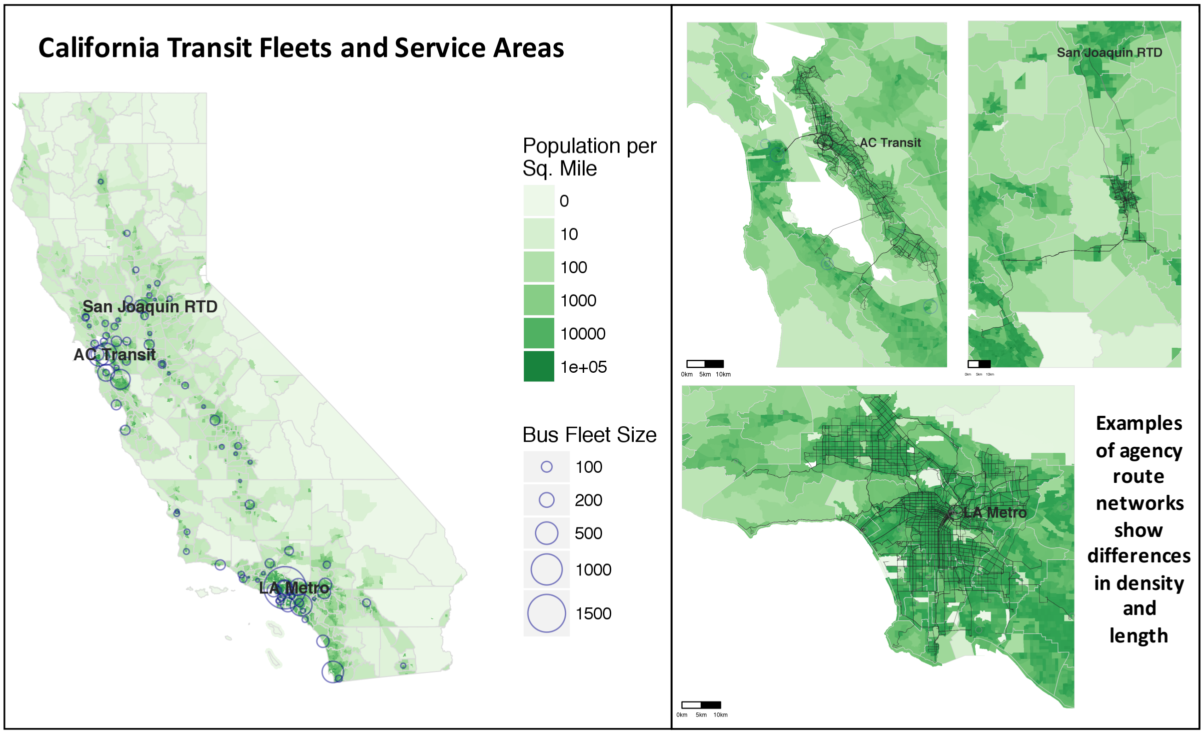

Figure 7.1 California Transit Fleets and Service Areas

(AC Transit = Alameda County Transit, LA Metro = Los Angeles County Metropolitan Transportation Authority)

Transit agencies in California operate a wide range of fleets in a diversity of service areas and route systems, all of which will impact the costs of agency or route electrification. There are over 150 transit bus agencies in California operating more than 9000 buses that collectively travel 316 million vehicle miles annually. The 20 largest agencies by vehicles in service represent over 75% of all transit buses in California, and 85% of all passenger miles reported to the Federal Transit Administration (FTA). Los Angeles County Metro (LACMTA) operates nearly one quarter of all transit buses in the state, about four times that of the second largest fleet.

Among and within these transit agencies, route distance and frequency are highly variable (Figure 1). Route distance and frequency affect the substitutability of E-buses for diesel and natural gas buses. Approximately 40% of the 6500 buses operated by the 20 largest agencies drive less than 150 miles per day and could be substituted for an E-bus given today's technology.

The State of California provides approximately a quarter of the capital and operating funds for transit agencies, with a slightly higher percentage for large agencies than small agencies by fleet size. Additional subsidies designed to accelerate the market for electric vehicles and to increase the use of alternative fuels in fleets are currently available to transit agencies adopting E-buses. These subsidies significantly affect the economics of adoption and should be considered alongside other costs of adoption. One issue raised around the discussion of the Advanced Clean Transit (ACT) regulation has been the future value of these subsidies. Transit agencies, who must make long term commitments to capital and operating expenditures on constrained funding cycles, are reticent to commit to relying on these subsidy programs, which they view as uncertain.

7.2.1 Objective of this Study

The objective of this study is to compare the TOC of adopting E-buses to the TOC of conventional transit buses under uncertain future cost and technology parameters. The study considers five possible vehicle and fuel technology combinations (referred to as pathways): diesel, diesel hybrid (hereafter called hybrid), compressed natural gas (CNG), CNG with a Low-NO_X engine[2] ($LoNO_X$) technology. The analysis includes adoption costs for transit agencies, considering expected changes in vehicle and fuel costs over subsequent purchase decisions. This report specifically considers:

- Purchase Costs
- Scheduled and Unscheduled Maintenance
- Midlife Repower/Refurbishment
- Fuel Costs
- Powertrain Efficiency
- Vehicle Duty Cycle
- Infrastructure Upgrades
- Existing Agency Infrastructure
- Vehicle Replacement Ratios and Schedules
- Vehicle Life
- Policy Subsidies

This study provides a rank ordering of how these factors contribute to uncertainty in predicting agency costs for adopting electric buses. The study also provides an estimate for how state-wide replacement costs might change between now and 2030, and discusses the role of policy incentives. The study does not directly consider some operational labor costs, such as bus drivers and dispatch staff. Aggregated per-mile costs, which include labor, are used for all repair and maintenance costs.

The study considers two purchase periods; each period represents intervals over which agencies will commit to bus replacement purchase decisions, and the likely costs agencies will experience over those replacements. The first period compares prices for conventional alternatives to electric buses for 2016-2018 new vehicle deliveries. The second period represents costs agencies might experience over the subsequent replacement decision, or 2028-2032 new vehicle deliveries, incorporating forecasted vehicle and energy costs across technologies. As agencies replace approximately 7%-8% of their bus fleet each year[3], CA transit agencies are likely to replace approximately one quarter of the active transit bus fleet during the first purchase period. The second five-year period represents the range of time when these same buses are likely to be replaced again.

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[2] CNG and LoNOx CNG engines include buses using Renewable Natural Gas (RNG). Further discussion of RNG costs and incentives can be found in the section on fuel costs.

[3] This is consistent with a 12 to 14 year service life for transit buses.

Purchases are simulated for different agency profiles identified by agency size, route structure, historical financial performance, and existing infrastructure. Three agency clusters (large, small, and rural transit agencies) were identified based on fleet size, operations data, route network, and service schedule:

Scenarios for Agency Type:

- **Rural** – less than 20 vehicles, limited depot infrastructure, NTD partial or rural reporter,
- **Small –** less than 300 vehicles, mid-sized depots, split of dense and rural routes (<2 stops per-mile)
- **Large** – 300 – 1500 vehicles, over 100 vehicles per depot, high number of dense routes (>5 stops per-mile)

Extrapolating from the current population of buses and major agency characteristics, we then estimate system-wide replacement costs under three scenarios for each time period.

Scenarios for System Cost Estimates:

- **BAU –** Full replacement of existing fleet with same vehicle and fuel pathway
- **All Electric –** 100% replacement of existing fleet with electric buses
- **All LoNO$_X$ CNG -** 100% replacement of existing fleet with LoNO$_X$ CNG buses

These scenarios are used to simulate statewide transition costs over the same time intervals based on the current population of transit agencies and fleet composition. All results are presented in net present value, discounted to the year of purchase, assuming a 5% discount rate for base model runs. Further discussion of methodological choices are addressed in the Appendix. The next section discusses the key parameters affecting adoption costs, how these parameters were incorporated into this study, and the specific assumptions adopted.

7.3 FACTORS AFFECTING THE COSTS OF OWNERSHIP FOR TRANSIT BUSES

The lifetime cost of ownership for a vehicle is an important indicator for transit agency operators considering new bus technologies and fuels. The lifetime cost of ownership generally includes changes in capital expenses (vehicle purchase, infrastructure, and facility upgrades) as well as operational expenses (fuel, repairs, and maintenance). Additional considerations that could impact the costs of adopting electric transit buses include the effects of route structure, planning for infrastructure investment, and decisions about technical configurations (i.e. on-route vs. optimized depot charging vs. convenience charging only).

This section of the report discusses each of these issues in more detail. Each subsection begins with background on the available data related to a set of key cost considerations, and closes with the specific assumptions adopted by the study. In each case, a probability distribution for parameter assumptions is estimated for each purchase period. Infrastructure investments, including storage depots, maintenance bays, and refueling facilities, are amortized through the use of a capital recovery factor and normalized by service life or mileage. In the sections on purchase prices and fuel prices respectively, we discuss state policies which incentivize the use of E-buses and significantly affect the cost structure of E-bus operations. Finally, we discuss some of methodological issues in estimating lifetime cost of ownership, and how certain methodological choices might lead to different conclusions.

A key focus of this study is characterizing how changes to key parameter assumptions contribute to uncertainty in estimating the lifetime costs of transit bus ownership. Including uncertainty is crucial to making robust cost comparisons. Uncertainty in lifetime costs stems from stochastic and cyclical variability in key costs, as well as uncertainty that arises from a lack of knowledge about likely parameter values. The latter is especially important when considering future costs, as costs for emerging technologies are not well established and are subject to considerable future change. It is also difficult to disaggregate variability from measurement errors and conflicts in the historical data for existing powertrains and fuels. To assess the effects of these variations on total cost, probabilistic parameter assumptions are combined through economic discounting and correlated random sampling to estimate the net present value of lifetime vehicle costs.

7.3.1 PURCHASE COSTS

The American Public Transportation Association (APTA) Public Transportation Vehicle Database offers a micro-level view on transit bus fleet composition with information including purchase price, vehicle age, and powertrain type. The APTA database includes purchase prices for 1,000 price points of 40' diesel, CNG, diesel hybrid, battery, and hydrogen bus purchases made by reporting transit agencies, and was used to assess the distribution of bus purchase prices by powertrain type for this study.

The average costs California agencies paid for buses over the most recent replacement decisions is shown in Table 7.1. Over the last ten vehicle model years (2005 to 2015), diesel bus prices have increased by 13-15%, while CNG bus prices have increased by almost 20% in California. For comparison, CARB's Transit Agency Workgroup reported from stakeholders that new 2016 diesel and CNG bus costs were approximately \$480,000 and \$520,000 respectively. This also aligns with trends in the APTA data for California; conventional bus prices are forecast to continue to increase by more than 2.3% per year between now and 2030 (CARB, 2015). Agencies we spoke with during this study also cited increasing costs for conventional buses.

Table 7.1 Average Bus Prices for 2010 to 2015 Model Year Vehicles Reported to APTA

Bus Length	CNG	Diesel	Hybrid	Std. Error
35 ft	$475,000	$441,639	$606,620	$14,308
40 ft	$485,038	$446,651	$619,439	$2,125
45 ft	$550,307	$541,112	$702,794	$2,109
60 ft	$802,000	$724,442	$850,000	$6,433

The use of diesel and gas engines with improved combustion and emissions control is part of the CARB mobile sources strategy to achieve ozone attainment in the South Coast Air Quality Management District. Engines meeting the 2023 NOx emissions standard of 0.02 gNOx/bhp are common referred to as Low-NOx ($LoNO_X$) LoNOx engines that are compatible with renewable natural gas (RNG) have also been proposed as a low-carbon heavy-duty fuel pathway. As an example, CNG transit buses are available with a Cummins Westport ISL G-Near Zero (NZ) engine, which achieves 2023 NOx standards. An ISL G-NZ upgrade is estimated to cost from $8,000-$25,000 more than the traditional ISL G engine, and currently there is no diesel engine on the market that meets the same emissions standard (Kassel & Leonard, 2016). In contrast, E-bus and hydrogen fuel cell bus purchase costs are expected to continue to decline with advances in battery technology (Eudy et al., 2016) and fuel cell systems. The CARB Transit Agency Workgroup expects that a 300 kWh battery bus will decline from roughly $850,000 in 2015 to $730,000 in 2030, assuming that the battery is the sole source of cost reduction (CARB, 2015). While the cost reductions for E-buses could be moderate to negligible, low cost reductions will likely coincide with considerable performance improvements, which could enable further system resizing and impact the costs of adoption.

Many E-buses are eligible for special incentive programs which can decrease purchase costs. The Hybrid and Zero-Emission Truck and Bus Voucher Incentive Project (HVIP) is a program implemented by CARB that provides purchase subsidies for vehicle purchases, including E-bus transit buses. Several E-buses were eligible for the HVIP under the most recent funding period, with subsidies ranging from $80,000 to $101,000 per vehicle[4]. HVIP funding is allocated by the state each year through the budget process. The principal sources of funds, the Low Carbon Transportation and Air Quality Improvements Program (AQIP), is also experiencing high competition, and ARB maintains a tracker on its website to display how quickly and when HVIP funds are exhausted. In general, the HVIP program is not expected

[4] A complete list of HVIP approved vehicles is released by the ARB each year: https://www.californiahvip.org/docs/HVIP_EligibleVehicles.pdf

to serve as a reliable, long-term funding source for transit agencies; but, it is likely the state will continue to provide some form of subsidies for fleet electrification, perhaps in a reduced form.

This study assumes the purchase prices for buses shown in Figure 7.2.The price distribution in the current period is derived from the APTA purchase data. For the future purchase period, conventional vehicles' purchase price are assumed to increase 3% per year, while the average costs of E-buses decreases by ~1% (Figure 7.2). This assumes that E-bus battery costs reductions and increasing production scale will be equal to or greater than price inflation for conventional buses between the two periods.

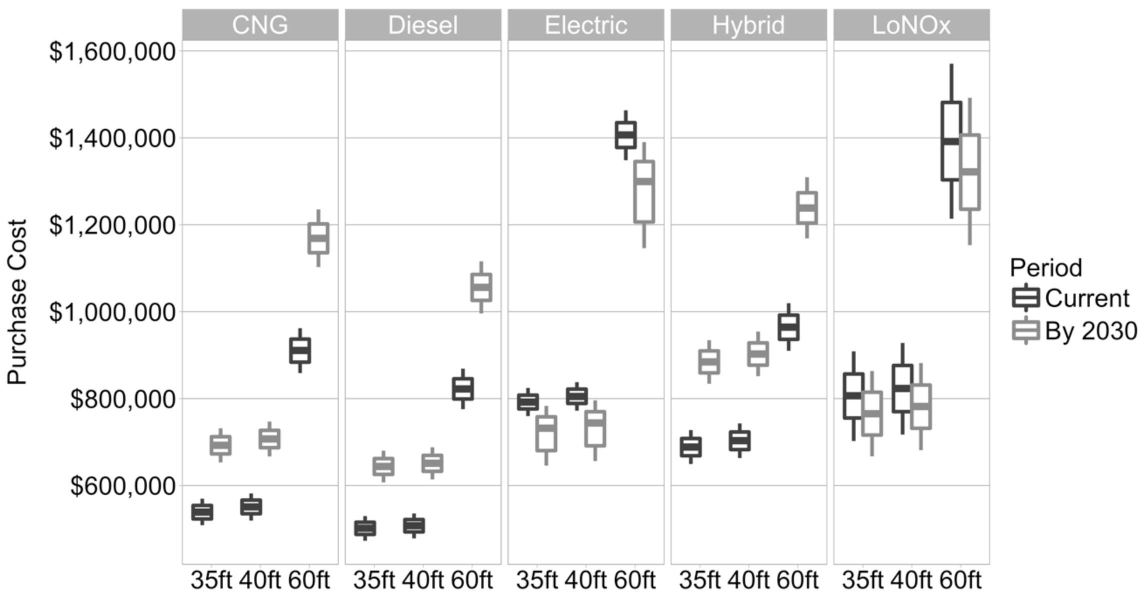

Figure 7.2 Bus Purchase Cost Assumptions

This study also assumes continued subsidization by the state of both E-bus fuel and vehicle purchases. For comparison, purchase subsidies are also included for the $LoNO_X$ pathway. Subsidies are assumed to decrease by ~50% between the current and future purchase period, from just under $95,000 on average, to $50,000 (Figure 7.3).

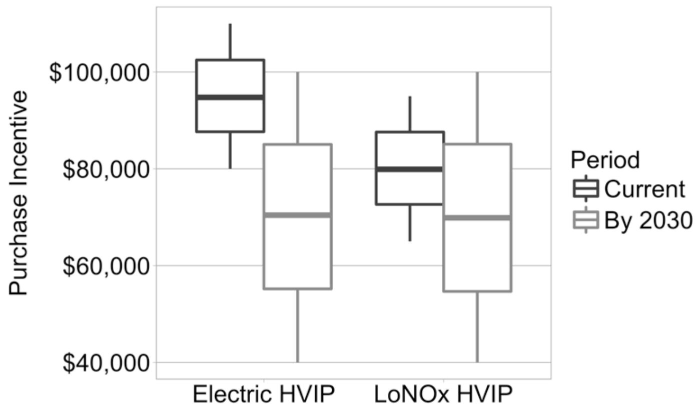

Figure 7.3 Bus Purchase Subsidy Assumption

7.3.2 Fuel Costs

The Low Carbon Fuel Standard (LCFS) provides a per unit of fuel subsidy for the use of low carbon fuels, such as the electricity consumed by E-buses or hydrogen consumed by fuel cell vehicles. The LCFS credit for E-buses replacing conventional transit buses is $0.10-$0.14 per kWh of charging energy (the credit value fluctuates with the LCFS market). The LCFS credit can represent 100% or more of the electricity rate proposed by some utilities for over-night, managed charging. The LCFS credit value potentially reduces the fuel costs of E-buses to a few cents per-mile (Figure 7.4). The range for diesel cost in Figure 4 reflects vehicle fuel economy for both conventional and hybrid powertrains. Boxes show 25th and 75th percentile of per-mile costs with medians indicated on the centerline, while the whiskers represent maximum and minimum costs. "Electricity with LCFS Credit" represents the expected per-mile fuel costs with credit revenue. [5]

LCFS is one of several state climate programs intended to improve the value proposition of low-carbon alternatives, including Cap and Trade, which generates considerable funding for low-carbon projects. Cap and Trade funds have become a robust source of funding for many of the state's GHG-related initiatives, with $2.2 billion in Cap and Trade funds budgeted for the 2017-2018 fiscal year alone.[6] While the LCFS

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[5] This analysis assumes diesel or diesel-hybrid fuel economy of 2.5-6.5 MPDGE, a CNG fuel economy of 2-5 MPDGE, and electric bus energy requirements of 2-3 kWh/mile. These ranges are drawn both from the NTD 2014 data, and the range of E-bus fuel economies from Eudy et al. (2014) and data from Antelope Valley Transit. The LCFS prices assume an LCFS credit price of $100 with energy efficiency ratio for diesel displacement. The net LCFS credit was calculated to be $0.11 to $0.13 per kWh using the CARB LCFS credit calculator or $0.10 to $0.29 per MPDGE for RNG (https://www.arb.ca.gov/fuels/lcfs/dashboard/creditpricecalculator.xlsx).

[6] For a longer discussion of issues to be considered in the long-term viability of Cap and Trade Funds and LCFS linkage see http://www.lao.ca.gov/Publications/Report/3553

is authorized until 2030 under SB32 (signed in 2016), the recently passed extension to Cap and Trade also gives the ARB authority to apply additional market-based declining annual emissions limits to 2020 (AB398 Sec. 5. 38562.(a)). For these reasons, E-bus fuel subsidies are likely a secure source of funding for the expected life of vehicles. Thus the net fuel costs for agencies using electricity will depend on both the utility rate structure and policy incentives.

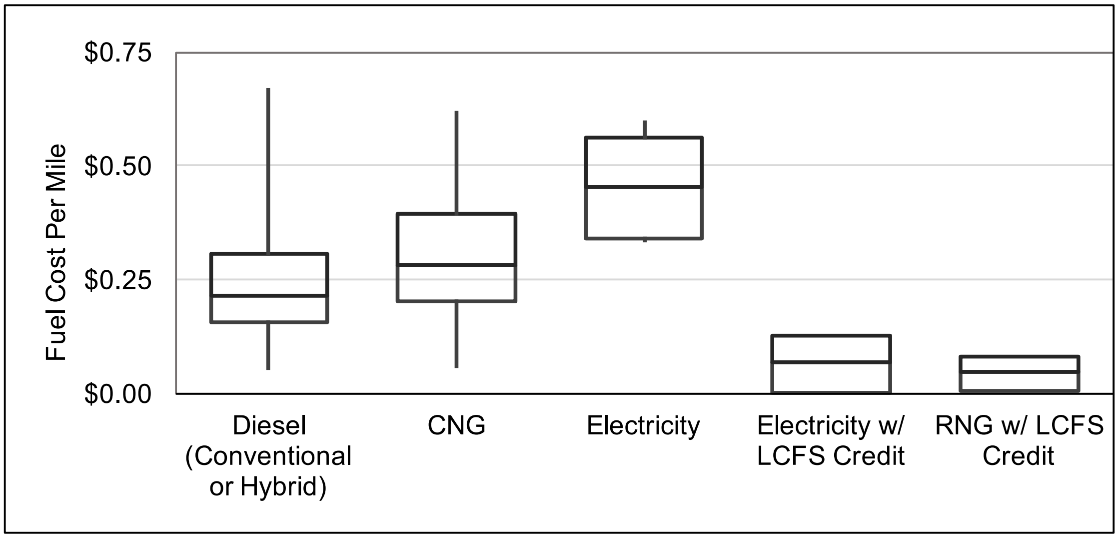

Figure 7.4 Average per-mile fuel costs for transit buses

Predicting and accounting for electricity costs is fundamental to understanding the overall costs of transit electrification. However, accurate prediction of electricity costs is complicated by complex and changing utility pricing structures. Utility services are generally billed with multiple components, including a commodity component (in kilowatt-hours), a capacity component (in kilowatts) billed at the customer's peak monthly or annual capacity, and customer charges billed per meter regardless of usage. These can be highly variable depending on the time of year, time of day, location of charging, and other factors, and pricing structures will depend on the size of the fleet being charged. Further, utility pricing is not fixed for the life of the fleet. Unlike most procurement, utility contracts are generally not developed bilaterally between the customer and the utility, but instead developed by the utility and approved by a regulator or local governing board. As a result, agencies are not able to secure fixed price contracts over the life of a bus or of charging infrastructure.

Diesel has historically been the dominant fuel for transit buses, and continues to be at the national level. In California, about 37% of active buses in the state rely on diesel fuel. Diesel prices have shown considerable volatility over the last 15 years, ranging from $1.12 to $4.97 (Figure 7.5). Adjusting for seasonality, the average expected price currently is $2.21 per gallon, with 90% prediction interval of $1.86 to $3.82 per gallon. The price of diesel is expected to increase by 2030 in part due to climate and renewable fuel policies like LCFS. If LCFS credit prices increase, the costs of offsets for diesel refiners will also increase, which in turn is likely to be passed through to consumers.

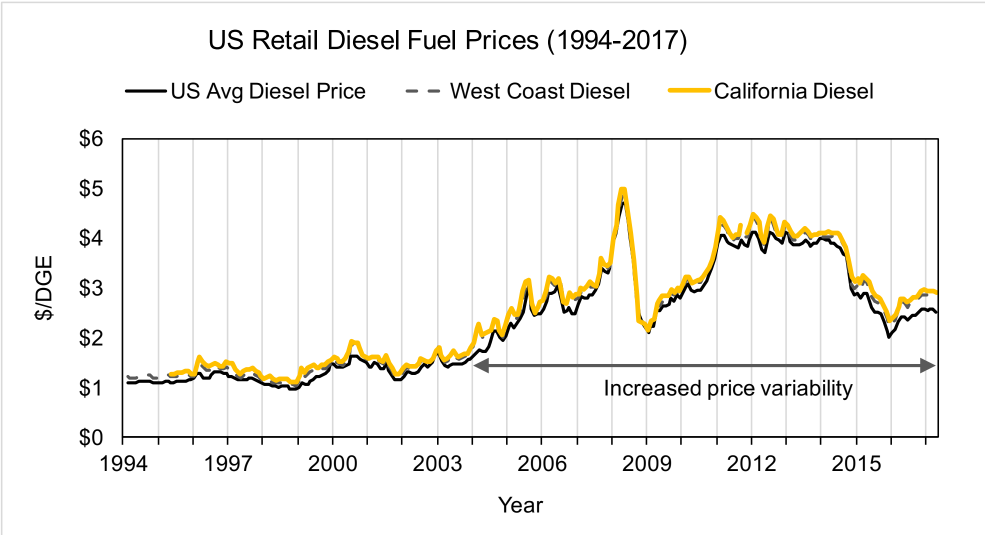

Figure 7.5 California and U.S. Retail Diesel Prices (DGE = Diesel Gallon Equivalent) [7]

CNG buses deliver very competitive per-mile fuel costs due to the low market price of natural gas. Average CNG transit bus fuel economy is actually equivalent to or lower than conventional diesel buses for most routes (Clark, 2009; Lajunen & Lipman, 2016). As recently as 2015, agencies reported paying less than $0.50 per diesel gallon equivalent for CNG. Prices of CNG have increased moderately in the last two years, and are expected to continue to do so. In 2016, the average prices of CNG were $0.60 to $0.84 per DGE for commercial and residential deliveries respectively ($8.4 - $12 per thousand cubic feet)[8]. The EIA Annual Energy Outlook forecasts that commercial CNG prices will increase almost 40% by 2030, which is slightly more than the forecast increases in diesel fuel prices over the same period (33%). Individual agencies are likely to enter into fuel price contracts, which could offer more competitive rates than average retail prices.

RNG is an alternative fuel option for CNG fleets. RNG can be produced from biomass or animal wastes and can generate revenue through LCFS credit sales. Recent reports and response to solicitations offered to transit agencies suggest that RNG would be available at the market rate for CNG.[9] In this case, the natural gas provider would collect any revenue from LCFS and reflect those offsets in the market price offered. LCFS credit generation varies depending on the fuel production pathway (geography and feedstock); as there is little information on where RNG would be sourced, the impact of LCFS revenue on

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[7] U.S. Energy Information Administration, Gas and Diesel Fuel Updates https://www.eia.gov/petroleum/gasdiesel/

[8] California Natural Gas Prices, https://www.eia.gov/dnav/ng/hist/n3010ca3m.htm

[9] Ramboll Environ and MJ Bradley & Associates, 2016, "Zero Emissions Bus Options: Analysis of 2015-2055 Fleet Costs and Emissions."

market pricing for RNG is difficult to estimate. RNG is also an approved pathway under the Federal Renewable Fuel Standard (RFS), and credits earned under the RFS (Category D3) represent a significant potential source of revenue for RNG producers. Considering average prices for D3 RINs, the overall impact of RFS credits on RNG prices is likely much greater than the LCFS ($3000 per MMBTU in RFS revenue vs. <$100 per MMBTU for LCFS). This further complicates predicting the price of RNG.

At current electricity prices, agencies can only anticipate significant reductions in fuel operating costs from electrification with credit incentives through the LCFS. These credits may change over time. A $100 dollar LCFS credit price, with the conversion ratio for displacing fossil fuels in buses, would amount to a credit of $0.11-$0.12 per kWh consumed for E-bus charging. The price of electricity and the per-mile E-bus efficiency likely need to be below $0.10/kWh and 2 kWh/mile respectively for per-mile E-bus fuel costs to fall below $0.20/mile (the low end of conventional per-mile fuel costs). With the LCFS credit, electric buses could deliver a fivefold reduction in per-mile fuel costs; without the LCFS credit, there could be no significant differences in per-mile prices *when compared against current prices for CNG*.

This study assumes the relative fuel costs depicted in Figure 7; prices are shown for both the current and future purchase period. In the future purchase period, the range of electricity prices are assumed to be effectively constant. Diesel and CNG costs are assumed to increase in the future purchase period by approximately 3.5% per year, in line with forecasts from the U.S. Energy Information Administration and CARB.[10] Fuel system maintenance includes costs for maintaining compressors and tanks (in the case of a CNG system), as well as chargers (in the case of Electric).

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[10] The Annual Energy Outlook and complete pricing forecasts are available at the EIA website https://www.eia.gov/outlooks/aeo/data/browser/

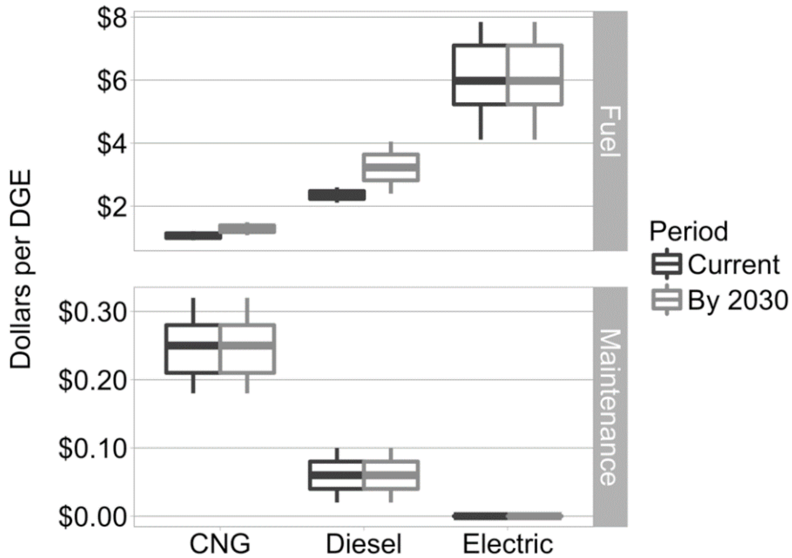

Figure 7.6 Fuel Cost Assumptions (DGE=Diesel Gallon Equivalents)

For electricity, an LCFS credit price of $100 is assumed for both periods. In the future period, the energy equivalent ratio (EER) used to calculate the displacement credit value is decreased from 4.2 to 2.7, making the incentive equivalent to that received for heavy truck electrification and other heavy duty fuel displacements. Simultaneously, the carbon intensity of grid electricity decreases due to the State's Renewable Portfolio Standard and increasing penetration of lower-carbon electricity generators. The net effect is a decrease in the future per kWh LCFS subsidy of 12.5% (Figure 8). Overall, the net cost of electricity for E-buses will be highly sensitive to changes in the EER.

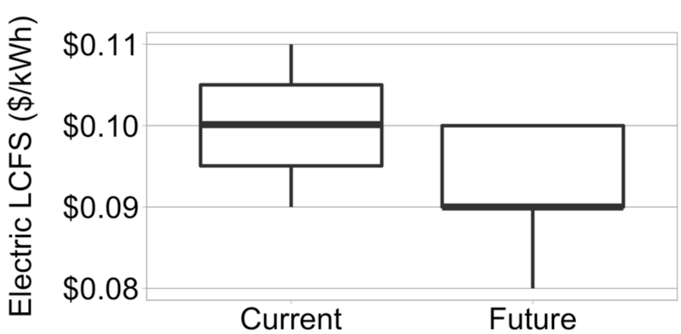

Figure 7.7 LCFS Credit Value for E-buses

7.3.3 Repair and Maintenance Costs

Operations and maintenance costs at some agencies represent over 75% of annual expenditures. With the exception of labor,[11] maintenance and fuel are the most significant contributors to per-mile operations and maintenance costs. A long-range study of early model Proterra E-buses at Foothill Transit reported 10% lower per-mile maintenance costs and 50% lower overall maintenance costs compared to CNG buses. This was owing to the simpler propulsion systems of electric buses and fewer replaceable/serviceable power or drivetrain components.[12] The Foothill Study has been very influential in setting initial cost expectations; however, forecasting remain uncertain due to a lack of other data to corroborate the results of this early work.

In addition to the lower maintenance and repair costs, the study also showed that the E-buses had higher rates of unscheduled maintenance issues or repairs that required the bus to be taken out of service. Unscheduled maintenance events decreased the overall utilization of the E-buses (as measured by days of available service), which can increase overall operating costs. The study found that decreases to scheduled maintenance repair and maintenance costs offset the increases in unscheduled maintenance issues and additional labor hours. But the net 10% per-mile cost reduction does not include potentially significant cost considerations resulting from these reliability issues. These could range from providing roadside assistance or compensating passengers due to drained batteries, to the need to purchase additional reserve buses to compensate for limited bus range. These issues were not addressed by the study.

The Federal Transit Administration (FTA) National Transit Database (NTD) contains extensive data on a wide array of operational attributes of transit agencies.

Illustrates the heterogeneity among the 20 largest transit agencies in California in terms of vehicle operating expenses, maintenance costs, and per passenger costs. The variability in costs reflects the diversity of operating structures, conditions, and systems experienced by agencies.

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[11] One potential source of uncertainty for this assumption is the time duration of bus assignments. Where CNG buses are replaced with multiple electric buses due to range restrictions, changing out buses may require additional return trips to a depot facility or require additional labor hours. In general, buses are in service longer than a single driver's shift and are already organized around changing drivers during shifts, but labor costs could be significant.

[12] Proterra Model BE-35, See L. Eudy, R. Prohaska, K. Kelly, M. Post, "Foothill Transit Battery Electric Bus Demonstration Results," National Renewable Energy Laboratory (NREL), Golden, CO, 2016.

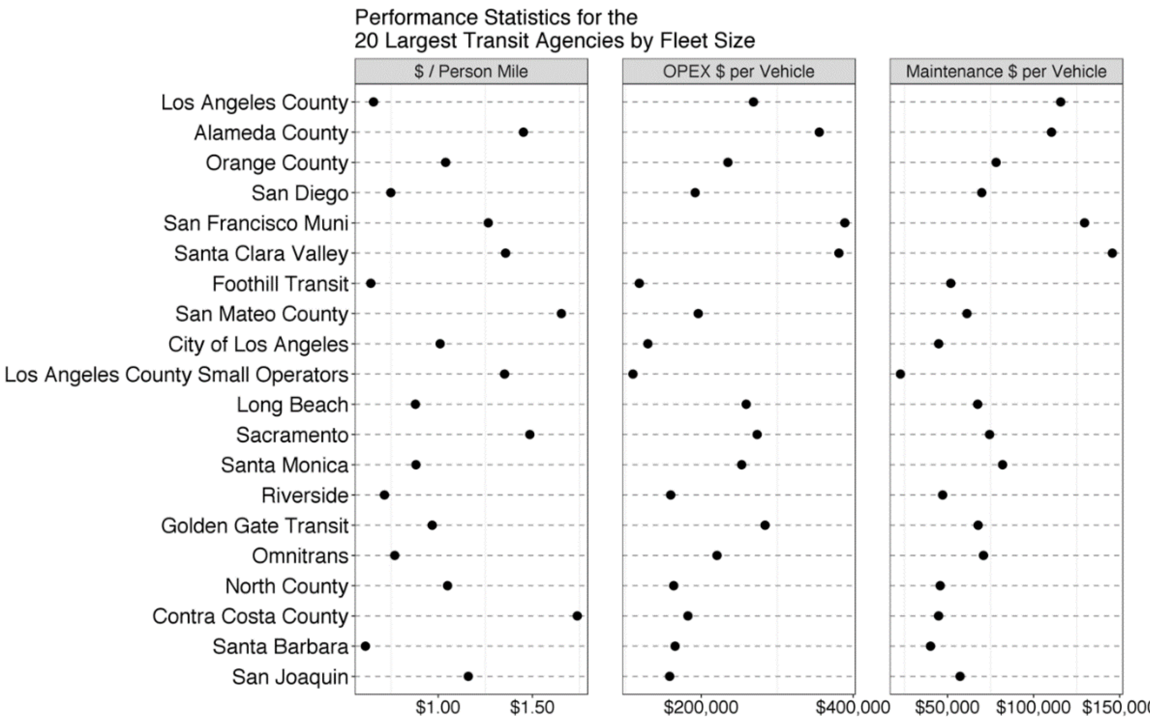

Figure 7.8 Financial Service and Maintenance Statistics for the 20 Largest Agencies by Bus Fleet

NTD 2014 database tables were used to inform maintenance cost analysis, collision probabilities, and the distribution of bus age by powertrain type. 2014 NTD maintenance data for per-mile maintenance cost, including mechanical failures, was cross-referenced with estimates from other sources. Because many transit fleets have heterogeneous fleets in terms of powertrain type and bus size, weighting is required to estimate operating costs and service mileage by fuel type from the NTD. For any given fleet, if more than 80% of agency fuel costs came from a single fuel type (on an energy equivalent basis), maintenance cost observations for that fleet were assigned to that fuel type. Figure 10a shows the aggregate distribution of per-mile expenses for diesel, diesel-hybrid, and CNG active transit buses in California. Historically, per-mile maintenance costs often exceed fuel costs for conventional diesel buses. Figure 10b shows that per-mile maintenance related vehicle failures have very low occurrence for transit buses on average, which suggests that a small portion of the fleet is likely to experience a majority of issues. The highly-skewed distribution of per-mile maintenance costs also suggests that average maintenance costs may be inflated by a small number of vehicles with significantly higher-than-average occurrence of high cost maintenance events.

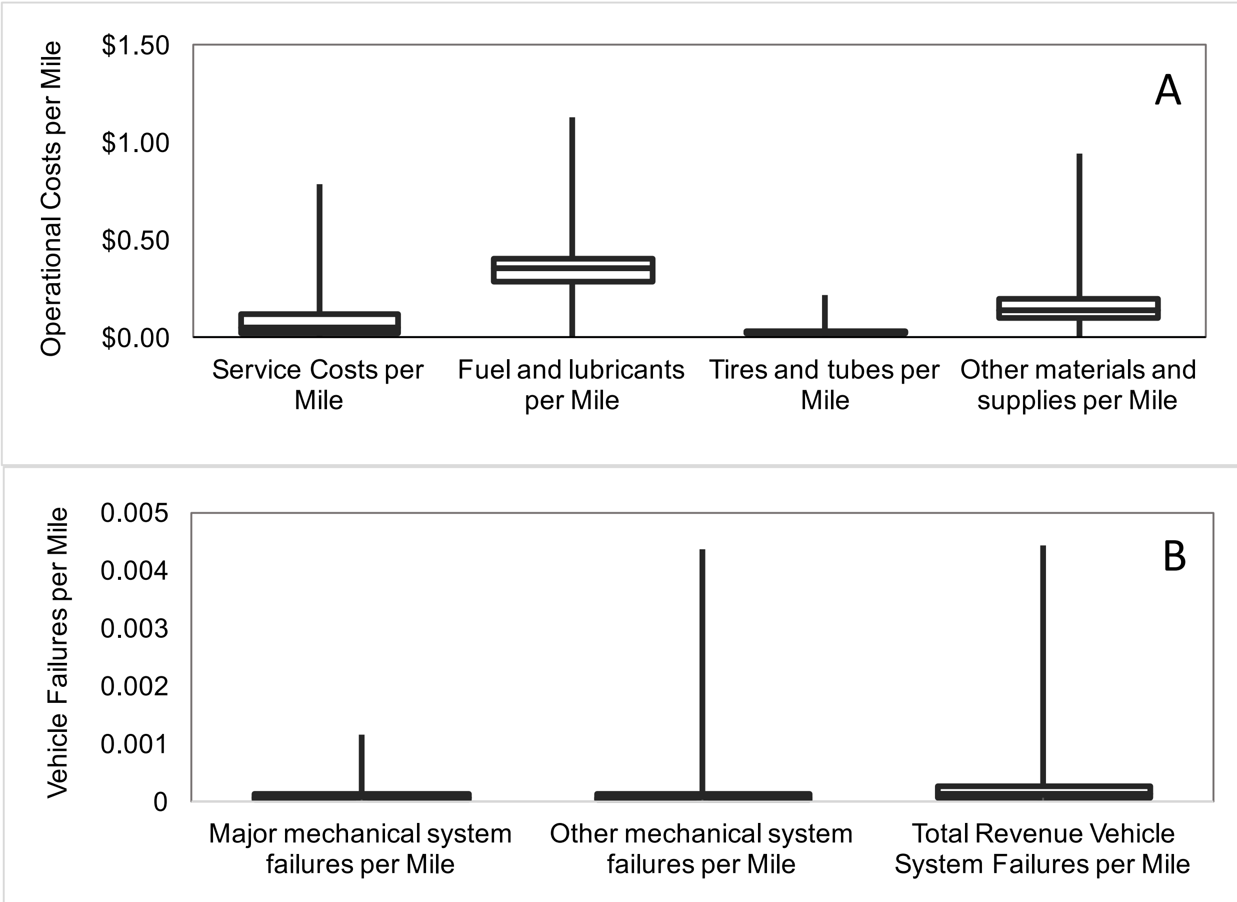

Figure 7.9 Distribution of Expenses per Mile and Failure Type per Mile in 2014 NTD

A: service costs per-mile for all vehicle types in the NTD, and B: occurrences of mechanical failure during service.

This study assumes maintenance costs to be constant for each powertrain type. Table 2 shows the assumed range of per-mile maintenance costs by fuel type estimated from the NTD. E-bus maintenance costs are estimated based on reporting to the ARB, the study by Eudy et al. (2014), and data provided by LACMTA. Per mile maintenance costs for the LoNOx scenario assumes the same per-mile maintenance costs of CNG. Future maintenance costs of E-buses are highly uncertain; past transitions and pilot studies suggest that initial deployment may involve increased maintenance costs and unscheduled vehicle outages. Over the long run, E-buses are expected to deliver lower per-mile maintenance costs compared to conventional vehicles because of simplified powertrains and service schedules. However, decreasing maintenance costs may be attributable to improved operational systems and best practices, knowledge that may be slow to spread between firms. System improvements may also be predicated on significant capital investments or be restricted by existing agreements (i.e. new maintenance facilities or union contracts). As there is little data to reliably estimate the potential decrease in maintenance costs for E-buses, the study adopts the conservative assumption that there are no improvements to maintenance costs between the study periods.

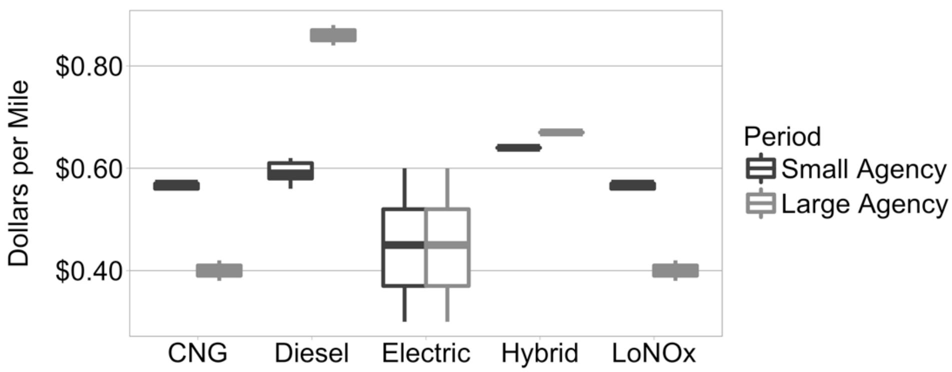

Figure 7.10 Maintenance Costs per Mile

7.3.3.1 MIDLIFE OVERHAULS

Midlife overhaul is a special kind of maintenance operation that has a high fixed cost and occurs at a dependable interval for many buses. It is also a key potential cost difference for electric buses, as the midlife may be a point for replacement of the traction batteries depending on current performance. Mid-life bus overhauls can cost between $35,000 and $65,000 dollars depending on the vehicle design, powertrain, and fuel system according to data reported to APTA. Battery replacement for a ~250 kWh battery is expected to be $50,000 to $75,000 based on target price of $200-$300 per kWh, making battery systems a significant portion of E-bus purchase costs and the largest cost of a mid-life overhaul if they require replacement.

One E-bus manufacturer, BYD, offers a 12 year warranty to 80% of the original capacity on their battery, suggesting that there would be no additional liability for battery replacement at midlife. For other E-buses, the used batteries could be sold for second-life applications, leading to a resale value and mitigating some of the replacement cost. Alternatively, used batteries could be used in stationary applications for strategic timing of electricity storage and charging and by the transit agency itself.

Many agencies do not conduct midlife overhauls for the entire fleet, instead focusing on only required maintenance schedules and other proactive activities including sample tear downs and inspections. While midlife overhauls are assumed to occur in this study, this reflects the conservative outlook of agencies that must prepare for a worst-case scenario of fleetwide midlife rebuilds.

This study assumes midlife overhauls occur for 95% of vehicles by the 7th year of service, with a small probability that some vehicles retire at 12 years of service with no overhaul; Figure 11 shows the assumed costs for each of the pathways. While this likely represents a much higher probability of midlife overhauls than agencies could require, it also represents a risk averse view of potential funding for midlife overhaul costs. Midlife overhaul costs are assumed to be 5% higher for $LoNO_X$ compared to conventional CNG engines, with a correlated 30% increase in the standard deviation of expected prices. E-bus midlife overhaul costs are expected to decrease significantly due to both declining battery prices and improvements to battery cycle life (i.e. fewer mid-life battery replacements).

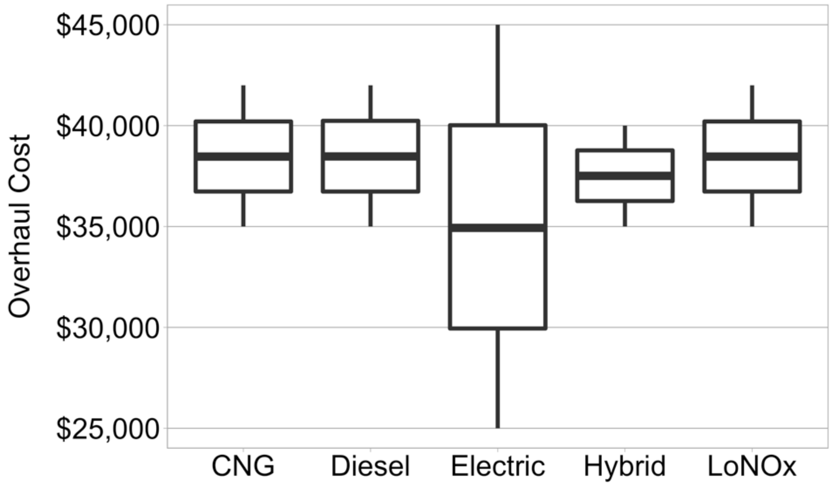

Figure 7.11 Midlife Overhaul Cost Assumptions

7.3.4 Depot and Infrastructure Costs

Infrastructure costs can be a significant driver of the overall costs of bus fleet operations over the long term. Infrastructure costs include construction of depots, maintenance, and refueling systems, as well as operations and maintenance of those assets. There are some examples of recent construction projects to draw on. The Los Angeles Metropolitan Transportation Authority, the largest agency in the state, opened its newest depot in 2014; a garage depot with maintenance, cleaning, and refueling infrastructure capacity for 200 buses. The construction cost was reported to be $95 million dollars which is equivalent to about $85,000 per bus in parking and storage costs per year[13].

A smaller operator, Antelope Valley Transit, is in the process of converting their fleet with 85 all-electric BYD buses and a depot upgrade. Costs for construction and upgrades to onsite electrical infrastructure were almost $6 million dollars, which included the construction of an onsite 1.5 MW diesel generator. The agency has plans to purchase renewable diesel to maintain the 77,000 gallon backup tank. While operations and maintenance costs for E-bus chargers might be very low, back-up electricity systems could pose extra costs.

The costs of additional electric charging infrastructure are likely to vary by depot due to a number of factors, including existing utility connections, facility age, and location. Recent filings at the California Public Utility Commission, including proposed rate cases for southern California utilities, suggest that interconnection costs may by significantly lower than these projections. In addition, BYD, one of the

[13] When the costs are amortized over the average number of buses that might occupy each unit of capacity over the life of the depot.

largest E-bus suppliers, provides depot chargers at no cost with purchased buses. Conversely, the selective use of on-route charging could significantly increase capital costs for agencies, as on-route charging systems currently cost as much as 10 times comparable depot systems. The study assumes all buses rely on depot charging in both purchase periods.

Yet another complicating factor for agency investments is the timing of previous capital investments in fuel infrastructure and vehicles. Several transit agencies in the South Coast Air Basin began transitioning to CNG fleets in response to the 2000 CARB Fleet Rule for Public Transit Agencies, which required that agencies either purchase advanced technology vehicles or switch to an alternative fuel in order to meet a 2007 engine model year standard for transit fleet emissions. The alternative fuel path required agencies to have 85% of bus purchases be diesel alternatives by 2009 or meet the 0.1 g/bhp-hr NO_X standard, essentially requiring extensive investment in CNG infrastructure. Some agencies are concerned that investments in fuel infrastructure, including CNG stations and storage, could become stranded before their scheduled depreciation. While diesel agencies tend to manage their own fuel systems, CNG fleets have options for third party CNG fueling station contracts. LA Metro, among others, has adopted this approach; in these cases, there is minimal ownership of CNG refueling systems and therefore no sunk-cost infrastructure investments.

Depot expansion costs are difficult to predict precisely, and do not necessarily scale with small changes in bus capacity. For instance, agency bus fleets can vary by 15% or more over five year periods without change to depot infrastructure. Attributing specific depot expansion to E-bus purchases is also highly uncertain. As agencies increase the share of their fleet running on electricity, it may become possible to explore additional economies of scale, including reducing the number of additional charger purchases per bus acquired. Further assessment is necessary to evaluate the costs of depot improvements or expansions for different agencies. This would include an evaluation of parking/service capacity, egress and right of ways, building electrical systems, and level of utility interconnection. This ranking process would also inform route prioritization and long-term planning.

In this study, infrastructure costs are amortized over their capacity and service life through the use of a capital recovery factor. Figure 7.12 shows the amortization of depot retrofits based on the agency type. Capital recovery factors for electric and conventional depot infrastructure are based on a 40 year and 50 year life respectively, with fixed costs identified based on reported depot capacity and operating structure in NTD. Depot upgrade costs are assumed to range from $2 to $7 million dollars. Average depot capacity and occupancy was used to identify likely quadrants for depot costs (only a portion of the table is shown for larger agencies).

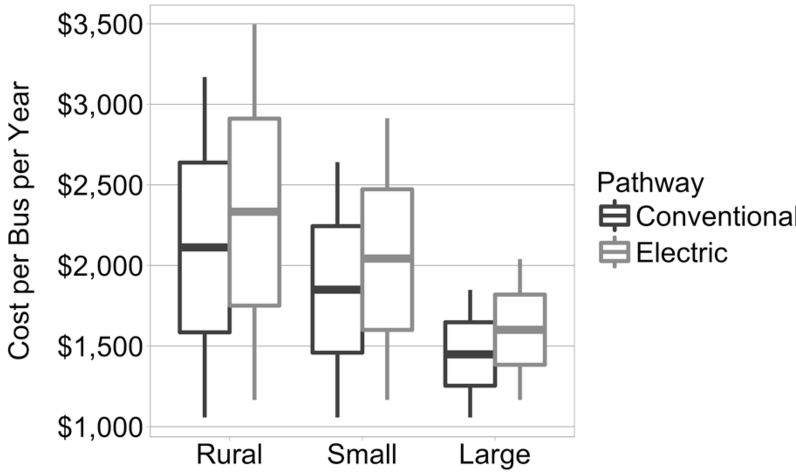

Figure 7.12 Depot Capital Amortization

Table 7.2 shows the average buses per depot for California transit agencies, which were used to estimate depot upgrade costs for agencies. Despite the presence of a number of depots reported with 200 and 300 bus capacity by some mid-sized agencies, the average number of active buses per depot facility is usually low. Comparing with Table 2, we see the large differences between the expected per bus costs of depot retrofits, which are not expected to scale linearly with depot capacity. For this reason, we assume a conservative minimum cost of $2 million dollars per depot.

Table 7.2 Average Active Buses per Depot for California Agencies

	Excluding Rural	With Rural Agencies	> 75 Buses/Depot Average	< 25 Buses/Depot Average
Mean	**38**	**28**	**112**	***8***
Median	25	14		
Max	175	175		
Min	2	1		
St Dev	37.8	34.8		
Total Buses	**8016**	**8285**	**5087**	**928**
Agency Count	**89**	**128**	**13**	**80**

7.3.5 VEHICLE LIFE

While the service life of some buses exceeds or falls short of the average expected lifetime, the majority of transit buses in the state are replaced based on a set schedule dictated by funding. The largest of these programs for California agencies are the FTA Urbanized Area Formula Program (5307) and Bus Facilities (5339), as well as FTA Capital Program (5309) and State of Good Repair (5337), which have requirements for the minimum service life of capital assets. Buses are generally required to meet a minimum service life of 12 years, but many agencies keep their vehicles for 14 years to minimize their lifetime costs of ownership on a per-mile basis. A countervailing factor is that agencies are motivated to take advantage of replacement funds when they become available. Because of these constraints, we do not assess potential differences in vehicle life across powertrain technologies as it is assumed all vehicles are designed to meet these requirements.

Figure 7.13 shows the age distribution for active transit buses in the state from the 2015 reporting to APTA, which shows a sharp decline in active buses after 14 years of service in 2001.

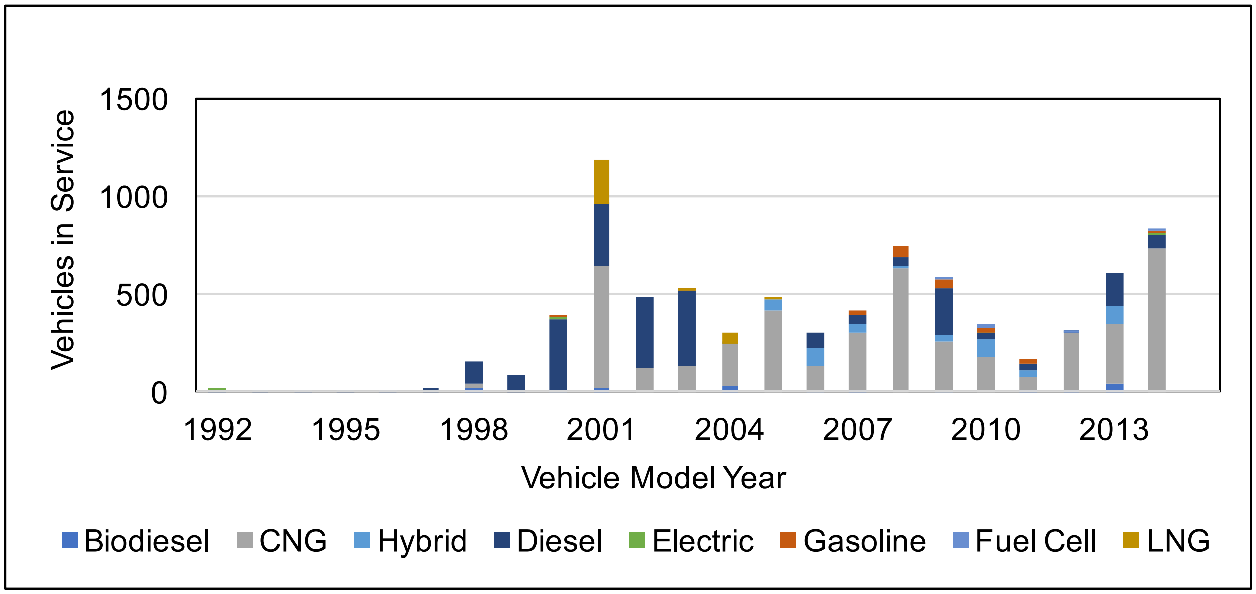

Figure 7.13 Age Distribution for Active Transit Buses in 2014

In this study, the distribution of average vehicle lifetimes is assumed to be governed by two key factors: one, each agency's decisions on how long to keep buses after they are eligible for replacement; and two, the random chance that buses fail due to accident or mechanical issue prior to their expected retirement. The probability of serious mechanical failure is simulated based on early retirement and accident data from NTD. The resulting distribution of vehicle lifetimes is assumed to be constant in both purchase periods for all powertrains. $LoNO_X$ CNG engines are assumed to have the same probability of failure and vehicle lifetime as conventional CNG buses, as the service lifetime is driven primarily by funding requirements.

7.3.6 Technology Performance

Technology performance, in particular range and downtime, may affect the number of vehicles required by an agency. Because E-buses have shorter ranges and longer fueling times than CNG, diesel and hybrid buses, E-bus adoption may require a larger fleet.

7.3.6.1 RANGE

Agencies may require additional buses if the effective range a bus can travel per charge is insufficient to meet the distance required by the duty cycle. The number of additional buses that must be purchased depends on the route structure, the vehicle range per charge, and the charging system. Examining routes for the 20 largest agencies, we conclude that roughly 9% more bus purchases may be required if the fleet is fully electrified by 2030; that number drops to 8% or 4% if the target year is 2034 or 2040, respectively.

However, this estimate assumes no alternatives to depot charging. Depending on the route structure, on-route charging can decrease the number of additional buses needed by facilitating a longer daily service range. However, on-route charging systems can currently cost more than three times as much as depot charging systems.

On-route charging systems come in multiple varieties. Fast-charging systems can cost as much as $500,000 for a 500 kW system, while smaller 60 to 80 kW systems have been installed at much lower costs. Depot systems are typically $20,000 to $60,000 per charger for 20 to 80 kW.[14] The costs of additional buses and charging systems and the route-specific logistics of charging would need to be evaluated in more detail to determine whether on-route or depot charging is more cost-effective for specific agencies.

The real-world deployments of E-buses in California can provide some insights on the technology performance factors that affect fleet size requirements. Antelope Valley Transit, which recently transitioned their entire fleet to electric, has been experiencing high variance in effective range across drivers (from 120 miles to 220 miles for the same vehicle). But, this also indicates that current market E-bus technology is capable of delivering nearly 220 miles of effective service in some cases on ~300kWh batteries. Proterra is currently marketing a new E2 series with a proposed capacity up to 660kWh. While no E2 buses are currently in service, expected improvements to battery capacity and performance suggest that longer range E-buses will be available in the near term.

7.3.6.1 REPLACEMENT RATE

Replacement rate is a difficult performance metric to generalize across agencies because of the diversity of design solutions agencies might adopt. In addition, replacement rate is also a function of both effective range and bus daily travel distance, both of which are correlated with the route structure. In most cases, transit agencies do not assign specific buses to specific routes, and in some, rotate buses between domicile depots for maintenance purposes. This makes it increasingly difficult to estimate the number of buses that will be required for agencies to replace their existing active and spare flees.

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[14] For further discussion of charging system costs, see the ACT working group discussion documents or data assumptions at https://www.arb.ca.gov/msprog/bus/actmeetings.htm.

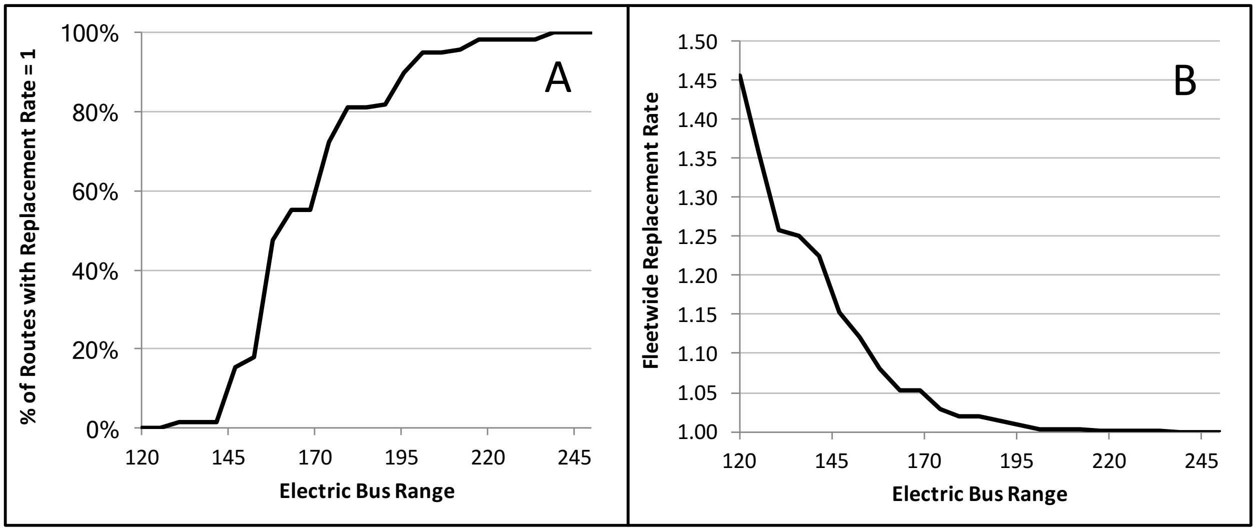

Figure 7.14 Electric Bus Replacement Rate Assumption for Large Agencies

Figure 7.14a illustrates the relationship between E-bus range and the percent of routes that can be replaced with E-buses on a 1:1 basis. Figure 7.14b illustrates how that relationship translates into fleet-wide replacement rates. Once E-buses reach a range of 245 miles, replacement rates settle at one. In the most conservative case, every bus in the fleet must be available to meet any random series of assignments at an agency. A series of assignments represents some number of trips (>1), for all or a portion of a given route, over a given service day. Based on these assignments, we can quantify the distribution of daily effective range required by buses at agencies. Electric buses, particularly in the near term, cannot always meet daily range requirements. Over the course of a year, these mismatches result in electric buses realizing fewer miles, which in turn increases per-mile costs over the lifetime of the vehicle.

In this study, replacement rate is estimated for each class of agency based on their current service patterns. The E-bus effective range constraint in the current replacement period is assumed to be 120 miles per charge. This represents a conservative view on the reliable range delivered by buses currently in operation or being delivered. For the second replacement period, effective range is assumed to improve to 220 miles. This translates to a ~73% reduction in average daily mileage mismatch, but varies between agencies. Figure 7.15 shows the shows the replacement ratios assumed for each agency type by period.

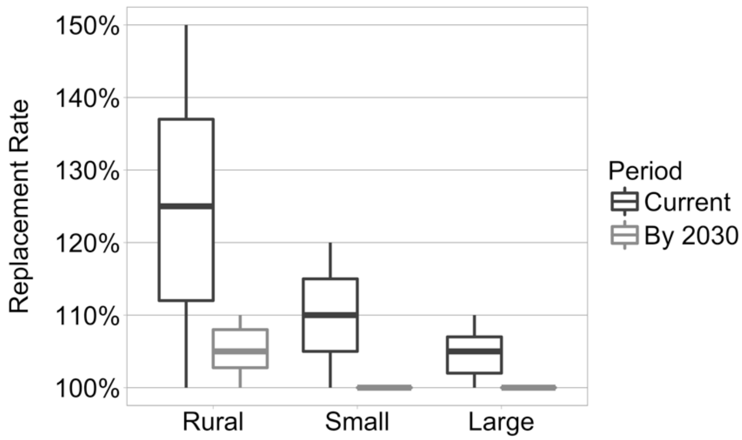

Figure 7.15 Replacement Rates by Agency and Period

7.3.7 Vehicle Fuel Efficiency

Variability in fuel efficiency is an important consideration when comparing transit buses, as the variability across powertrains can directly translate to fuel savings. Fuel economy can also be variable across agency routes and schedules. The duty cycle variability represents the combined and interacting effects of powertrain, route, traffic conditions, operator, and other environmental factors. Numerous studies have pointed to the strong correlation between operating conditions and average efficiency of transit buses. Because transit bus efficiency is so low, small improvements in fuel economy can translate to substantial savings. A five percent fuel economy improvement can produce savings of $25,000 to $50,000 dollars over the life of a bus (approximately 500,000 miles). Transit bus fuel economy can vary by as much as 2-3 times across combinations of duty cycles.

Vehicle fuel consumption is often modelled as a function of the forces acting on the vehicle, otherwise known as road load. Excepting for auxiliary energy demands, the energy required to power a vehicle can be attributed to the need to overcome primary physical forces including inertia, aerodynamic resistance, friction at the wheels, and internal friction (e.g. transmission). Aerodynamic resistance is a significant driver of fuel consumption at higher speeds. Acceleration forces, which urban transit buses experience more often, have high power demands and translate to energy fuel consumption differences depending on powertrain. Both speed and acceleration are important for estimating fuel consumption for a given duty cycle.

The specific fuel consumption (SFC) represents the average vehicle energy demands per unit mass and distance travelled. SFC is a function of aerodynamic resistance, rolling resistance, average speed, acceleration, powertrain efficiency, auxiliary loads, and vehicle mass. Aerodynamic resistance is a function of air density, the frontal area of the vehicle, the mass of the vehicle, and the square of the velocity. Rolling resistance is a function of the vehicle mass and the tires; different tires and tire configurations produce a range of coefficients of rolling resistance. Inertial forces relate to the energy required to accelerate and decelerate the vehicle mass.

In this study, we estimate vehicle fuel economy across a series of powertrains using route schedule information and data from Google Maps. Sixty-seven agencies were considered and route fuel economy projected based on average speed, stop density, and trip length. The average distribution of fuel economies was used, with subsets estimated for smaller and larger agencies by bus fleet size. Figure 7.16 is an example of the fuel economy modelling for routes operated by Golden Gate Transit. Further discussion of the route fuel economy modelling is included in the appendix.

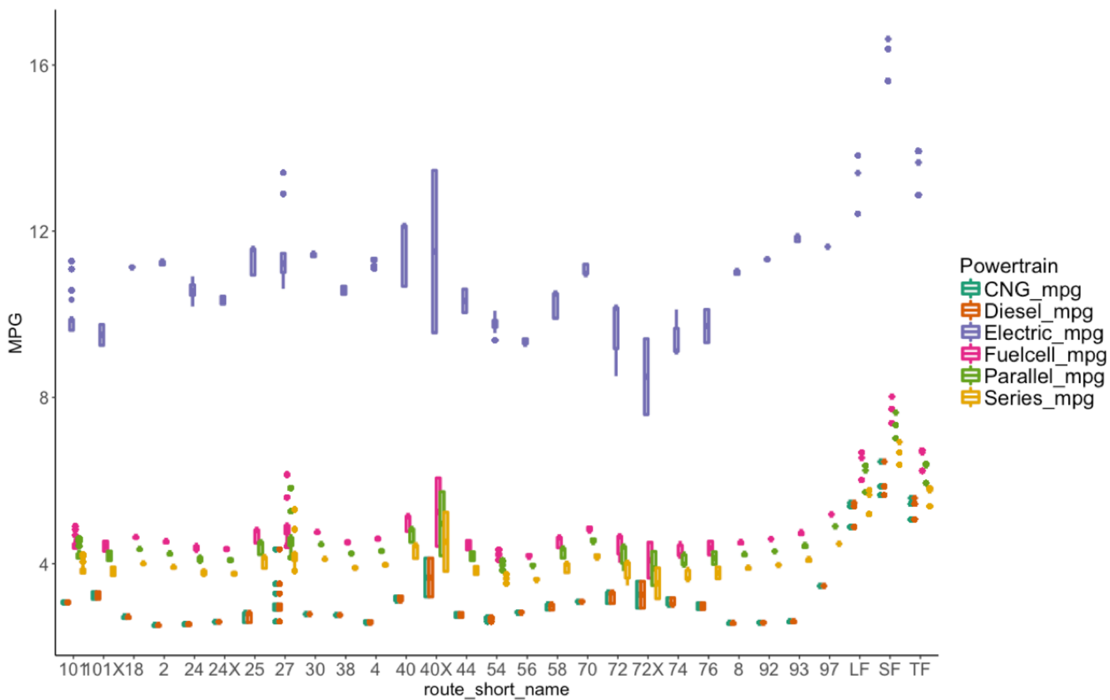

Figure 7.15 Vehicle Fuel Economy Example

The average fuel economy by bus length and agency type is depicted in Figure 7.17. Due to a lack of grade data which significantly affects the fuel requirements on many rural routes, no reliable estimates were available for fuel economy for rural agencies.

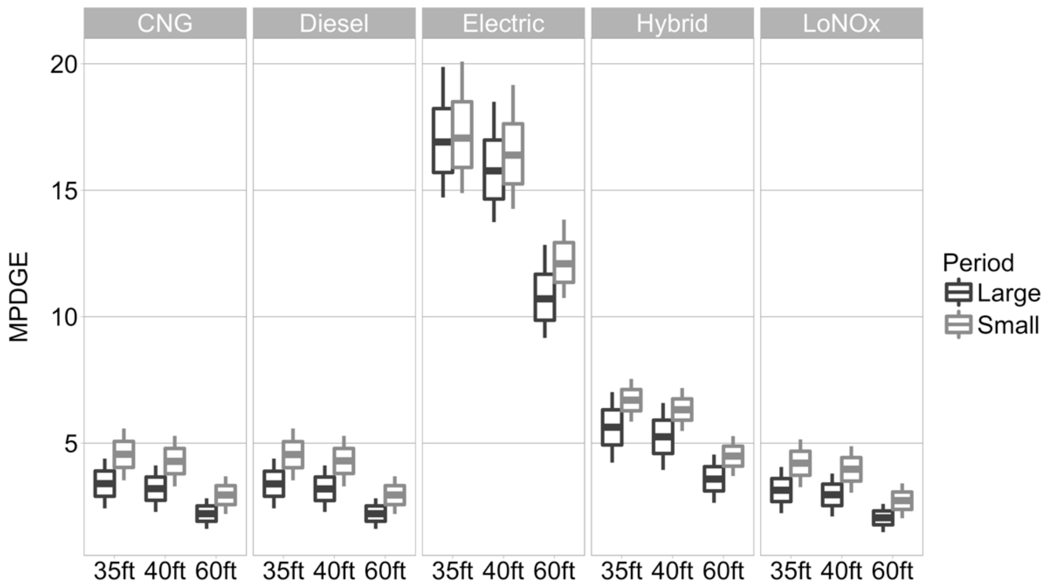

Figure 7.16 Average Fuel Economy by Agency, Fuel, and Length

7.3.8 ANNUAL MILEAGE

While transit buses on average experience approximately 40,000 miles per year, the actual annual mileage can vary strongly by agency. In general, agencies do not assign buses to specific routes or even tours; but agencies do have buses that generally operate on a set of routes or domicile in certain depots. Low average speed routes generate fewer miles travelled for the equivalent service hours. While there is little resolution at the top and bottom end of annual mileage (Figure 7.18), we can observe a longer tail in the buses experiencing higher-than-average mileage. While average mileage variation is very high, variation in lifetime mileage is expected to be far lower for each agency. Over the course of the bus lifetime, transit agencies are also incentivized to even out the mileage of buses to ensure maximum utilization of the asset.

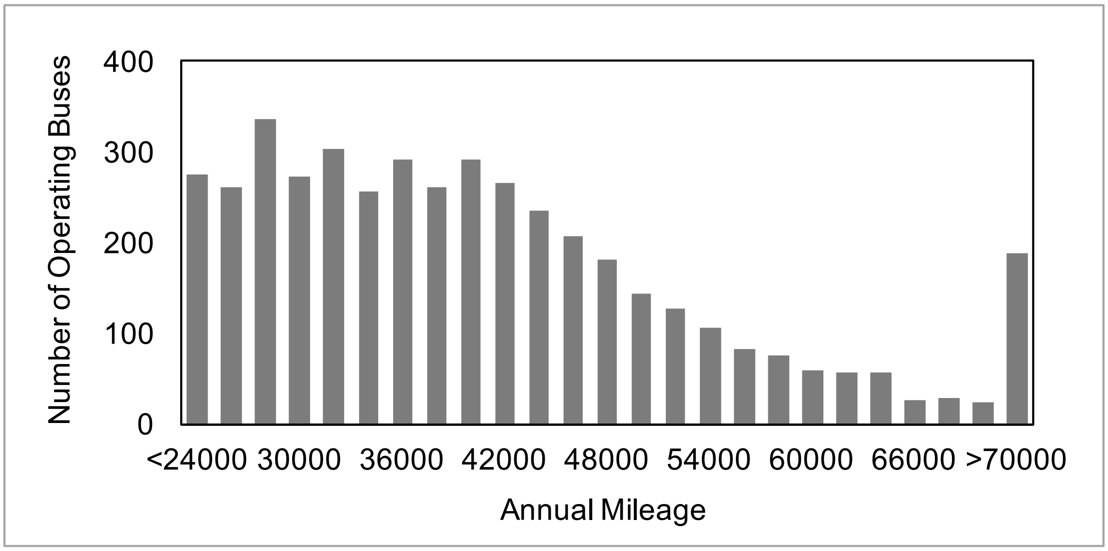

Figure 7.17 Annual Mileage Distribution of Active 40ft Buses

In this study, buses are assumed to average between 440,000 to 590,000 revenue service miles over their life, which translates to 36,000 and 42,000 miles per year. To estimate the range mismatch of electric buses (e.g. replacement rate), daily estimated travel mileage was used. Daily travel mileage has much higher variance than annual travel mileage; to improve estimates, both revenue and non-revenue annual miles are estimated for each agency class (Figure 7.19). Annual mileage is assumed to be constant across the two periods.

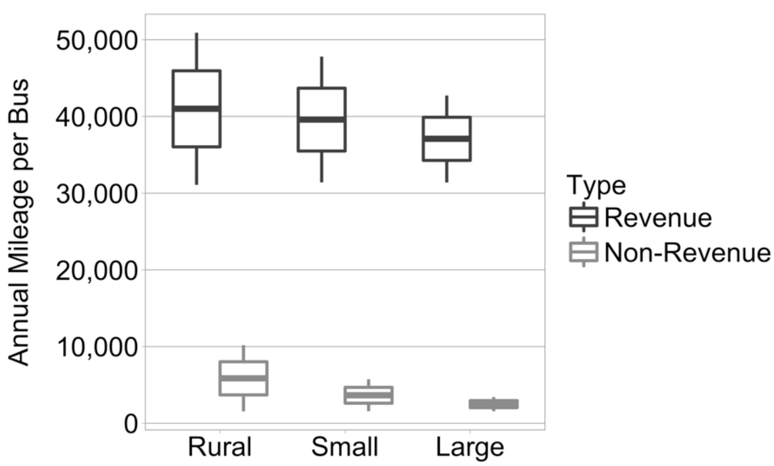

Figure 7.19 Annual Revenue and Non-Revenue Mileage Assumptions

7.3.9 Externalities and Damages

Air quality effects and changes in service quality are also important outcomes for the communities served by transit agencies in the State; these effects might be considered alongside financial considerations or they may be integrated into an economic assessment by estimating their value. Environmental damages may have significant economic value, but are difficult to assess and there is still high methodological uncertainty. But there are many types of externalities of electrification that may prove beneficial, but difficult to quantify in this attributional cost assessment.

Many studies have pointed to the potentially significant health costs of emissions from large buses in urban areas. Tong et al. (2017) found that climate and are pollution damages for transit buses could range from $60,000 to $120,000 over the service lifetime (Tong, Hendrickson, Biehler, Jaramillo, & Seki, 2017). While health costs are not considered directly in this study, decreased or eliminated mobile source emissions from bus electrification are likely to offer additional benefits for transit agencies and urban centers. This is especially true in California, which has a high share of renewable generation in the electricity grid.

In addition to emissions, e-buses likely have other difficult to price benefits. Based on Altoona testing, electric buses are quieter for passengers, operators, and pedestrians, which reduces noise pollution.[15] Electric buses can be 6-9 decibels quieter than average CNG buses, and 12-17 dBA quieter than diesel. In addition, electric powertrains do not require a clutch or other transmission which can reduce driver fatigue. Decreased vehicle noise also creates a better environment for passengers and operators.

For the purpose of this study, the direct and indirect costs of environmental damages and social impacts are not considered. In the discussion section, we allude to some of the research needed to better internalize societal costs into purchase decisions and pricing.

7.3.10 Summary of factors affecting the costs of E-buses

- The purchase price of an E-bus is 40%-60% *higher* than a conventional bus, and some agencies must acquire more depot or maintenance yard capacity for bus electrification. This significantly increases capital costs, necessitating a shift in the quantity and source of income for agencies.
- Currently, federal sources provide a majority of capital funding for bus projects; however, the formula for calculating the capital cost subsidy is not cost reflective, and federal funding may not match increasing investment.

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[15] See Pennsylvania Transportation Institute and Bus Testing and Research Center. (2015). New Flyer, Model XE40, University Park: Pennsylvania State University. **LTI-BT-R1405**. And, Pennsylvania Transportation Institute and Bus Testing and Research Center. (2015). Proterra, Inc. Model BE-40, University Park: Pennsylvania State University. **LTI-BT-R1406**.

- Operating costs currently comprise 75% of annual expenditures, and fuel costs are a key contributor. Electricity costs can be highly variable over time and space, and a utility's contractual terms may change during the life of the bus. Given current prices, only with credit incentives through the Low Carbon Fuel Standard (LCFS) can an agency anticipate significant reductions in fuel operating costs.
- Variable maintenance costs for electric buses can be 50% *lower* per-mile thanks to simplified propulsion system, but maintenance costs at transit agencies show strong heterogeneity; not all agencies will experience the same magnitude in maintenance costs reductions from electrification
- Depot expansion costs are a significant investment for agencies but vary strongly by depot characteristics; amortized over the life of the vehicle, can represent $15,000-$40,000 in real additional costs.
- Vehicle fuel efficiency varies across agencies operating areas and route characteristics, but system planning on vehicle purchase are currently separate decision-making operations
- The costs of purchase and operation for conventional transit bus pathways, including Diesel and CNG, are expected to increase significantly over the next decade.
- E-bus effective range is increasingly rapidly, but technology performance mismatch when replacing conventional vehicles remains an issue

7.3.11 Limitations of the Unit Cost Approach

Uncertainty in comparing alternatives stems from multiple sources, including the parameter uncertainty and variability discussed in the previous section. An additional confounding factor for policy analysis could be described as decision uncertainty. There are two model frameworks traditionally adopted for comparing purchase alternatives in the context of fleet replacement. The first, a unit replacement model, is often used to compare the total cost of ownership across several purchase alternatives. The unit replacement model focuses on costs related to the acquisition, maintenance, and operation of an asset over its useful life. For example: does alternative A cost more than alternative B? The second, a systems operations model, looks at the total costs of a handful of state decisions over the course of some defined decision space. And an equivalent question, what is the cost of operating a given system over some time x given alternative A vs. alternative B. Analysis of unit or system costs can provide contrasting conclusions and support different decision making outcomes.

A potential key difference between unit and systems cost approaches is the endogeneity of labor costs. An agency system cost model could include an explicit ledger of positions and salaries for operations and overhead management. Due to the heterogeneity of agency operating structures, areas, and service requirements, a generalized agency system cost function is difficult to estimate. Even estimating individual agency operational labor costs requires assumptions about the route network and schedule, which could ignore the opportunity for optimization of system planning and technology deployment.

While it is possible to incorporate additional labor costs into unit cost comparisons, scaling of unit costs up to the system level is likely to provide only a coarse estimate of actual system costs. This can easily be illustrated by the fact that mean vehicle costs often do a poor job of representing the real costs experienced by each agency. Whether looking at system *or* unit costs, decision making is improved by an understanding of how a lack of knowledge about the future and variability in assumptions contribute to uncertainty when comparing technology alternatives.

This study focuses on uncertainty in comparing unit costs for agencies. Some agency system costs are considered by way of infrastructure investment and route structures, but the study does not directly consider labor costs for operations, including drivers, which can be a key component of per-mile system cost.

7.4 RESULTS

Based on the range of prices transit agencies have been experiencing, current replacements of CNG, Diesel, or Hybrid transit bus cost between $1,009,283 and $1,663,309 on average to own and operate over the lifetime of the vehicle (Table 7.3). The cost of an electric bus ranges from $1,457,594 for a 35 ft bus, to $2,243,745 for a 60 ft bus. While costs for electric buses are higher on average in the current replacement period compared to $LoNO_X$ and conventional options, they are also eligible for increased incentives which could mitigate the cost differential. In the current period, purchase and fuel incentives decrease Electric TCO by $224,00 to $284,000, compared to $80,000 on average for purchase incentives on $LoNO_X$ options.

Table 7.3 Total Costs by Fuel-pathway and Length (Current Prices, No Incentives)

	length	***mean***	*sd*	*min*	*max*
CNG	*35ft*	**$1,009,283**	$68,705	$830,996	$1,306,957
	40ft	**$1,031,649**	$70,115	$844,422	$1,272,759
	60ft	**$1,467,920**	$82,703	$1,255,888	$1,796,200
Diesel	*35ft*	**$1,184,842**	$88,692	$948,543	$1,548,364
	40ft	**$1,207,792**	$90,434	$968,066	$1,563,480
	60ft	**$1,663,309**	$112,114	$1,349,373	$2,133,882
Electric	*35ft*	**$1,457,594**	$103,484	$1,124,418	$1,926,870
	40ft	**$1,482,993**	$105,591	$1,172,864	$1,955,112
	60ft	**$2,243,745**	$142,617	$1,837,121	$2,859,840
Hybrid	*35ft*	**$1,255,245**	$75,394	$1,049,107	$1,544,680
	40ft	**$1,281,118**	$76,627	$1,078,655	$1,579,615
	60ft	**$1,629,124**	$89,927	$1,397,001	$1,993,127
LoNOx	*35ft*	**$1,291,721**	$92,078	$1,056,398	$1,602,729
	40ft	**$1,320,942**	$91,622	$1,076,154	$1,635,541
	60ft	**$1,874,295**	$127,055	$1,547,259	$2,291,260

By 2030, the costs of replacing the conventional transit bus fleet is expected to increase; 2030 TCOs for conventional options ranged from $1,190,00 to $2,060,000. The average TCO of an electric bus decreased by 16% on average by 2030, in-line with CNG and $LoNO_X$ options. While the average costs of buses all increase, electric buses are expected to have the lowest lifetime vehicle cost by after 2030. As reported in Table 7.4, by 2030, purchase and fuel incentives were on average 12% of the electric bus TCO.

Table 7.4 Total Costs by Fuel-pathway and Length by 2030 (No Incentives)

	length	***mean***	*sd*	*min*	*max*
CNG	*35ft*	**$1,190,605**	$73,872	$982,589	$1,517,056
	40ft	**$1,216,324**	$74,706	$1,012,306	$1,533,674
	60ft	**$1,767,293**	$91,485	$1,510,232	$2,157,085
Diesel	*35ft*	**$1,433,000**	$116,296	$1,110,427	$1,975,647
	40ft	**$1,463,584**	$120,193	$1,113,982	$2,050,889
	60ft	**$2,060,027**	$159,178	$1,575,978	$2,753,648
Electric	*35ft*	**$1,222,590**	$84,708	$935,251	$1,548,293
	40ft	**$1,243,567**	$85,936	$945,470	$1,596,988
	60ft	**$1,864,846**	$119,013	$1,495,618	$2,319,163
Hybrid	*35ft*	**$1,518,651**	$90,247	$1,262,949	$1,918,517
	40ft	**$1,553,500**	$92,826	$1,266,178	$1,948,299
	60ft	**$2,007,075**	$115,926	$1,653,252	$2,530,584
LoNOx	*35ft*	**$1,279,258**	$94,312	$984,840	$1,616,734
	40ft	**$1,308,181**	$95,588	$1,045,794	$1,670,869
	60ft	**$1,829,271**	$125,366	$1,494,942	$2,275,287

Looking at the distribution of likely cost outcomes in Figure 7.18, we observe the difficulty of reliably distinguishing the difference between powertrain or pathway costs. In both purchase periods, the differences between average costs may not fully characterize the experience of any agency, as evidenced by the large overlapping probability densities. We can also observe the strong delta caused by policy subsidies; in the current replacement period, HVIP and LCFS rebates over the vehicle life are worth ~$250,000 dollars, with a slight majority coming from fuel subsidies. By 2030, purchase subsidies are expected to decrease but fuel subsidies increase as electric buses realize more annual miles due to improving range.

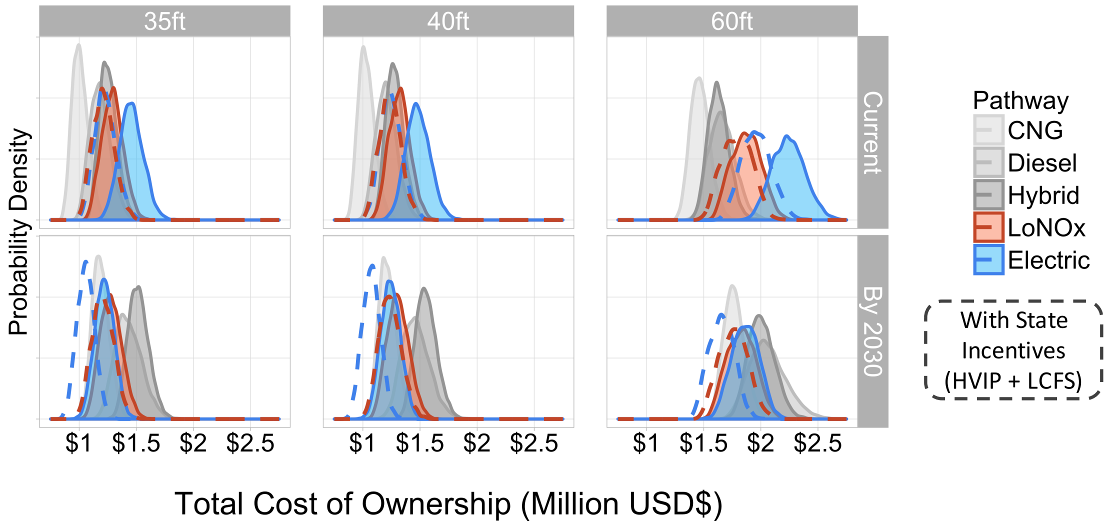

Figure 7.18 Lifetime Costs of Ownership per Bus

The current average per-mile cost of conventional transit bus operations is $1.82 to $3.01 per-mile (Table 7.5). Electric transit buses in the current replacement period had an average per-mile cost of $2.62 - $4.04, 18-20% higher than the comparable CNG bus. In the second replacement period (Table 7.5), the per-mile cost differential between CNG and Electric has decreased to less than 3%.

Table 7.5 Per Mile Costs by Pathway and Length (Current Prices, No Incentives)

	length	***mean***	*sd*	*min*	*max*
CNG	*35ft*	**$1.82**	$0.16	$1.38	$2.50
	40ft	**$1.86**	$0.17	$1.42	$2.54
	60ft	**$2.65**	$0.23	$2.05	$3.63
Diesel	*35ft*	**$2.14**	$0.19	$1.68	$2.87
	40ft	**$2.19**	$0.19	$1.69	$2.91
	60ft	**$3.01**	$0.26	$2.33	$3.90
Electric	*35ft*	**$2.62**	$0.25	$1.91	$3.71
	40ft	**$2.67**	$0.26	$1.92	$3.71
	60ft	**$4.04**	$0.39	$2.91	$5.52
Hybrid	*35ft*	**$2.27**	$0.19	$1.78	$2.99
	40ft	**$2.31**	$0.19	$1.79	$3.04
	60ft	**$2.95**	$0.24	$2.28	$3.88
LoNOx	*35ft*	**$2.33**	$0.23	$1.75	$3.40
	40ft	**$2.39**	$0.23	$1.75	$3.44
	60ft	**$3.38**	$0.34	$2.49	$4.53

Table 7.5 Per Mile Costs by Period and Bus Length by 2030 (No Incentives)

	length	***mean***	*sd*	*min*	*max*
CNG	*35ft*	**$2.15**	$0.19	$1.65	$2.83
	40ft	**$2.19**	$0.19	$1.67	$2.91
	60ft	**$3.19**	$0.27	$2.46	$4.27
Diesel	*35ft*	**$2.59**	$0.24	$1.86	$3.54
	40ft	**$2.65**	$0.25	$1.92	$3.67
	60ft	**$3.73**	$0.35	$2.72	$5.07
Electric	*35ft*	**$2.21**	$0.21	$1.57	$3.01
	40ft	**$2.24**	$0.21	$1.55	$3.05
	60ft	**$3.37**	$0.33	$2.42	$4.67
Hybrid	*35ft*	**$2.74**	$0.23	$2.10	$3.65
	40ft	**$2.81**	$0.24	$2.09	$3.65
	60ft	**$3.63**	$0.31	$2.67	$4.78
LoNOx	*35ft*	**$2.31**	$0.23	$1.71	$3.24
	40ft	**$2.36**	$0.23	$1.71	$3.24
	60ft	**$3.29**	$0.33	$2.43	$4.57

Turning back to the graphical representation, Figure 21 shows the high probability of equivalent per-mile costs from conventional and $LoNO_X$ buses for near-term replacement period. For the second replacement period, costs for replacing any bus with an electric or CNG could have similar per-mile costs over the vehicle lifetime. With state incentives, the costs of E-buses in the next replacement period are lower than CNG or $LoNO_x$ options.

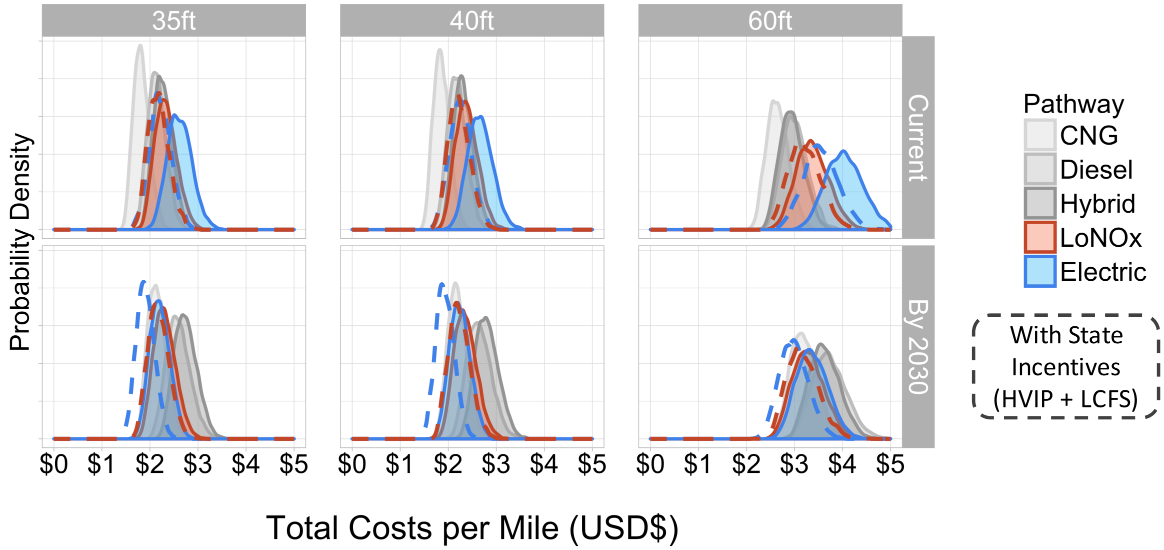

Figure 7.19 Lifetime Costs of Ownership per Mile

The effects of electric buses range restrictions are more apparent in the near term when looking at lifetime costs of ownership normalized on a per-mile basis by agency. In the left panel of Figure 7.20, we can observe the wide range of potential costs for electric buses in rural applications, with ~50% higher cost uncertainty compared to large agencies.

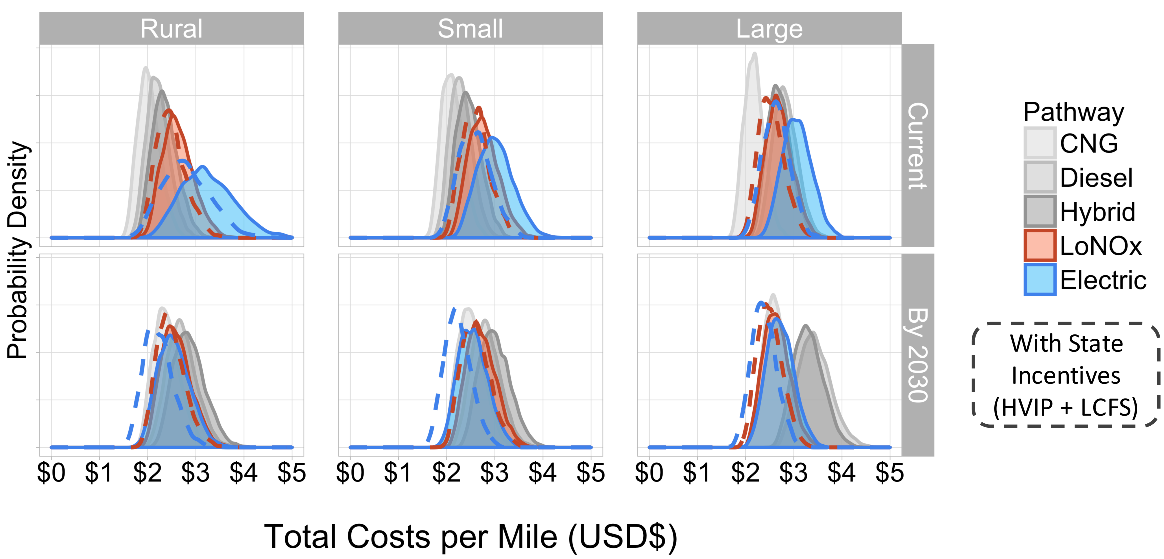

Figure 7.20 Per Mile Costs by Agency and Length

Finally, averaging across bus lengths and agency types, Table shows the average TCO in both the current and 2030 period, as well as the value of incentives. The magnitude and direction of change in E-bus costs relative to conventional options between the first and second purchase period are indicative of both the change in average costs for conventional alternatives and the change in E-bus prices. In the second replacement period, the lifetime costs of E-buses are 16% lower on average. Incentives in the 2030 period are likely to lower the costs of electric buses by an additional 12%. When incentives are included, the $LoNO_X$ pathway is not significantly different than the average price of CNG buses by 2030. In both periods, incentives decrease TCO for $LoNO_X$ by 5% on average.

Table 7.7 Summary of Average TCO by Pathway and Period

	Current Average TCO	Average TCO 2030
CNG	\$1,169,617	\$1,391,407
Diesel	\$1,351,981	\$1,652,203
Hybrid	\$1,388,495	\$1,693,075
LoNOx	\$1,495,652	\$1,472,237
Electric	\$1,728,110	\$1,443,667
LoNOx Incentives	-\$80,658	-\$68,598
Electric Incentives	-\$249,389	-\$180,008

7.4.1 SYSTEM-WIDE REPLACEMENT COSTS

If a regulation is adopted that shifts the entire fleet to E-buses over a normal replacement cycle (i.e. no accelerated retirement of existing buses), another important question is how the costs of full fleet replacement differ, given uncertainty in how costs vary across agencies of different characteristics. Table provides an estimate of the costs of replacing the entire fleet for E-buses in both the current and next replacement cycle. This type of analysis ignores the intertemporal cost changes (i.e. exchanging capital for operating costs), but provides a rough estimate for the direction and magnitude of expected changes in replacement costs over the near term.

The mean lifetime cost for replacing and operating the current fleet is \$7.7 billion dollars (Table). The lifetime cost of replacing the current fleet with 100% electric buses with current prices increases net costs for agencies by \$1.24 to \$1.28 billion dollars (~17%). Electrification increases total costs by \$2.92-\$2.97 billion dollars, of which \$1.67 to \$1.71 billion dollars is offset by HVIP and LCFS subsidies. By 2030, replacing the fleet with 100% electric is estimated to decrease net lifetime costs by \$730 to \$768 million dollars, with \$1.21 to \$1.25 in HVIP and LCFS subsidy.

Table 7.8 Total System Replacement Costs (Billion USD$)

	period	***mean***	*sd*	*min*	*max*
BAU	Current	**$11.87**	$0.77	$10.01	$14.59
	By 2030	**$14.32**	$0.92	$11.79	$17.99
All LoNOx	Current	**$13.03**	$0.80	$10.86	$16.16
	By 2030	**$12.85**	$0.84	$10.50	$15.93
All Electric	Current	**$14.37**	$0.77	$12.11	$17.62
	By 2030	**$12.57**	$0.83	$9.78	$15.56

Figure 7.21 shows the expected changes in likely system cost outcomes over the next two vehicle replacement cycles. As evident, the likelihood of an all-electric fleet increasing or decreasing costs is not necessarily well-represented by a comparison of average (mean) costs. There is also a significant difference in the total subsidies required to bring costs for E-buses in line with business as usual replacement costs across the two periods. By 2030, both the cost difference between BAU replacement and the value of subsidies offered to E-buses appear to decline significantly.

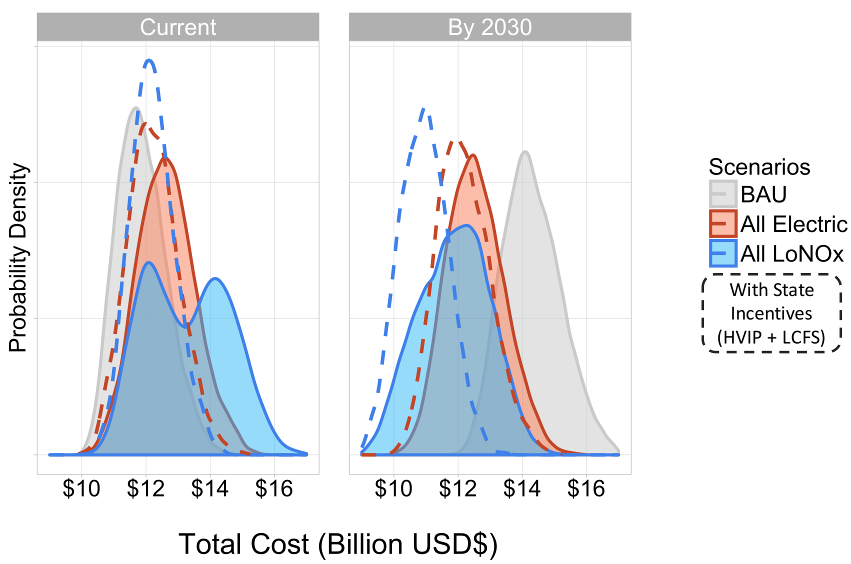

Figure 7.21 Statewide Bus Transition Costs

Another important consideration regarding costs of a statewide bus electrification goal is the variability in costs experienced by different agencies. In particular, small and rural agencies have orders of magnitude smaller fleets, operate fewer high density routes (e.g. a higher percentage of low stop density/high speed routes), and smaller reserve fleets compared to urban agencies. For these reasons, they are likely to experience higher fixed infrastructure costs and more problems with accommodating E-bus range and service issues in the near term. Figure 25 shows how these factors can contribute to differences in TCO for buses. Smaller agencies have higher lifetime ownership costs for transit buses on average, but some smaller agencies are likely to have costs for electric buses 7.5% higher than larger agencies. At the extremes, a small rural agency could experience 75% higher adoption costs compared to the largest urban fleets.

Diesel powertrains are a notable exception to the general cost trend for large vs. small agencies; this is in part due to lower per-mile maintenance costs for diesel vehicles at small agencies compared to large agencies. The group of small, rural agencies may operate 5% of active buses, but represent more than half of transit agencies in the state. Including these agencies in the scope of an electrification target significantly increases the uncertainty of predicting the costs of the regulation with regard to the costs of system-wide replacement for a given powertrain.

7.4.2 Drivers of Variance in Current Vehicle Costs

As illustrated above, uncertainty can be a confounding factor when comparing the lifetime cost of transit bus ownership. The variance in TCO for both conventional diesel and CNG buses is primarily driven by the annual miles, purchase costs, fuel efficiency, and vehicle life (Figure 7.). Total spending on fuel over the vehicle life is a significant operational cost, but its contribution to uncertainty is reflected across vehicle fuel efficiency, annual miles, vehicle life, and fuel costs. In Figure 25, bar width shows range of per mile costs, values are minimum and maximum range of parameter considered, ordered by contribution to variance.

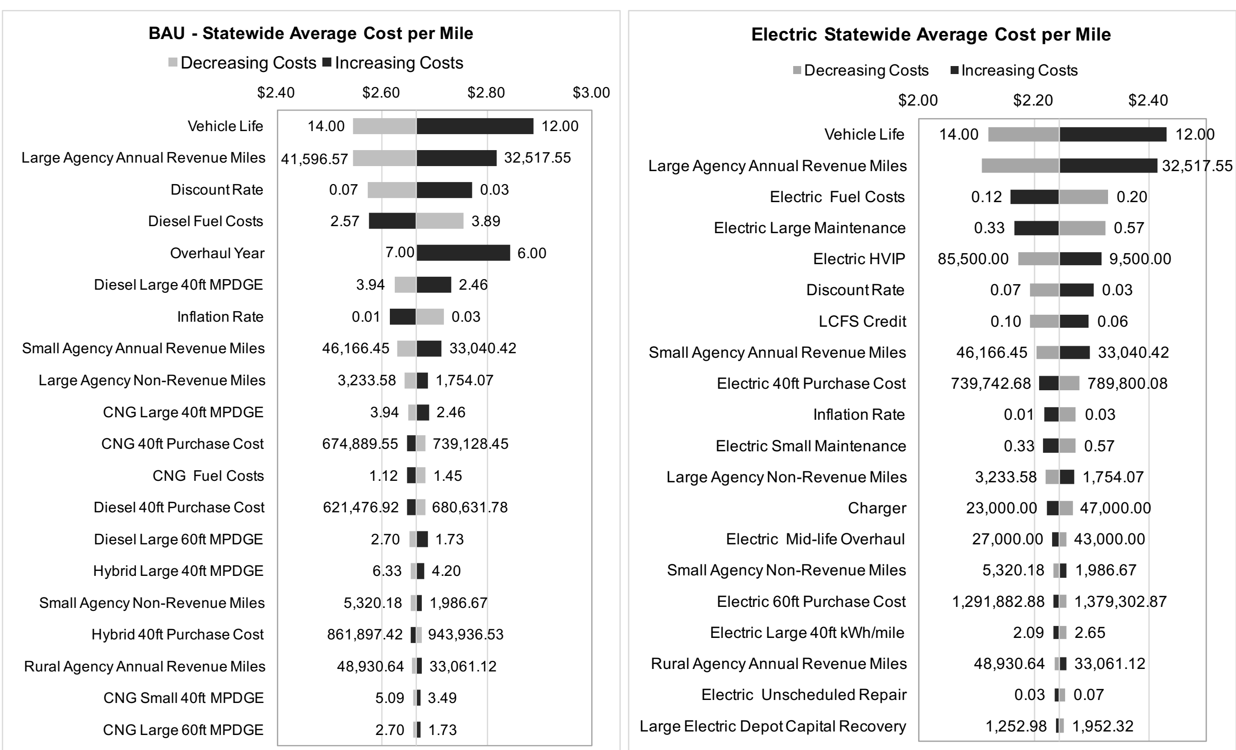

Figure 7.24 Screening Sensitivity Analysis of Parameters Affecting TCO of Transit Buses by 2030

A change of $0.10/kWh in the cost of electricity for E-buses represents approximately $72,000 dollars in net present value. At $0.12/kWh, the upper end of expected LCFS subsidy for E-bus charging, the LCFS subsidy decreases the total cost of ownership of e-buses by almost 10%. While overall, electricity costs are likely to be contractually predictable, a lack of empirical data contributes to increased uncertainty about e-bus maintenance costs. Despite the low costs suggested by initial demonstrations, the maintenance costs, including training and capital investments, will remain a potentialt concern.

E-buses represent a different value proposition for transit agencies transitioning from conventional buses; diesel buses and CNG buses historically have relatively low fixed upfront costs and high variable operations costs. Given the variability in purchase prices for conventional buses, upfront costs have a significant effect on the uncertainty in lifetime costs. If agencies transition to a fleet that has higher fixed upfront costs and lower operations costs, the uncertainty in a question of whether total costs are equivalent becomes one about variable costs. Maintenance, fuel costs, purchase and fuel subsidies are all primary sources of uncertainty for E-bus lifetime costs.

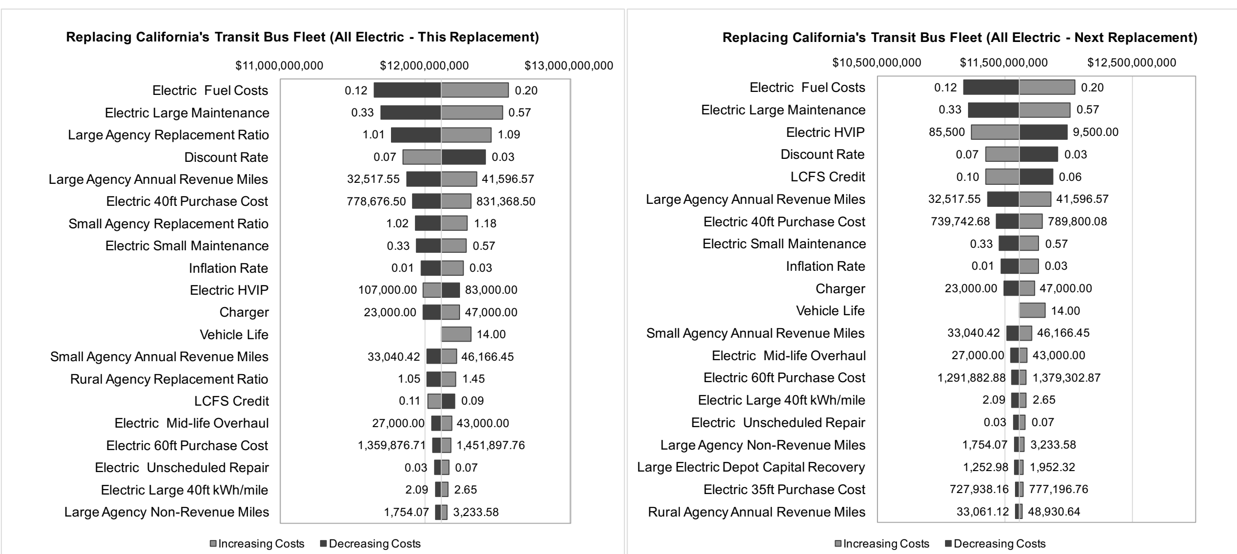

Figure 7.25 Screening Analysis of Statewide Fleet Replacement with 100% Electric Buses

At the state level, uncertainty in transition costs for electric buses in the current term are driven in large part by bus range limitations and technology replacement issues (Figure - Left). Replacement ratios for large and small agencies will be a key concern in transition costs. By 2030 (Figure 27 – Right), the effects of range mismatch and replacement ratio is signfiiantly reduced. Over both periods, uncertainty in fuel costs, state incentives, and maintenance costs, are signficant hurdles to accurately predicting transition costs.

7.5 DISCUSSION

A key limitation of this study is the assumption of independent costs between the first and subsequent purchase periods. E-buses currently represent a new market entry, and will face continued barriers to widespread commercialization. Near-term adoption of E-buses may be critical to ensuring long term viability (i.e. lower costs and improved technology performance) of E-buses. Any deterministic projection of medium to long term costs that does not consider near-term rates of adoption may overestimate potential improvements to the economics of E-buses. A "purchase period" scenario model was chosen in this study to illustrate how expected cost changes between now and the next time an agency replaces the same bus could affect TCO. It is unclear what levels of E-bus deployment are necessary to ensure that E-bus prices continue to fall. But, the costs of owning and operating a conventional bus has been increasing steadily. The results of this study suggest that if conventional bus prices continue to increase, E-buses will quickly become the most cost effective alternative given current policy.

The current purchase price of an E-bus can be more than 40% *higher* than what agencies have paid for conventional alternatives. But the economics of E-buses are improving rapidly, in part due to spillover effects from widespread deployment of electric powertrains and lithium batteries in light duty vehicle applications. E-bus battery costs are expected to decline by $85,000 or more, while the per-kW costs of electric motors and power electronics are expected to fall by almost 40%.[16] This study adopts a conservative assumption that all cost reductions over the next decade will enable further performance improvements for E-buses, not price reductions. In turn, E-buses in the next replacement period offer little to no mismatch in technical service potential, but still have slightly higher purchase costs. The assumption is notably conservative as some E-buses available today can replace conventional buses over a variety of duty cycles. A key exception to this price assumption is the possible replacement of lithium batteries before the end of its service life; these costs are assumed to fall dramatically in the second replacement period.

Even with this conservative assumption on pricing, E-buses are likely to become the most cost effective choice for transit agencies within their next two major replacement cycles. While increased capital costs may be offset by lower operating expenses, whether all agencies are able to realize these lower lifetime costs is still in question. At the system level, significant cost reductions are realized from full replacement with E-buses. However, there is heterogeneity, and small rural agencies may be forced to increase costs or decrease service to electrify their fleets. Perhaps equally important, purchase costs for diesel and CNG fueled buses have and are expected to continue to increase over time. This is driven in part by increasingly stringent emissions regulations, but also by a range of performance improvements.

It is also important to consider whether agencies will be able to achieve equivalent technical performance and maintain current service levels without additional capital outlays on E-buses. Agencies may require

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[16] The Department of Energy, Electric Drive Program expects the cost of electric motor and power electronic costs to fall from $12/kW to $8/kW by 2022 https://energy.gov/sites/prod/files/2016/06/f32/edt000_rogers_2016_o_web.pdf

additional buses if the effective range a bus can travel per charge is insufficient to meet the distance required by the duty cycle, and the agency does not have sufficient schedule flexibility to reassign these buses. The number of buses that must be purchased will depend on the route structure, the vehicle range per charge, and the charging system.

In the real world, electric vehicle efficiency and range will depend on several factors, including driver behavior, route, environmental conditions, and traffic conditions. The average vehicle range and efficiency may also not be the appropriate metric for design of an electric bus system, as it may reflect suboptimal operation of the battery system with respect to maximizing its service life, or may increase the risk of adverse service events due to inadequate battery capacity. Nevertheless, fuel costs over the lifetime of a bus are more than 2-3 times greater than costs for midlife overhauls and battery replacement, which are expected to cost less than $100,000 over 14 years (for more discussion, see the section on Midlife Overhaul).

E-buses available in 2016 are assumed to have an effective range of 120 miles per charge, increasing linearly to 250 miles per charge by 2035. Proterra[17] currently markets XR and E2 series Catalyst buses, respectively listed with 130-190 and 250-350 miles of range per charge. Proterra is a small, start-up manufacturer and the E2 is not yet available (Proterra has delivered 100 buses into service,[18] equivalent to less than 5% of the LACMTA fleet). Regardless, it is widely expected that longer range power systems will become available in the coming decade. This will be due to improvements in battery technology, decreasing battery costs, and improvements to vehicle efficiency. Average vehicle range may also not be the appropriate metric for design of an electric bus system; average range may reflect suboptimal operation of the battery system with respect to maximizing its service life. To minimize the risk of adverse service events due to inadequate battery capacity, buses may be purchased to meet a minimum daily range.

Depending on the route structure, on-route charging can decrease the number of additional buses needed by facilitating a longer daily service range. However, on-route charging systems can currently cost more than three times as much as depot charging systems. On-route charging systems come in multiple varieties. Fast-charging systems can cost as much as $500,000 for a 500 kW system, while smaller 60 to 80 kW systems have been installed at much lower costs. Depot systems are typically $20,000 to $60,000 per charger for 20 to 80 kW.[19] The costs of additional buses and charging systems and the route-specific logistics of charging would need to be evaluated in more detail to determine whether on-route of depot charging is more suitable, and what the overall costs of buses and chargers would be.

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[17] https://www.proterra.com/products/catalyst-40ft/

[18] https://www.proterra.com/press-release/proterra-continues-north-american-market-leadership-with-milestone-deployment-to-san-joaquin-rtd/

[19] For further discussion of charging system costs, please see the ACT working group discussion documents or data assumptions at https://www.arb.ca.gov/msprog/bus/actmeetings.htm.

As agencies increase the size of their electric fleets, each may also be able to optimize charging infrastructure and decrease the number of additional chargers required per additional bus acquired. In addition, E-bus ranges are improving rapidly even as the costs of energy storage fall and the market for electric buses is growing. This suggests that capital costs for electric may fall faster than other conventional technologies that have already achieved learning and scale economies.

Agencies face clear tradeoffs between expanding service and increasing investments into existing services, like electrifying routes. Historically, route and service planning and maintenance operations separate decision-making processes. Preparing for an all-electric fleet will likely require better integration of maintenance and planning departments. Future route and system planning should consider the performance characteristics of electric vehicles and strategic build-out of electric bus depots. In addition, fuel costs may vary across prospective charging facilities by location; route planning could also consider how routes might be reorganized to improve service without requiring the purchase of additional buses.

7.5.1 Battery Replacement

Lithium-ion batteries have become the preferred choice for electric vehicles because of high-energy densities, long cycle life, robust operating range, and low cost. Charge and discharge cycles progressively degrade the performance of lithium batteries in electric buses, eventually resulting in the need for replacement.[20] Electric battery warranties typically cover a range of service with a guaranteed percentage of the new capacity; for instance, a typical electric bus warranty might guarantee a battery to deliver a minimum of 80% of its initial discharge capacity after 12 years. Discharge capacity or depth of discharge (DOD) is commonly used to rate the functional capacity of a battery over a duty cycle. A 12 year to 80% DOD schedule translates to a loss in effective vehicle range of approximately 1.5% per year.

Capacity degradation has clear impacts on vehicle range, but the combination of resistance-induced power fade and diminished capacity will ultimately determine battery end-of-service. Increases to battery internal resistance reduce round-trip efficiency and will gradually render the battery inoperable in high-power applications. While both phenomena reduce the battery's capabilities, resistance increases make stored energy inaccessible.

While stored energy is rendered inaccessible for the high-power output typical of heavy-duty electric vehicle duty cycles, batteries could be functional in lower-power applications. A retired electric bus battery could retain upwards of 70% of its new capacity in some applications. A growing body of research has pointed to the opportunities for potential secondary-use of retired electric vehicle batteries in stationary applications.[21] Unfortunately, this research has also indicated that there may be limited

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[20] See Schaltz, E., Khaligh, A., & Rasmussen, P. O. (2009). Influence of battery/ultracapacitor energy-storage sizing on battery lifetime in a fuel cell hybrid electric vehicle. IEEE Transactions on Vehicular Technology, 58(8), 3882-3891; Cooney, G., Hawkins, T. R., & Marriott, J. (2013). Life cycle assessment of diesel and electric public transportation buses. Journal of Industrial Ecology, 17(5), 689-699.

[21] See H. Ambrose, D. Gershenson, A. Gershenson, D. Kammen, Driving rural energy access: a second-life application for electric-vehicle batteries. *Environmental Research Letters* **9**, 094004 (2014); S. J. Tong, A. Same, M. A. Kootstra, J. W. Park, Off-grid photovoltaic vehicle charge using second life lithium batteries: An experimental

economic viability in repurposing electric vehicle batteries, primarily due to consistently improving performance and lower costs from newer batteries, as well as uncertain performance from degraded batteries. Nevertheless, given the large size and capacity of electric bus batteries (>300 kWh compared with ~25 kWh for passenger electric vehicles), repurposing may prove a viable revenue stream in the presence of policies promoting the provision of additional grid-tied storage (e.g. California's AB 2514).

7.5.2 Uncertainty in State-Wide Adoption Costs

When considering total compliance costs for the state (given a goal to transition to 100% E-buses), it is also important to consider the structure of existing fleets. Fleets that have already transitioned to CNG have likely made significant investments in CNG refueling infrastructure and maintenance facilities. As such, there is a significantly different change in costs for CNG compared to diesel fleets. As the majority of the state's CNG fleet operates in the Southern portion of the state, this creates a divide between incentives for Northern and Southern California Transit Agencies, although there are also a number of large, urban fleets in the South Coast that may be well positioned to electrify some of their routes.

Another interesting finding of the screening analysis depicted in Figure 7.26 is that given the wide range of potential depot improvement costs considered ($15,000-$40,000 dollars per bus), capital cost improvements were not the most important factor when considering uncertainty in statewide adoption costs. While this range of assumed costs did not include some of the most extreme estimates, it seems unlikely that infrastructure improvements are the biggest source of uncertainty for whether a transition to electric buses would decrease costs on the whole and on average for California transit agencies.

Finally, another consideration is how annual expenditures will change over time given a move to adopt electric buses. Given a 2040 target for transit fleet electrification, we might expect agencies to delay the majority of purchases of E-buses till ~2030, and instead focus early efforts on small demonstration or pilot projects while waiting for E-bus technology and prices to improve. This type of purchase or replacement schedule is consistent with the likely costs reflected in Figure 7.26. Transitioning to electric buses increases annual expenditures as new investments in infrastructure are made. Over time, E-buses deliver lower operating costs and overall decrease total expenditures. The time required for agencies to realize savings from electrification (blue arrow) is due to uncertainty in technology and policy; namely fuel costs and subsidies. The overall investment required to achieve the lower operating costs suggested by E-buses is driven by uncertainty in capital costs.

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and numerical investigation. *Applied Energy* **104**, 740-750 (2013); J. Neubauer, A. Pesaran, B. Williams, M. Ferry, J. Eyer, paper presented at the 2012 SAE World Congress and Exhibition, Detroit, Michigan, 2012.

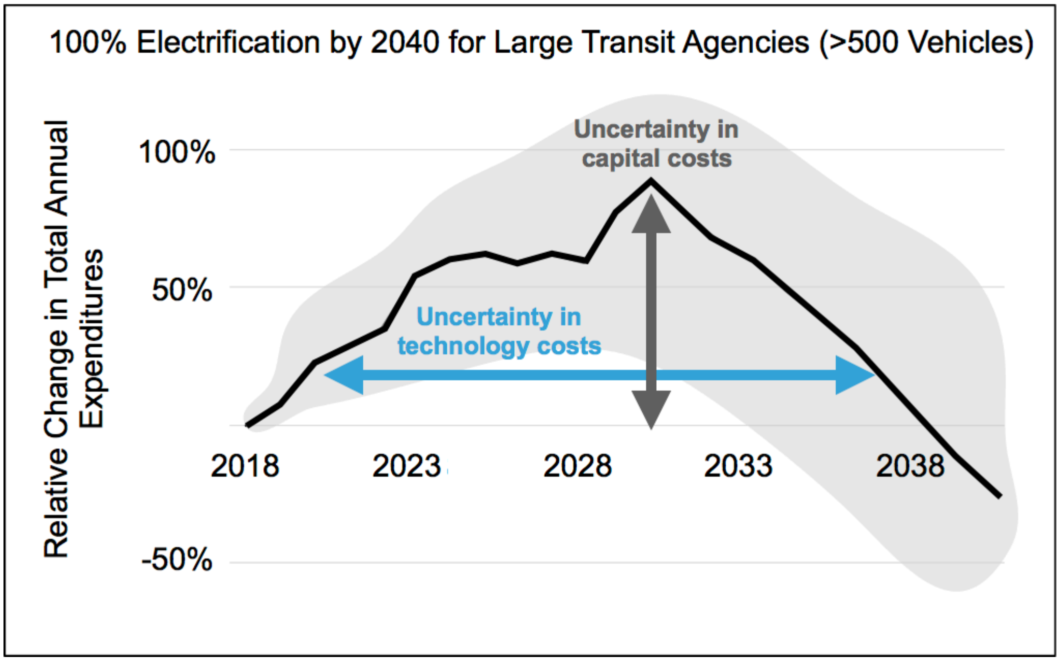

Figure 7.26 Change in Annual Expenditures for Large Agency with 100% Electric by 2040

7.5.3 Emissions Benefits

A shift to E-buses can effectively eliminate tailpipe emissions, potentially leading to local air quality improvements. These air quality benefits may accrue to pedestrians, cyclists, drivers and passengers as well as to individuals living, working, and traveling near transit routes. These local air quality improvements are likely to be of particular interest to communities currently experiencing air pollution burdens from other mobile and stationary sources. Even when considering the lifecycle emissions associated with electricity generation, the high penetration of renewables and other low-emitting generators in the California grid mean that E-buses have lower per-mile emissions rates than buses using other fuels (Ercan & Tatari, 2015; Lajunen & Lipman, 2016). In addition to air quality benefits, electric buses also significantly reduce GHG emissions (Table 7.8). An 85% reduction in per-mile emissions of GHGs could avoid more than a million metric tonnes of CO_2-equivalent per year.

Any comparison of emissions rates should take into account potential changes in the technology used to generate the electricity. California's strong target for renewable generation suggests E-buses will continue to deliver reliably low emissions electricity.

Table 7.6 Per Mile Emissions Comparison for E-buses and CNG (grams/mile)[22]

	2018 Electric	2030 Electric	CNG (Conventional)
VOC	0.14	0.10	2.01
CO	0.78	0.56	4.97
NO_X	0.87	0.63	2.74
PM_{10}	0.08	0.07	0.03
$PM_{2.5}$	0.06	0.05	0.03
SO_X	0.52	0.43	0.57
CH_4	2.16	1.50	22.26
N_2O	0.02	0.02	0.24
CO_2	742.07	524.61	2898.65
CO_2e (GWP_{100})	802.40	566.55	3527.24

The reduction in NO_X emissions and local pollutants (VOC and CO) will also have significant economic benefits in terms of reduced public health impacts. While these costs are not considered here, they entail a potentially substantial economic benefit in addition to those associated with carbon abatement.

7.6 References

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[22] This estimate is based on the CAGREET2016 model for electricity and CNG production emissions. Combustion emissions are estimated from EMFAC. Assumes a vehicle efficiency of 0.475 Therms/mile for CNG, and 2.1 kWh per-mile for Electric). The electricity mix assumption can be found the Appendix. All units are in grams per-mile.

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8. Life Cycle Modelling of Truck Electrification

8.1 Purpose and Scope

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 local 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 already 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. This chapter contains text from: Ambrose, H., & Kendall, A. (Under Review). *Life Cycle Modelling of Technologies and Strategies for a Sustainable Freight System in California*. Institute of Transportation Studies, University of California, Davis, Research Report.

8.2 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 US 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 (Davis, Williams, & Boundy, 2016). Liquid fuel use from medium and heavy duty vehicles has increased more rapidly in both relative and absolute terms than consumption by other sectors (Council, 2010). 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 (Grenzeback et al., 2013).

California has a history of critical air quality issues, including persistent non-attainment areas for federal ozone and air borne 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 (Adar & Kaufman, 2007; Heinrich & Wichmann, 2004; Seagrave et al., 2006). 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. 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 NOx, 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 NOx in the South Coast and San Joaquin air districts 80% by 2032. California has also set a target to reduce GHG emissions by 40% by 2030 under the Global Warming Solutions Act SB32. 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/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 (Lade & Lin Lawell, 2015; McCollum & Yang, 2009; Witcover, Kessler, Eggert, & Yeh, 2015; Yeh et al., 2012). There has been considerable scholarly debate over the emissions reductions potential of biofuels (Searchinger et al., 2008), particularly for heavy duty vehicles (Delucchi, 2010; Durbin, Collins, Norbeck, & Smith, 2000; Janaun & Ellis, 2010; McCormick, Graboski, Alleman, Herring, & Tyson, 2001; O'Hare et al., 2011; Richard J Plevin, Delucchi, & Creutzig, 2014; Shi et al., 2006), and the proper methodology for estimating the emissions of grid-tied electric vehicles (Cai, Wang, Elgowainy, & Han, 2012; Soimakallio, Kiviluoma, & Saikku, 2011; Venkatesh, Jaramillo, Griffin, & Matthews, 2011; Weber, Jaramillo, Marriott, & Samaras, 2010; Whitaker, Heath, O'Donoughue, & Vorum, 2012). 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 (Clark, Kern, Atkinson, & Nine, 2002; Herner et al., 2011; Kado et al., 2005).

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 (Carlsson, Jacobsson, Holmén, & Rickne, 2002; Scherer, Harhoff, & Kukies, 2001), quantifying the impacts of incentives or funding (Reinganum, 1989), and the market structure of specific industries (Sutton, 2001). Substitution and other market-mediated effects also complicate prediction of impacts on pollution from technology change (Richard J Plevin et al., 2014). In total, these issues come down to capturing uncertainty and tradeoffs in the effects of technology change or the appropriate direction to incentivize change (O'Hare et al., 2011; Richard Jay Plevin, 2010; Richard J Plevin et al., 2014).

LCA is a standardized methodology for assessing the environmental impacts of a product system ((ISO), 2006). The scope of LCA is typically limited to environmental impacts, but the life-cycle framework is also used to assess costs (as in LCC) and other metrics for sustainability(Kloepffer, 2008; Reed, 2012). LCC applies life cycle principles to evaluate the economic impacts of decision-making (Fuller & Petersen, 1996; Woodward, 1997). 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" (Rebitzer et al., 2004). 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) (Ambrose & Kendall, 2016; Kim, Wallington, Sullivan, & Keoleian, 2015; Lajunen & Lipman, 2016; Xu et al., 2015). 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.

8.3 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 of freight truck population and travel for California 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, 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 mile 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. The result is a vector of cost per unit emissions avoided by emissions category and performance metric.

8.3.1 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, US Census Bureau, and

EPA maintain different definitions of heavy duty vehicles by gross vehicle weight, which can lead to confusion (DOE; USDOT). Table 2, adapted from Guilano 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) used in this study. The weight of the vehicle is one of the primary factors influencing fuel requirements, but varies considerably during the duty cycle due to the need for return links or 'dead-heading' in most goods distribution vocations.

Table 8.1 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 8.1 shows the estimated population of Class 3-8 in-state registered vehicles and total annual vehicle miles travelled 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 increases by 2.7 million VMT annually by 2040.

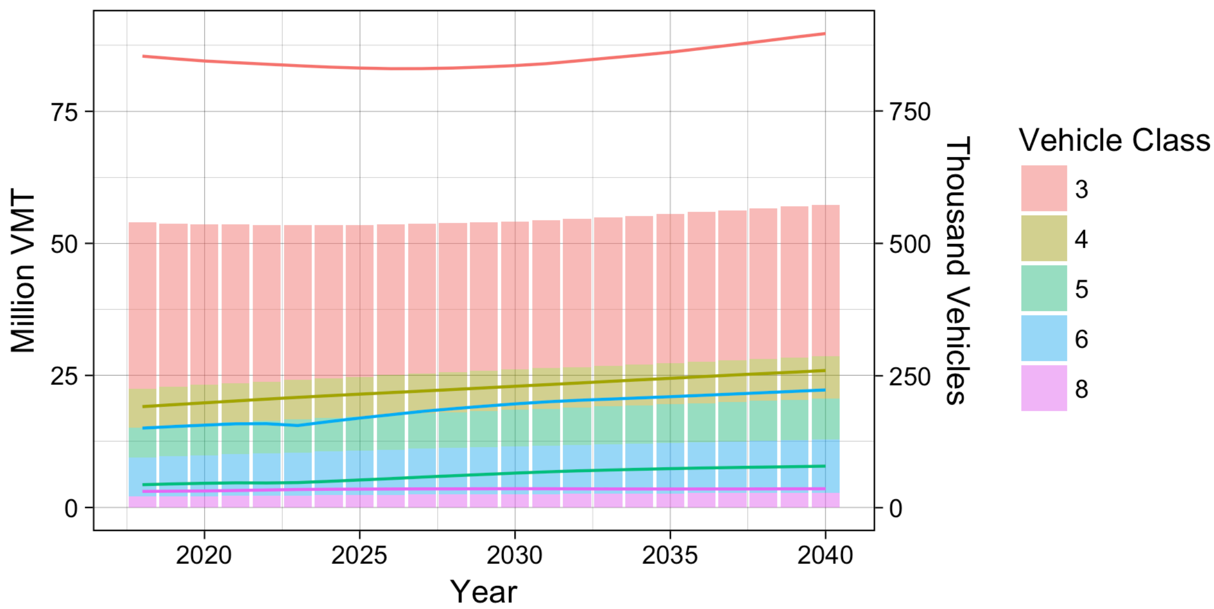

Figure 8.22 Vehicle Population (lines) and Annual Miles Travelled by Vehicle Class (Branch, 2017)

8.3.2 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 (Holmberg, Andersson, Nylund, Mäkelä, & Erdemir, 2014). 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 (Clark et al., 2002). Studies have established the close links between duty cycle, fuel type, and vehicle energy demands (Simpson, 2005; Sovran & Blaser, 2003). In fact, duty cycle can be the most significant driver of uncertainty in operational emissions estimates from HDVs (Yanowitz, McCormick, & Graboski, 2000).

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 (Walkowicz, Kelly, Duran, & Burton, 2014). FleetDNA 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 8.2 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 8.2 FleetDNA 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

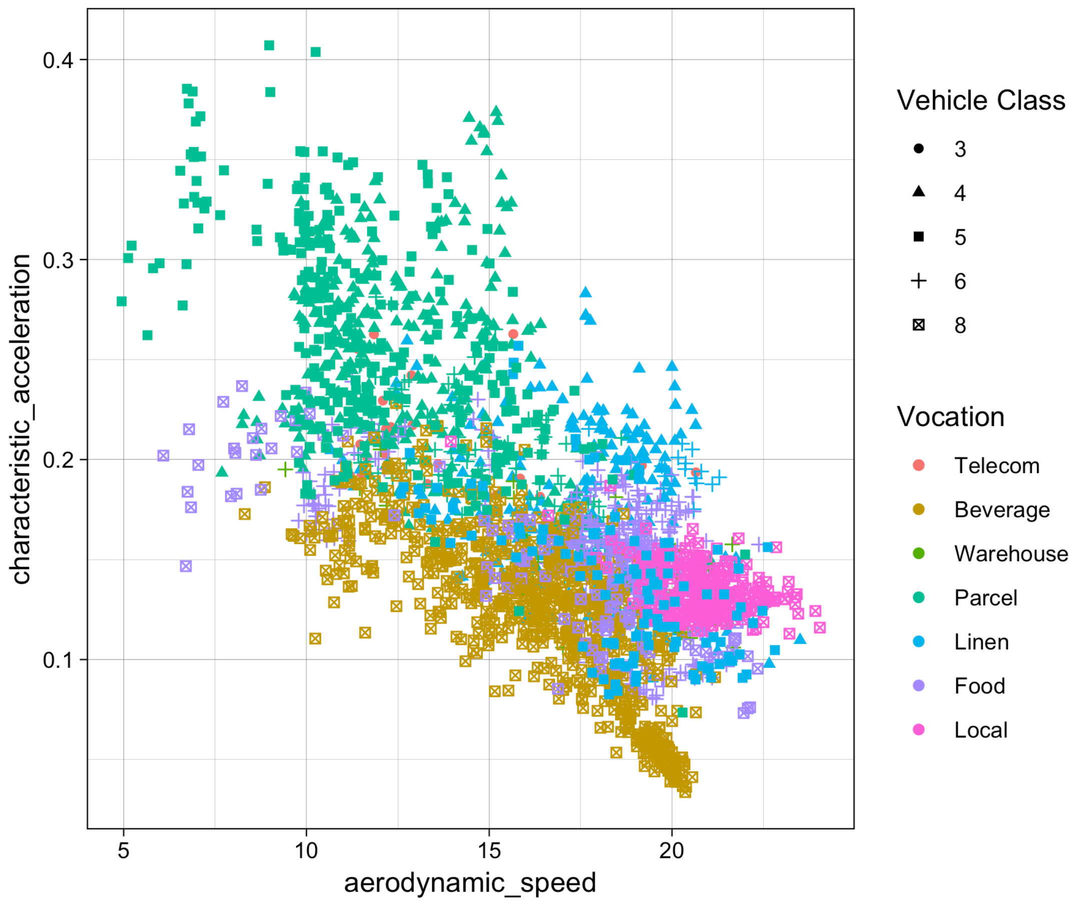

Figure 8.2 Average Speed and Acceleration by Duty Cycle and Vehicle Class in Fleet DNA Composite Data

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

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

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

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

Where:

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

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

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

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

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

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

$$\rho = air\ density$$

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

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 (O'Keefe, Simpson, Kelly, & Pedersen, 2007; Schwertner & Weidmann, 2016). 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 4. Comparison with diesel vehicle efficiency is discussed in the results section.

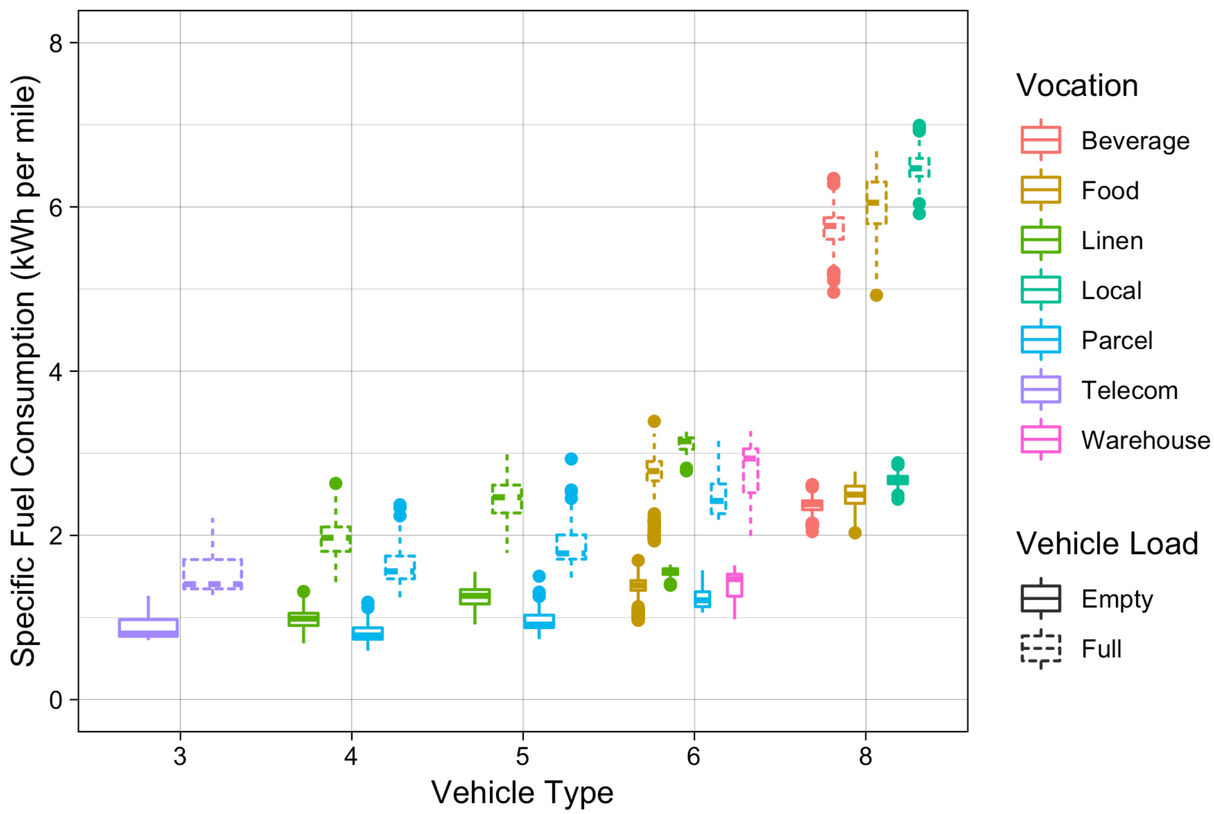

Figure 8.23 Estimated Electric Truck Energy Demands per Mile

8.3.3 Vehicle Purchase and Operating Costs

Vehicle purchase and operations cost data were drawn from the AFLEET model and other existing data sources (Burnham, 2016). 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% to 70% of the cost of new electric freight vehicles (Board, 2018), 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 8.3 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 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)

8.3.4 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 (Neij, 2008). Experience curves have a long history of use for examining the relationship between deployment of a technology and the price of a technology (Wright, 1936). Equation (1) 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 (2), 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 (de La Tour, Glachant, & Ménière, 2013; Harmon, 2000), gas (Colpier & Cornland, 2002), and energy storage technologies (Matteson & Williams, 2015; Weiss, Junginger, Patel, & Blok, 2010). 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 (Nykvist & Nilsson, 2015): one, a whole industry average for large-format LIBs; and two, 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= \$1585 USD/kWh (2011USD) 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 (Kittner, Lill, & Kammen, 2017), these represent relatively conservative assumptions.

Historical sales and production data were combined with forecasts of manufacturing capacity to estimate cumulative production (Figure 8.24 8.4). 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 (Chung, Elgqvist, & Santhanagopalan, 2016; Curry, 2017). 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.

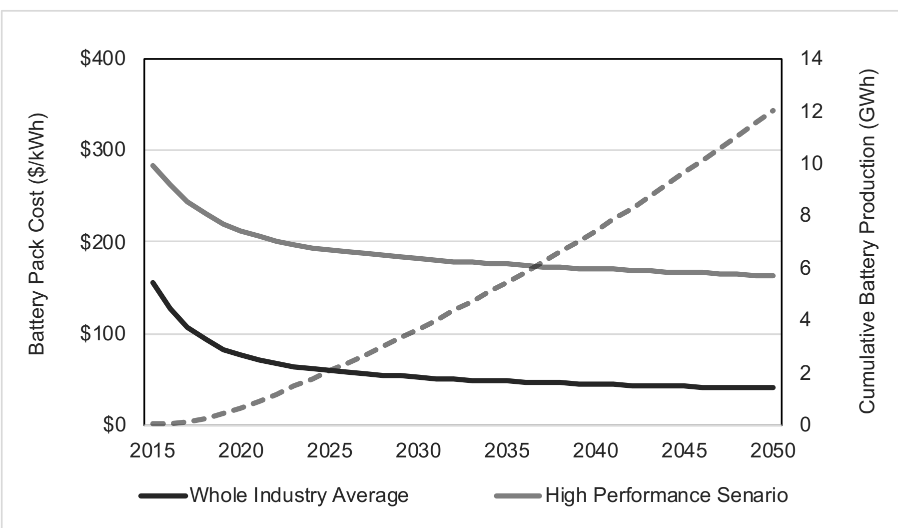

Figure 8.24 Estimated Vehicle Battery Pack Costs 2015 to 2050

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 (Thackeray, Wolverton, & Isaacs, 2012). Figure 8.25 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 forecast based on theoretical values for current automotive cathode materials and technology development targets set by the Department of Energy for LIB cells and packs (Energy, 2017). Current pack energy density was estimated using the BatPAC Model for a pack based on nickel manganese cobalt (NMC) cells (Dunn, Gaines, Barnes, Sullivan, & Wang, 2014). 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.

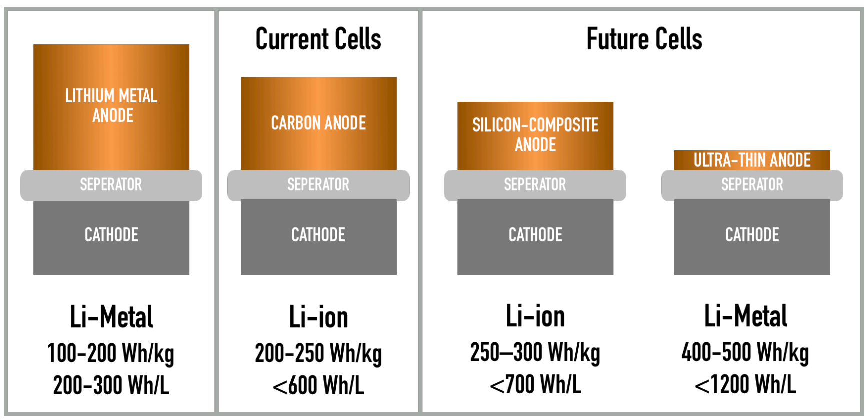

Figure 8.25 Potential Improvements in Li-ion Cell Energy Density

8.3.5 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 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 over-night depot charging for a small fleet; managed Level 2 over-night depot charging for a large fleet; managed depot DC Fast Charging; and finally, opportunistic DC fast charging. Table 8.4 shows the main costs for charger infrastructure for the three charging systems considered.

Table 8.4 Electric Truck Charger System Costs (Burnham, 2016)

EVSE 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
Elect. 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 - $0.26
On-Route Charging ($/kWh)	-	-	$0.06 - $0.09
Demand Rate ($/kW)	-	$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 shows the average dwell time on the left. 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.

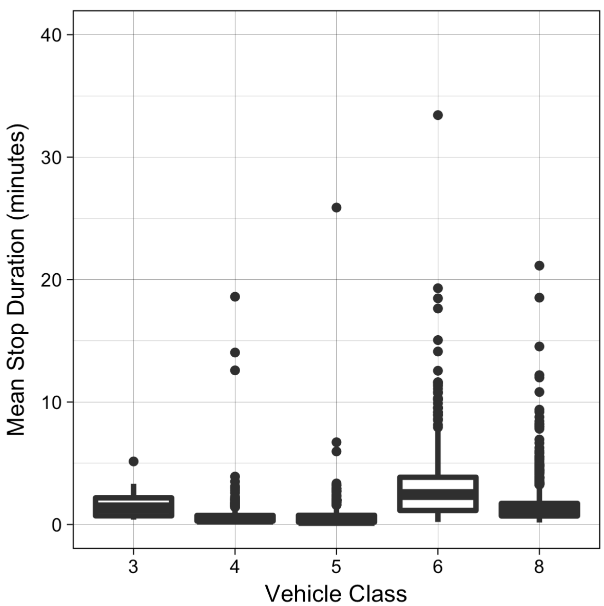

Figure 8.6 Average Dwell Time at Stops in Minutes

Based on the charging strategy, we then evaluated the potential battery capacities required to meet each duty cycle. Figure 8.7 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. For the depot charging scenario, the battery capacity must be sufficient to meet the 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, we assume 80% of the battery capacity in the depot charging scenario is sufficient to deliver 90% of daily energy requirements by duty cycle. In the opportunistic charging scenarios, the battery capacity is estimated to be the daily energy requirement, less energy delivered during opportunity DC fast charge event(s). The minimum battery size is constrained at 25 kWh for all scenarios.

For all scenarios, the maximum duration of over-night 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.

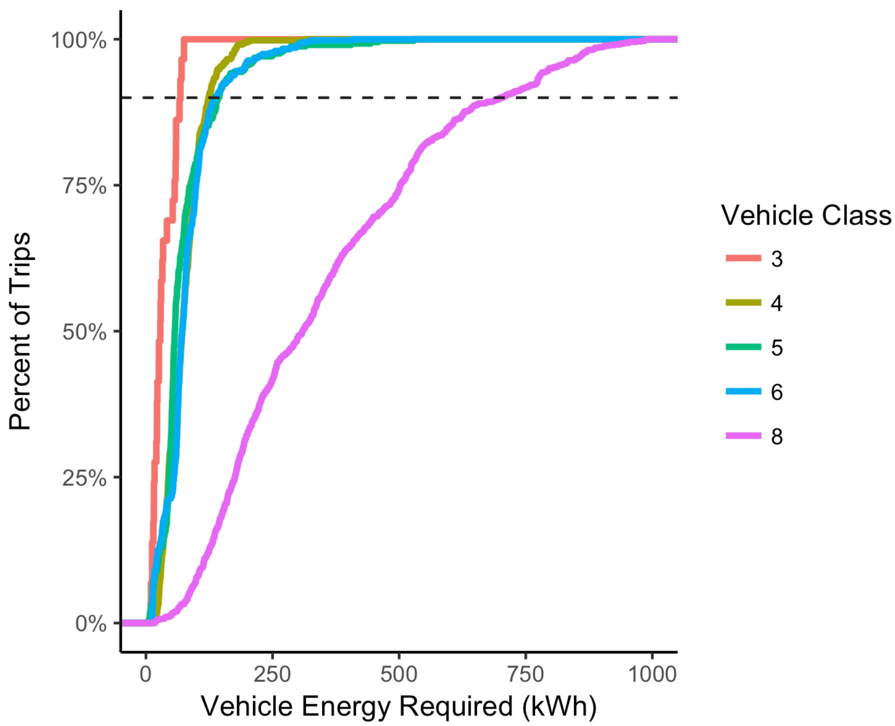

Figure 8.7 Energy Required by Duty Cycle and Daily Travel Distance

8.3.6 Generation of Electricity

A key factor in estimating emissions from 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 (Spath & Mann, 2000), so 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 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 rate (EF_t) is estimated as the mass of GHG equivalent emissions per unit of delivered energy with Equation 4, 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 (Argonne National Laboratory, 2017), and a representative LCI was estimated for each fuel source based on the net generation by generator type for each regional scenario (US EPA, 2016).

8.3.7 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 8.4 describes the categories of operations emissions tracked in the EMFAC database. While electric and conventional freight vehicles will both cause emissions from fuel production, break 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 start/stops, storage, or idling, which are key sources 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 8.5 Sources of Operations and Combustion Emissions for Freight Vehicles (Branch, 2017)

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 over all speed bin
Tire Wear	gram/veh-mile	VMT over all speed bin

8.3.8 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 US national average gasoline (Gasoline, Table 8.6), is provided for comparison.

Table 8.6 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
CO2 (w/ C in VOC & CO)	1,652	1,416	1,907	g/gal
CH4	19	21	22	g/gal
N2O	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
NOx	4	5	5	g/gal
PM10	0	1	0	g/gal
PM2.5	0	0	0	g/gal
SOx	3	3	3	g/gal
BC	0	0	0	g/gal
OC	0	0	0	g/gal

8.3.9 Conventional Fuel Prices

A forecast for conventional fuel prices was obtained from the US Energy Information Administration fuel price components analysis for the US pacific region. (Administration, 2019). The price of conventional fuels can be volatile, but average fuel prices are expected to increase steadily over the next two decades (Figure).

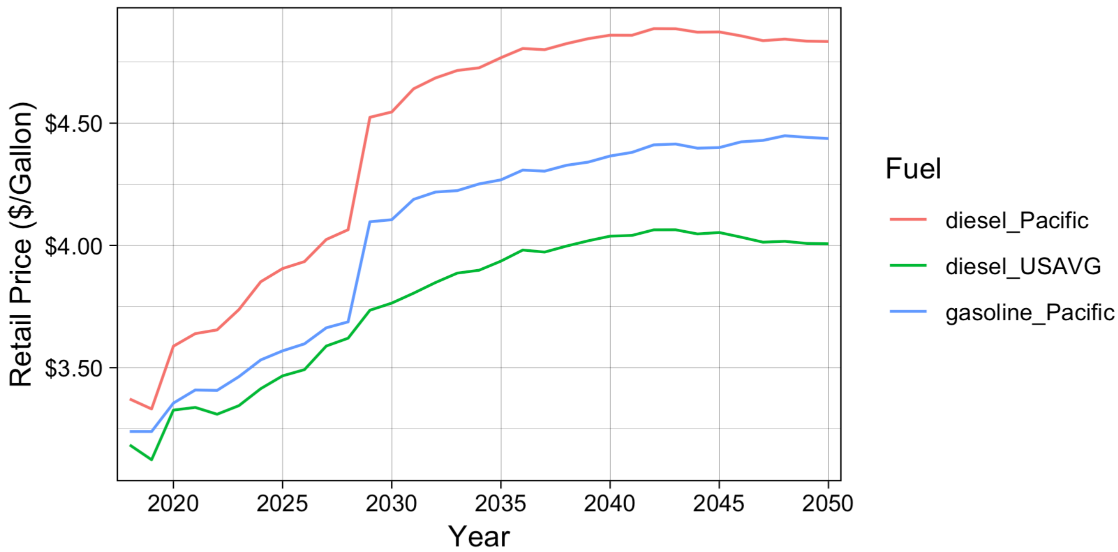

Figure 8.9 Retail Price of Gasoline and Diesel in California, 2018 – 2050

8.3.10 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 (Fann, Baker, & Fulcher, 2012). 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 US 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 NOx 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 (Muller & Mendelsohn, 2007). 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: one, a BAU scenario assuming continued use of conventional diesel and gas vehicles through 2040; and two, a scenario assuming 100% electrification of Class 3-8 vehicles by 2040.

8.4 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.

8.4.1 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. But, 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 8.10).

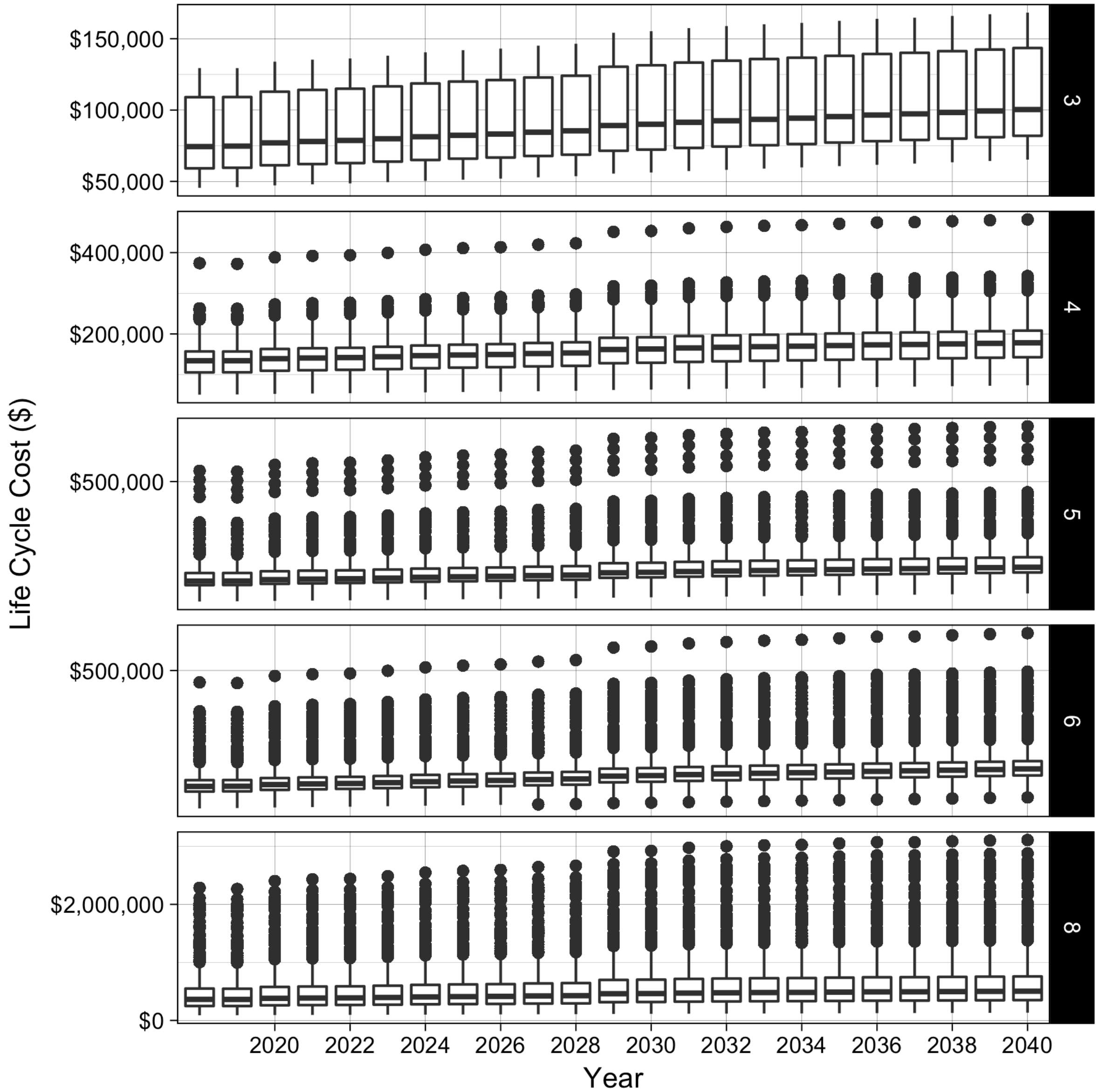

Figure 8.10 Life Cycle Cost of Conventional (Gasoline and Diesel) Class 3 to 8 Vehicles

The mean estimated GHG emissions rate of Class 3-8 gasoline and diesel vehicles are shown in Figure . For GHGs, emission range from 546 to 1622 g/mile on average. Emissions of oxides of nitrogen (NOx) were found to range from 0.3 g/mile for service trucks and vans, to 3.4 grams per 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.

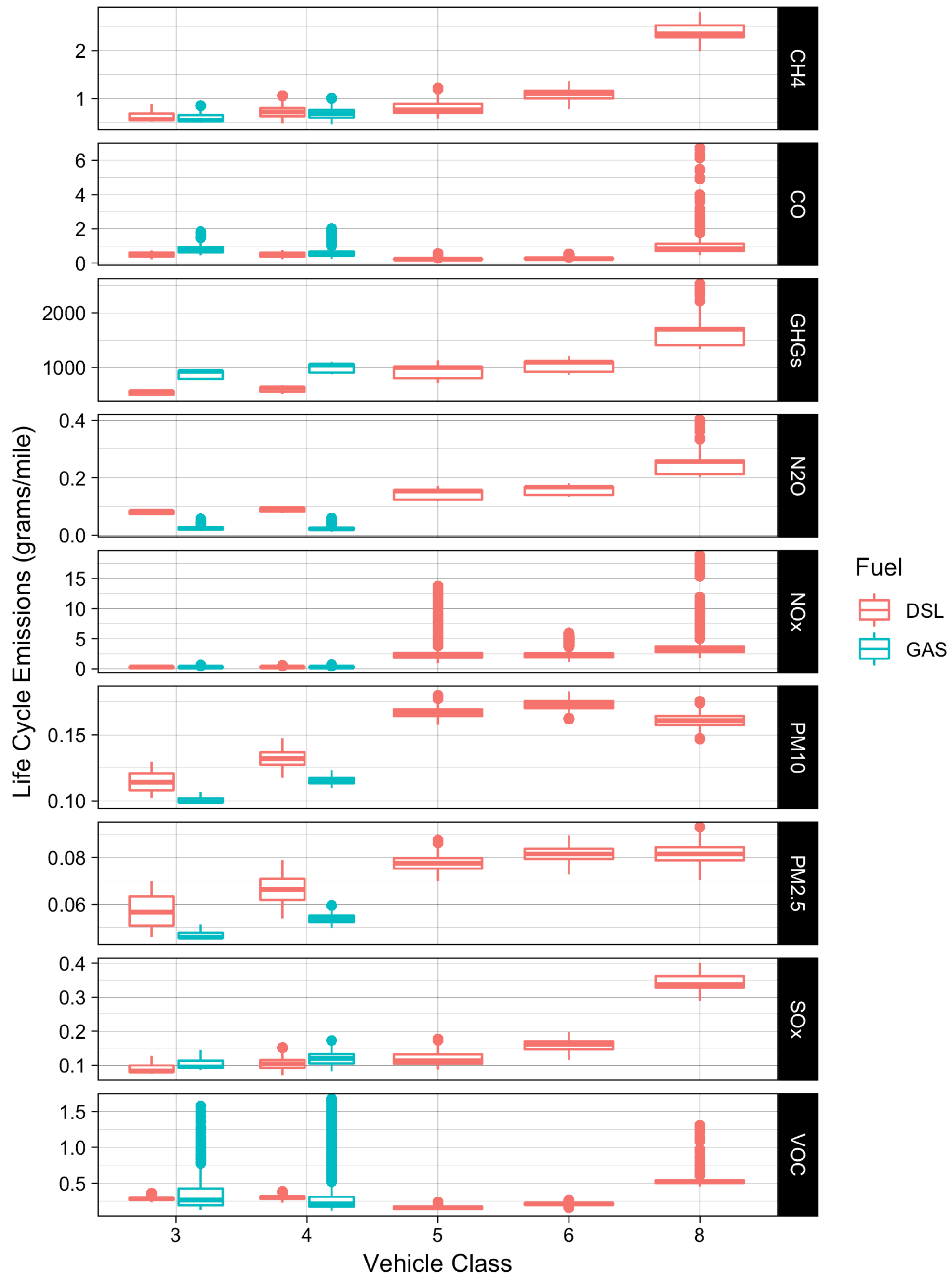

Figure 8.11 Emissions per Mile for Conventional Class 3-8 Vehicles (DSL = Diesel, GAS = Gasoline)

To calculate the ton-mile emissions, the emissions rate per mile was divided by the estimated average load for each vehicle class (March, 2001). 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 8.6 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 8.7 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			

8.4.2 E-TRUCK LIFE CYCLE COSTS AND EMISSIONS

The median life cycle cost of electric Class 3-8 vehicles is comparable or equivalent to current conventional vehicles in many applications (Figure 8.12). 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 thousand for Class 3 vehicles to $327 thousand 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 8.13)

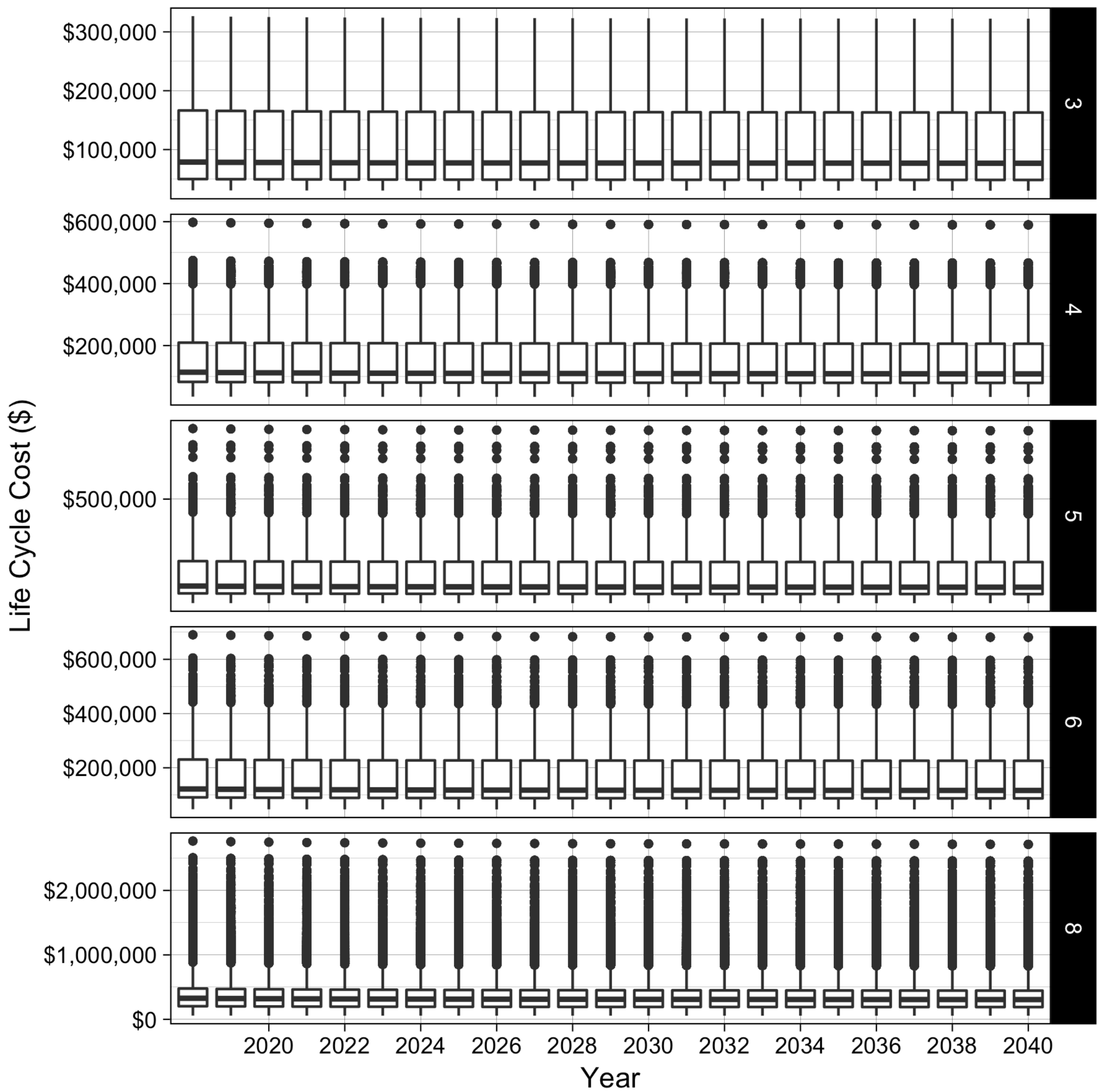

Figure 8.12 Life Cycle Costs of Electric Class 3-8 Vehicles

Figure 8.13 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 one dollar per mile.

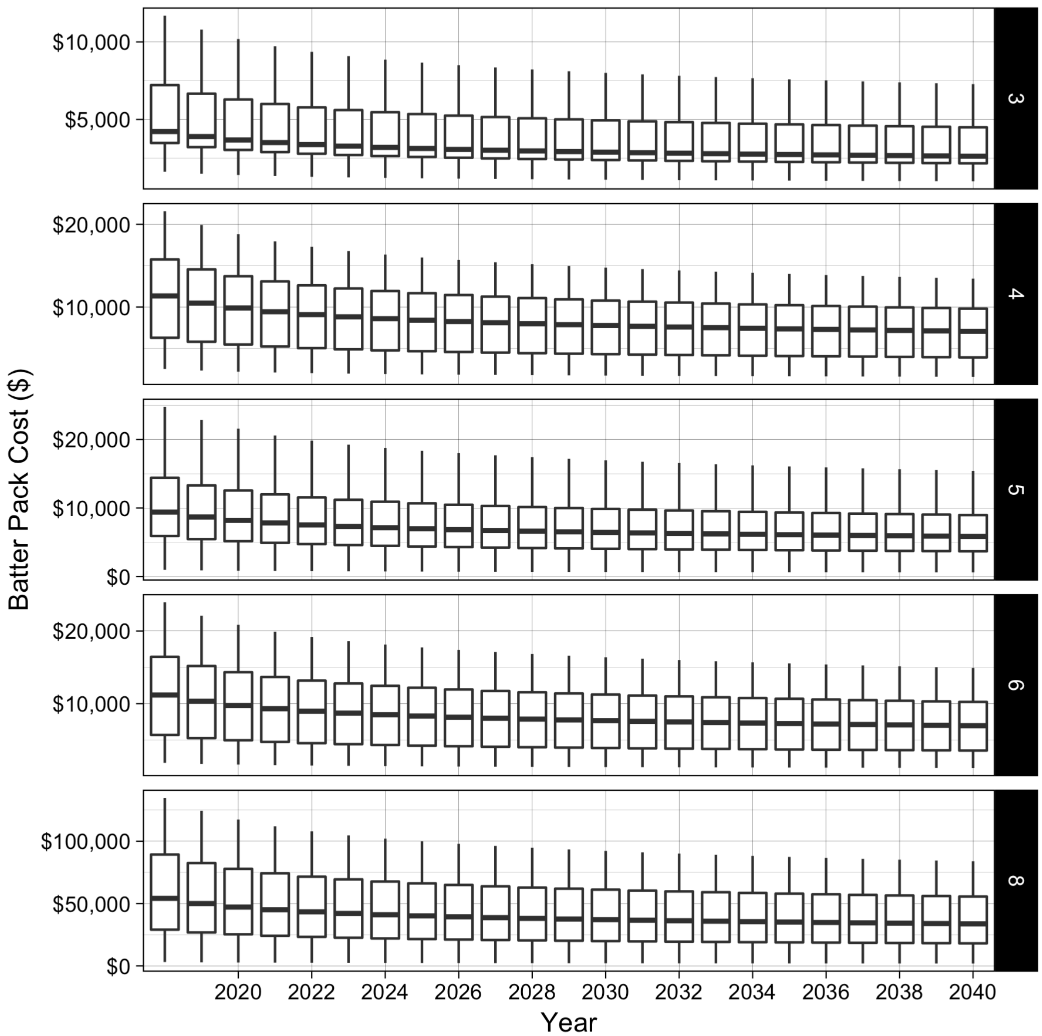

Figure 8.13 Battery Pack Cost by Year and Vehicle Class

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 shows the emissions rate per mile changing over time in line with these shifts in electricity generation.

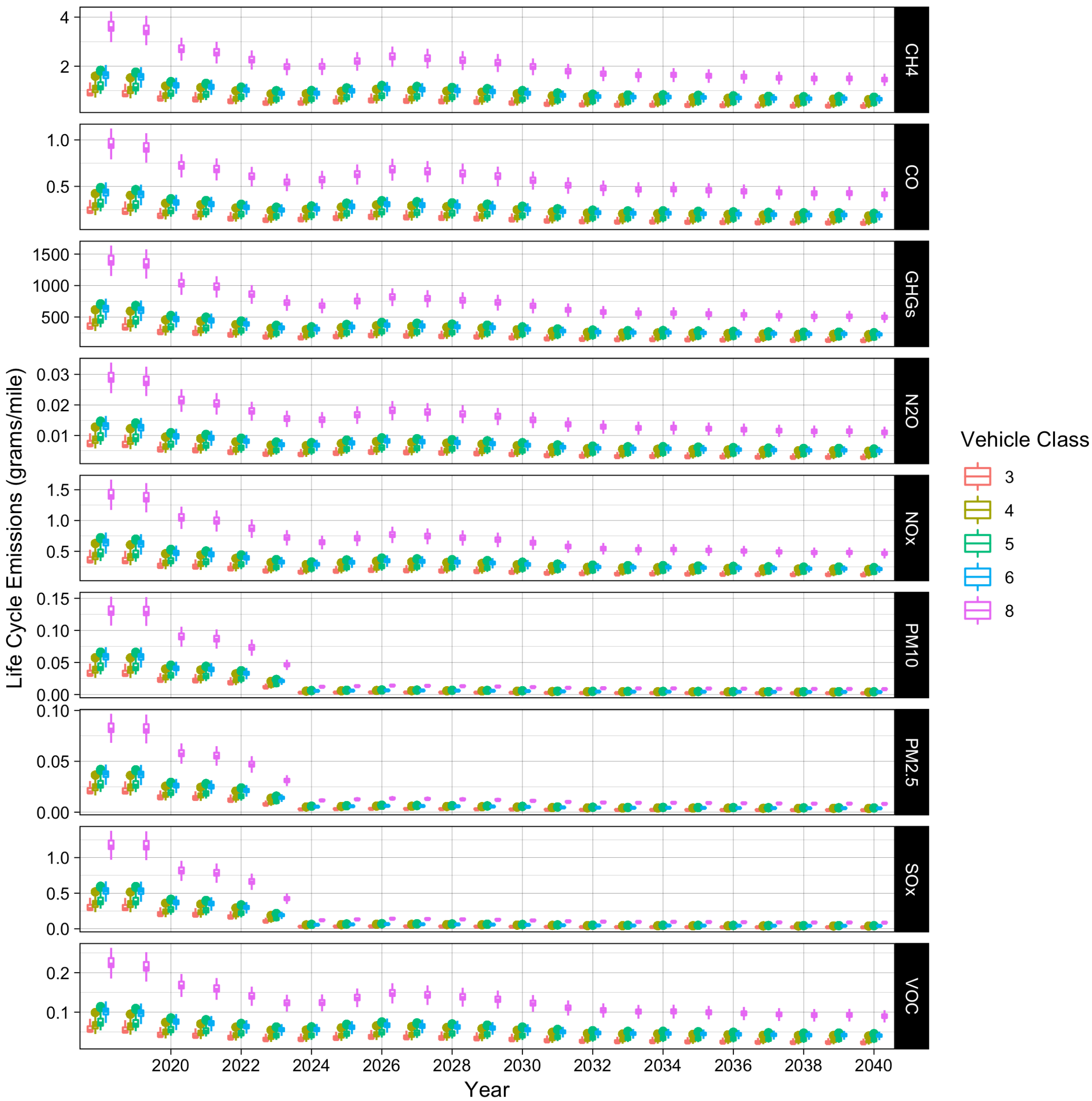

Figure 8.14 Emissions per Mile for Electric Trucks, 2018 - 2040

Table 8.8 shows the average emissions rate for electric trucks over the time horizon divided by the effective cargo capacity. While the emissions rates for electric trucks change dramatically, they are relatively constant after 2024 compared with the prior decade. The values in Table 8.8 then primarily reflect the estimated emissions rate for electric trucks operating in a future (cleaner) grid.

Table 8.8 Emissions per Ton-mile for Electric Class 3-8 Vehicles (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

8.4.3 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 to 2040.

Figure 8.15 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.

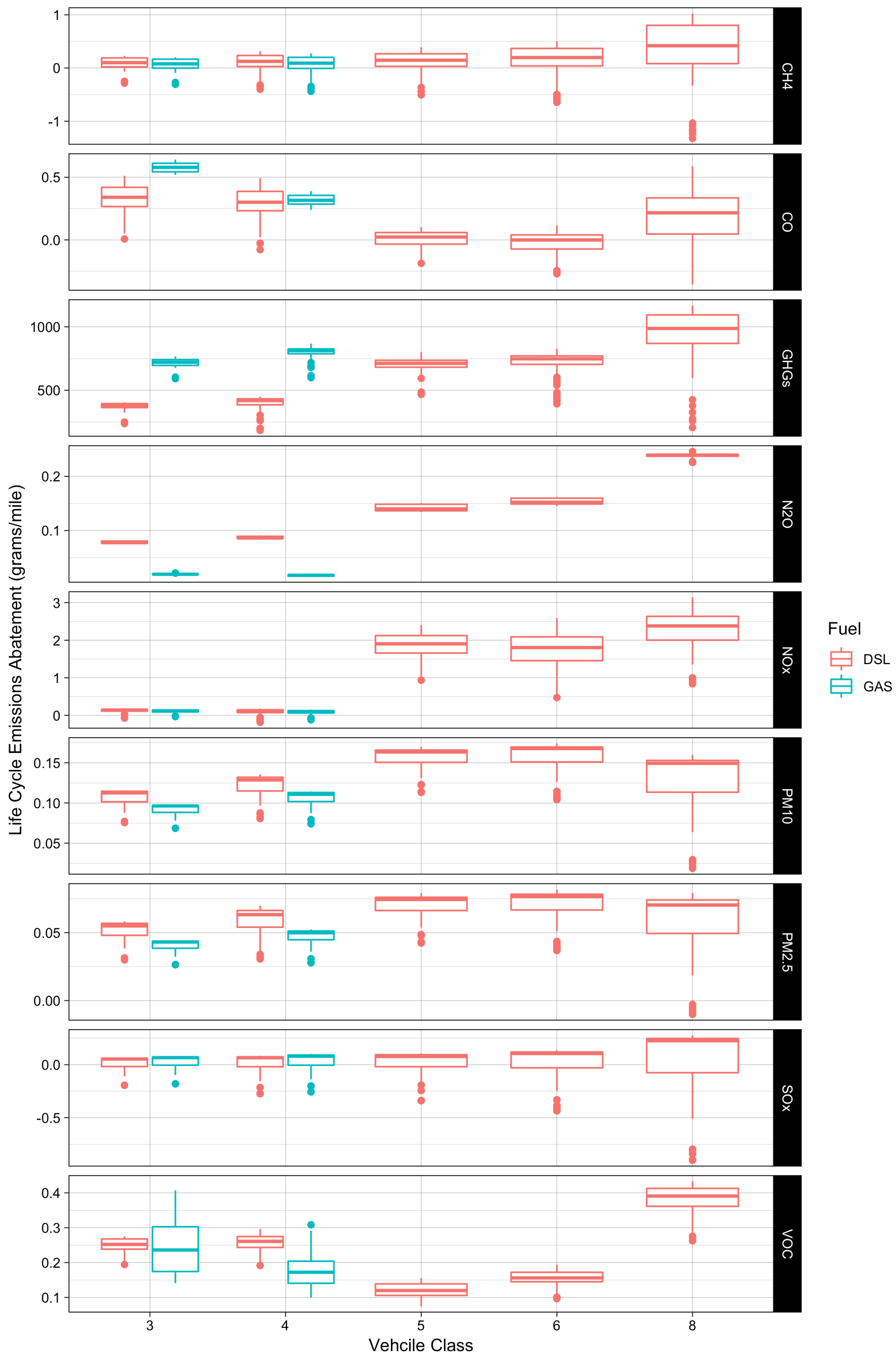

Figure 8.15 Emissions Abatement (grams/mile) from Electrification of Diesel (DSL) and Gasoline (GAS) Trucks by Vehicle Class.

8.4.4 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 8.22 with emissions rates for conventional vehicles by model year, we first estimated a baseline emissions inventory representing BAU (Figure 8.16). 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.

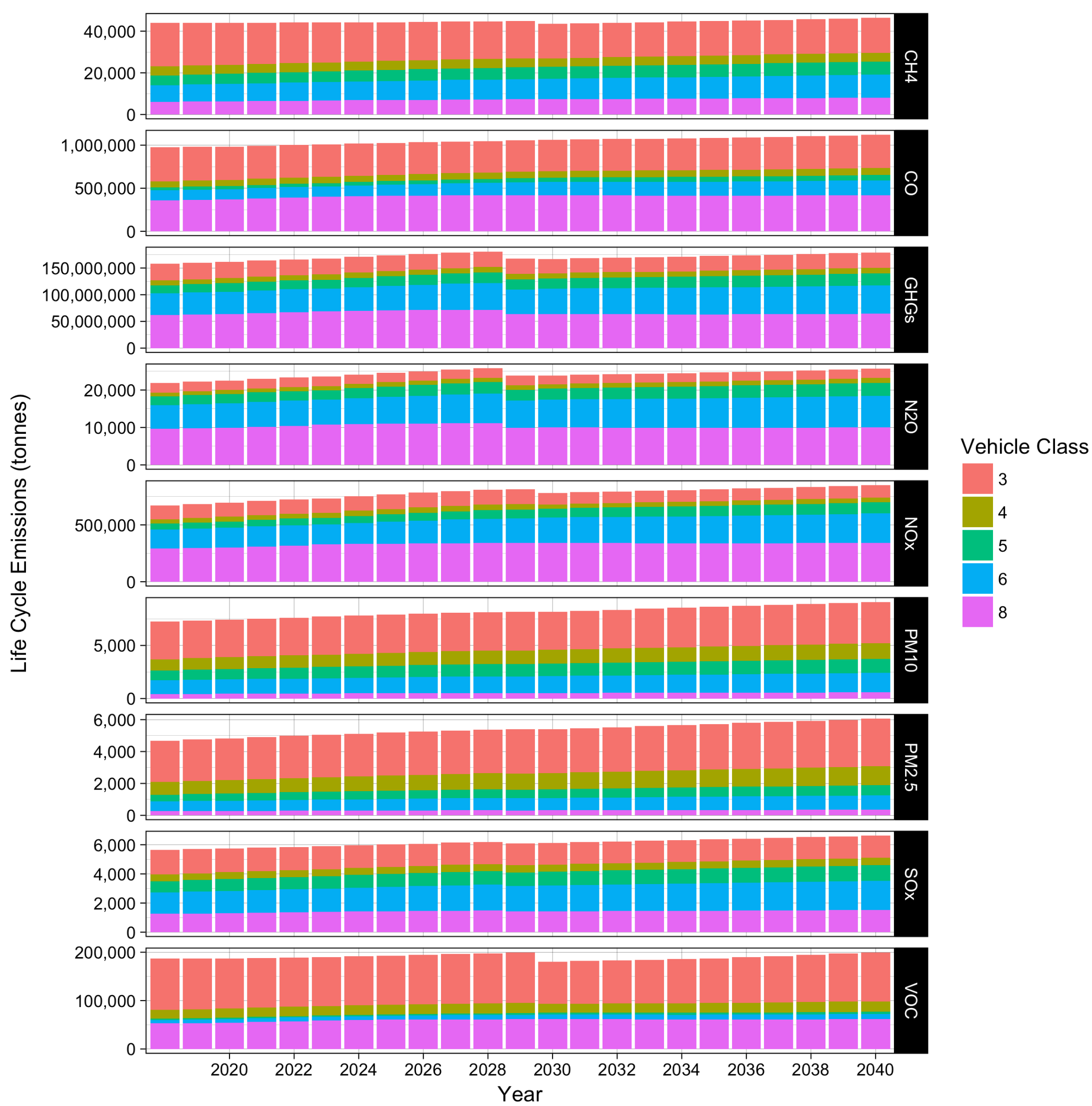

Figure 8.16 BAU Statewide Emissions from Conventional Class 3-8 Trucks

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 8.17). This translates to a target fleet of over 250 thousand Class 3-8 electric vehicles deployed by 2030, and 500 thousand by 2040.

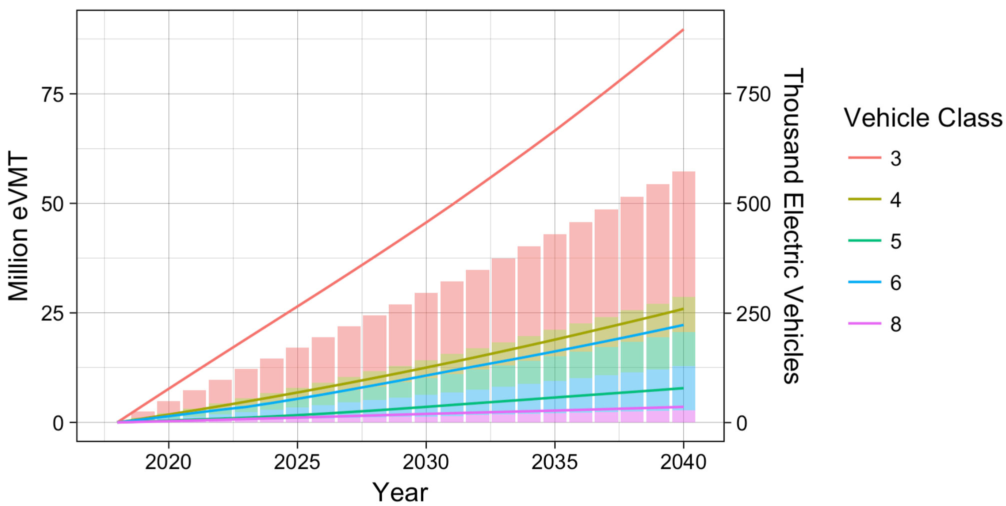

Figure 8.17 Assumed Electric Truck eVMT (Bars) and Vehicle Population (Lines)

Given the deployment trajectory in Figure 8.17, 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 8.18 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.

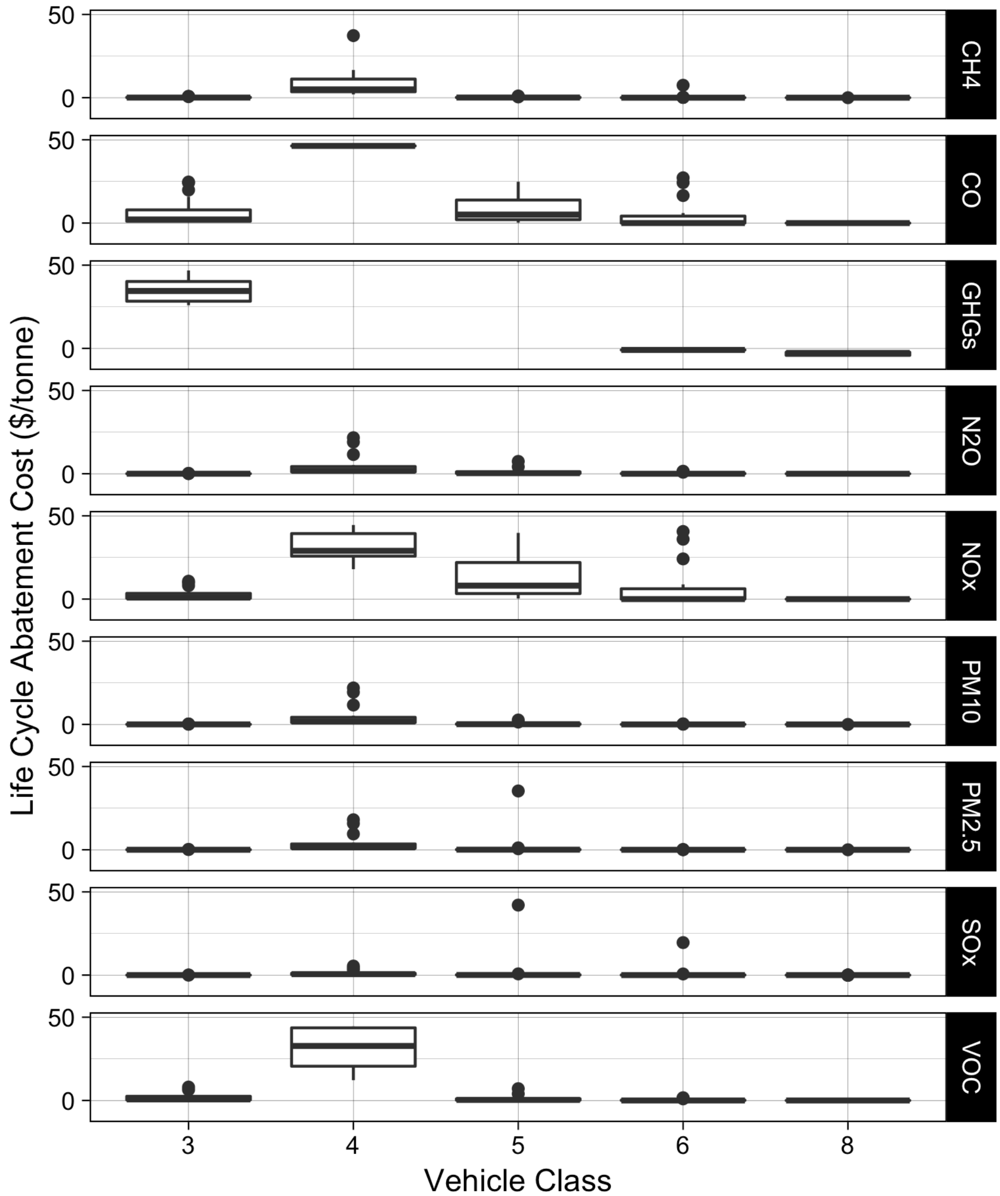

Figure 8.18 Abatement Costs for 100% Electrification by 2040 ($/tonne)

The estimated range of avoided emissions in metric tons per year by vehicle class is shown in Figure 8.19. 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_2 equivalents per year, and approximately 10 thousand metric tonnes of fine and ultra-fine particulate matter.

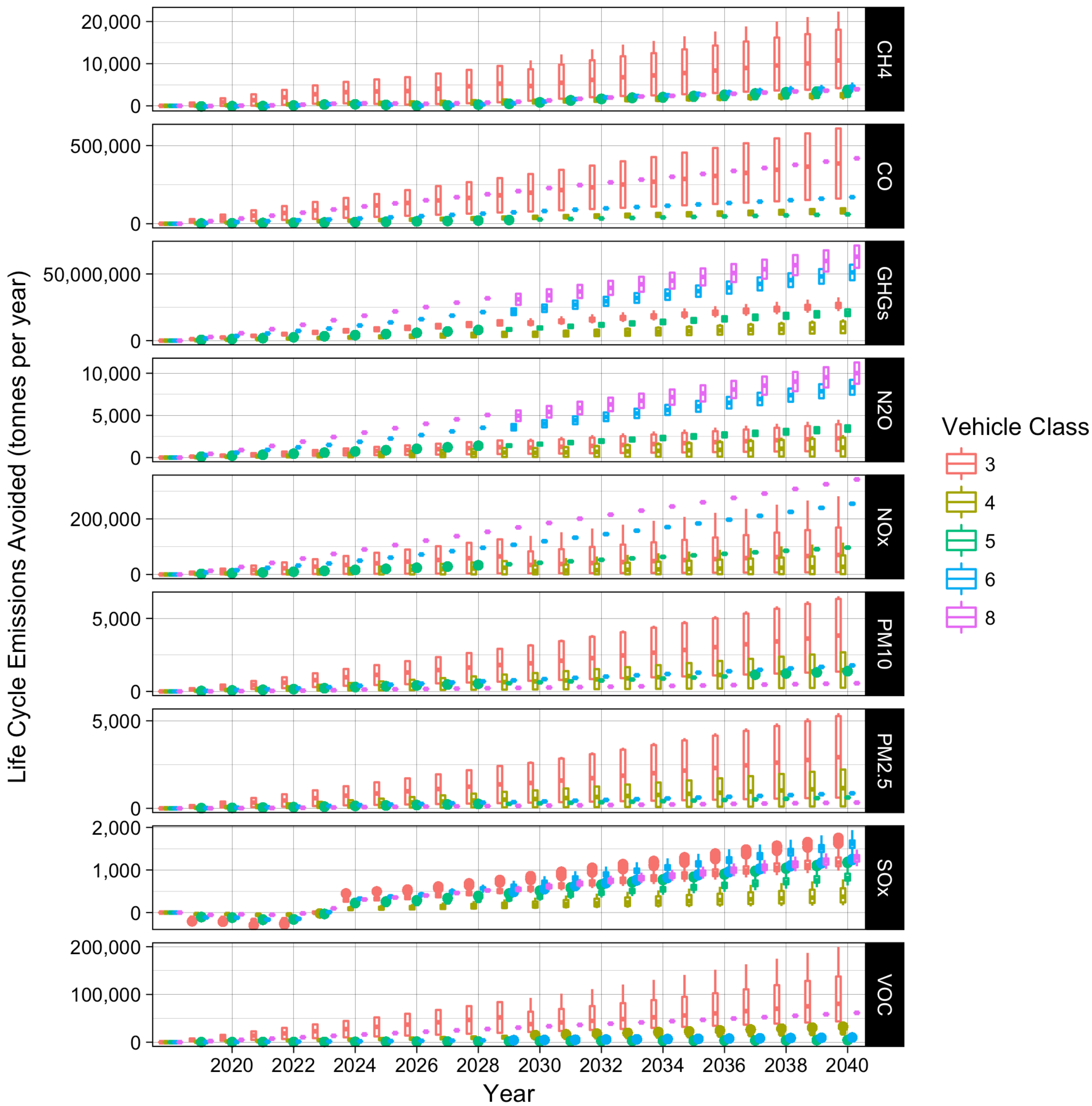

Figure 8.19 Statewide Emissions Abatement from Electrification of Class 3-8 Trucks

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 is estimated for in-state Class 3-8 vehicles, modelled based on the weighted pollution damages and truck activity in each air basin.

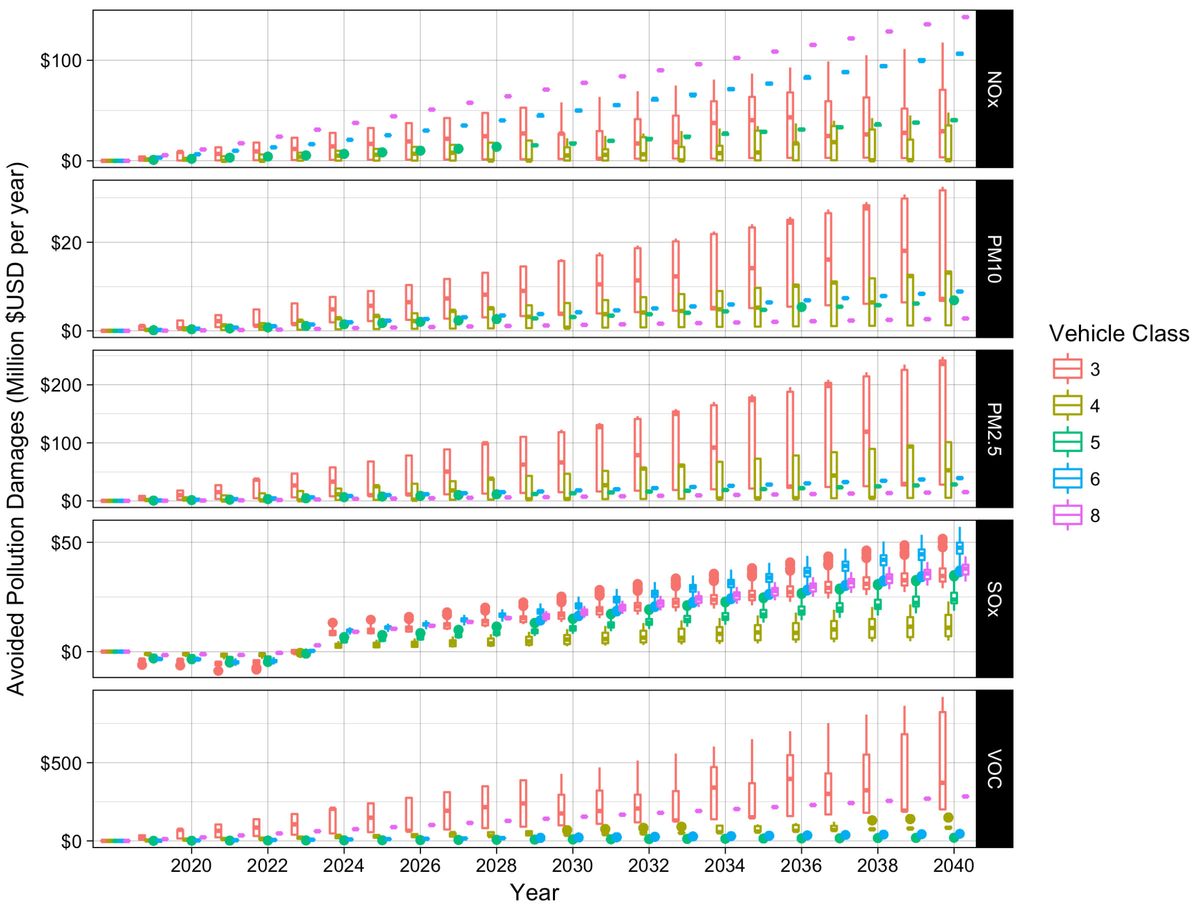

Figure 8.20 Avoided Pollution Damages per year in California from Class 3-8 Truck Electrification

Total pollution related health damages from conventional Class 3-8 vehicles were estimated to range from to $971 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 8.20).

8.5 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 US 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 (Yearbook, 2017). 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 (Curry, 2017). As sales of PEVs have increased, the average capacity of batteries in PEVs have also increased by some 32 kWh/vehicle in the US. 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 (IEA, 2017). 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 (Janaun & Ellis, 2010) as well as cases where emissions intensity were equivalent to conventional diesel and gasoline (O'Hare et al., 2011; Searchinger et al., 2008). Programs to incentivize the deployment of PEVs directly or indirectly subsidize the price and production of large format LIBs (Prior, Wäger, Stamp, Widmer, & Giurco, 2013). In the US, California and nine other states have EV sales targets through the Zero Emissions Vehicle credit program[23]; 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 (CARB, 2015; OPR, 2013; Witcover et al., 2015). 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.

8.5.1 Battery Pack Size and Cost

As LIBs have gotten cheaper, LIB systems for vehicles have gotten larger and demands higher. 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 (Center, 2012, 2017). Historically, the prohibitive costs and additional mass of large batteries have been the primary hurdle limiting PEV applications. Today, HDV applications are targeting systems between 350 and 600 kWh, such as the much publicized Tesla semi-truck.

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[23] 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 (Kelly, Sullivan, Burnham, & Elgowainy, 2015; Kendall & Price, 2012). Increasing vehicle weights is a concern for the maintenance and design of pavement and road infrastructure (Cebon, 1989), 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 8.21 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%.

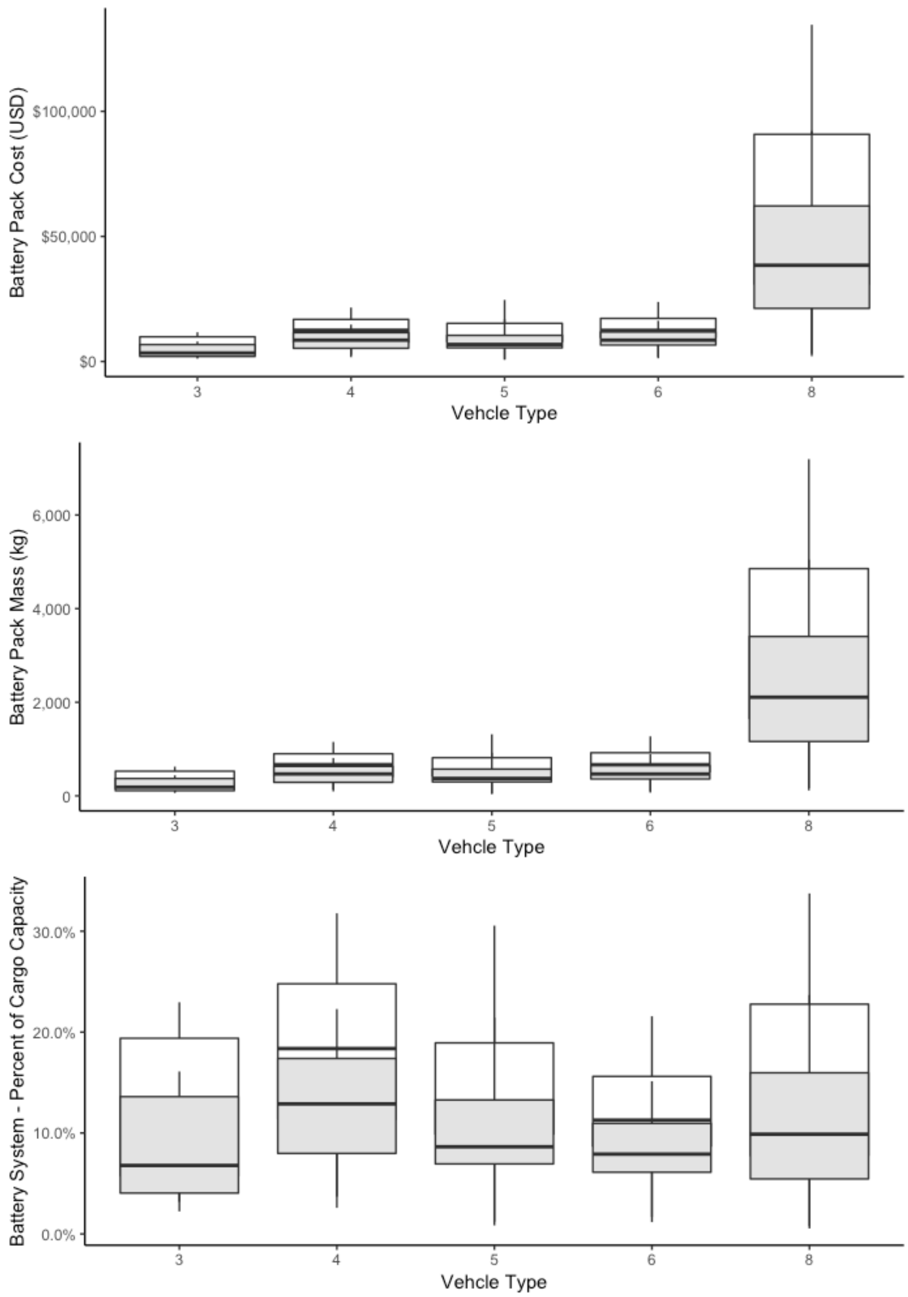

Figure 8.21 Electric Class 3-8 Vehicle Battery Cost and Mass 2018 vs 2030

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 (Barré, Suard, Gérard, & Riu, 2015). Given appropriate storage conditions (Waldmann, Wilka, Kasper, Fleischhammer, & Wohlfahrt-Mehrens, 2014), 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).

8.5.2 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 (Ciez & Whitacre, 2016; Maxwell, 2015), there are notable examples of local environmental and social impacts inflicted on communities in South America expanding demand for LIB cathode materials ("Clean energy—an increasingly precious metal," 2016; Jaffe, 2017), and cobalt in Africa (Frankel, 2016). There are also examples of supplies of minor materials disrupting the supply of major technologies (Eichstaedt, 2011).

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 (Erdmann & Graedel, 2011). 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 (Gruber et al., 2011; Mohr, Mudd, & Giurco, 2012; Pehlken, Albach, & Vogt, 2015; Speirs, Contestabile, Houari, & Gross, 2014; Swart, Dewulf, & Biernaux, 2014; Vikström, Davidsson, & Höök, 2013; Ziemann, Grunwald, Schebek, Müller, & Weil, 2013), with the exception of (Olivetti, Ceder, Gaustad, & Fu, 2017), none have included LIBs over 50 kWh. 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 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.

8.6 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.

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.

8.7 References

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9. CONCLUSIONS

Addressing climate change and local environmental impacts are the principle challenges for this and future generations. The confounding factors for these problems include inequity, social justice, and the drive for continued economic development. Vehicle electrification combined with energy system integration has emerged as one of the most viable pathways for deep decarbonization (Chu & Majumdar, 2012). The research interests underpinning this dissertation are guided by the larger movement towards electrification of light and heavy-duty vehicles and linkage with low-carbon, renewable energy systems. There is clearly a need to better understand the distribution of environmental impacts and costs on local and global scales.

This dissertation explores the performance, costs, and environmental impacts of batteries and electric vehicles. In general, it finds that vehicle electrification has the potential to deliver significant emissions reductions when compared to continued reliance on conventional gas and diesel vehicle technologies. However, the magnitude of these reductions is highly dependent on assumptions related to how vehicles are charged (e.g. electricity grids), how vehicles are operated, and to a lesser but still significant extent, how vehicles are designed. For light duty vehicles, this research shows that trends in vehicle and battery design have the potential to reduce the greenhouse gas emissions reduction potential of vehicle electrification. For heavy duty vehicles, this research suggest the benefits of vehicle electrification in reduced air pollution are significant and should be considered in any economic analysis.

The body of studies presented in this dissertation are limited. None consider the potential for modal substitution (e.g. switching from a private vehicle to a carpool, train, bus, bicycle, or electric scooter). While the travel patterns of vehicles are discussed, the actual determinants of travel behavior and impacts of travel behavior on emissions from light duty EVs are not considered. In summary, more research is required to address the central question examined in this dissertation (i.e. "*does vehicle electrification make transportation more sustainable?")*.

9.1 NEXT STEPS

This section discusses three potential next steps to be undertaken that would build upon this dissertation:

9.1.1 END OF LIFE MANAGEMENT OF ELECTRIC VEHICLE BATTERIES

Some 50 million metric tons of electronic wastes (E-waste) are generated globally each year, and less than one quarter of current global e-wastes are composed of "clean energy technologies" like large format LIBs used in EVs. In 2014, less than 16% of global e-waste recycling and end-of-life disposal was documented under formal processes (Balde, Forti, Gray, Kuehr, & Stegmann). The potential environmental impacts of disposed or recycled batteries and the appropriate management strategies for retired batteries remain open research questions (Richa, Babbitt, Gaustad, & Wang, 2014; Wang, Gaustad, Babbitt, & Richa, 2014; Zhang et al., 2018). Spent LIBs are considered hazardous wastes, due to their high concentrations of lead, cobalt, copper, and nickel (Kang, Chen, & Ogunseitan, 2013).

After primary use in a vehicle, potential end-of-life (EOL) pathways for LIBs include reuse or repurposing ("second life"), materials recovery (recycling), and disposal. Characterizing the EOL stage for LIBs is important in order to evaluate opportunities to reduce environmental impacts from improper disposal, and to account for benefits from displacement of mining and primary materials acquisition through recovery. E-wastes like photovoltaic modules and LIBs often have hazardous but potentially valuable materials (Fthenakis).

Given the large capacity and high performance of modern vehicle batteries, retired batteries could still offer significant capacity in lower-power, secondary applications (e.g. battery storage for electricity grid applications). A growing body of research has examined the economic feasibility and environmental impacts of second-life applications (Ahmadi, Young, Fowler, Fraser, & Achachlouei, 2017; Ambrose, Gershenson, Gershenson, & Kammen, 2014; Martinez-Laserna et al., 2018; Martinez-Laserna et al., 2016; Richa, Babbitt, Nenadic, & Gaustad, 2017). LIBs depend on a short list of materials with unique properties and few substitutes. There may be environmental and economic trade-offs between mandated recycling programs and encouraging repurposing for secondary use, as well as barriers to developing necessary recycling infrastructure.

There are important equity implications for managing the EOL of LIBs. Globally, much current e-waste recycling occurs in ad-hoc or informal facilities with no environmental controls. This can result in high levels of human exposure to dangerous chemicals and heavy metals, and high levels of risk for vulnerable segments of the population (Ericson et al.; Orlins & Guan). Studies have identified the continued role of informal disposers and middle-men in EOL management of LIBs from consumer electronics. With the potential for significant environmental impacts from even formal recycling operations (Ogunseitan, 2016), there is clear need for policies to promote safe and equitable disposal practices.

The proposed next steps would include using system dynamics models coupled with techno-economic, life cycle assessment (LCA) models to predict the future flow and condition of end-of-life (EOL) LIBs and quantify the environmental impacts and economics of EOL processes. The research would develop and refine strategies for sustainable life cycle management of LIBs, with a strategic focus on fleets and other large-scale deployments.

9.1.3 Global strategies for low-carbon, Urban mobility

In an increasingly global world, the potential environmental impacts of technology transitions on developing economies are often poorly addressed. Developing and industrializing economies will undoubted by low carbon technology transitions both through global supply chains and technology transfer. Developing economies will continue to demand more energy as their economies grow; the challenge for sustainable development is not just to meet this demand with progressively more efficient and renewable technologies, but transform current paradigms of development and consumption.

Not only does one quarter of the global population not have reliable access to electricity, even fewer have adequate access to mobility. Increasing rates of vehicle ownership and vehicle miles travelled are driving rapid increases in demand for energy in developing economies. For example, the Chinese vehicle fleet is projected to surpass that of the US within decade, and India now has the fourth largest volume of new vehicle sales globally (9). Most developed markets are characterized by saturated vehicle ownership and an ageing vehicle fleet, which contribute to slow fleet turnover. Developing vehicle markets are also characterized by a lack of appropriate alternative fuel vehicle designs or transit mode choices.

The proposed research would build upon methods and models developed in this dissertation and take a multimodal perspective on the drivers of demand for personal mobility. This would involve a focus on the underlying determinants of travel behavior (e.g. demand for goods and services), linking the potential for substitution of new modes/models (e.g. sharing, e-commerce, automation) and new technologies (e.g. electric vehicles and personal mobility devices) to reduce emissions and impacts associated with transportation systems. It could also involve consideration of marginal abatement costs for electricity generation and infrastructure. The research could reveal, among other trends, the potential distribution of environmental impacts and inform the efficacy of incentive programs to support climate policy objectives.

9.1.4 LIFE CYCLE BASED REGULATORY REFORM

"As we move toward a low-carbon economy, we need new policies that consider emissions in a systemic and systematic way." - Dan Sperling

In the context of sustainable transportation, policy must take a more dynamic view of technological development; this means allowing for new technologies to emerge that challenge conventional models of mobility (e.g. autonomy and personal vehicle ownership), while still achieving emissions reduction targets (e.g. net reduction in emissions or average emissions per person mile traveled). One challenge will be to reconcile the tension between the need for simplicity and transparency in developing implementable and enforceable policy and the desire for scientific accuracy in emissions accounting. LCA provides a set of analytical tools that could inform the design of performance-based evaluation systems. Life-cycle based policies potentially offer more methodological accuracy than current systems, but could increase the costs of administration, and likely require a more complete understanding of emissions over the product life cycle.

Previous research has shown that only regulating tailpipe emissions can lead to perverse outcomes for future vehicles, where vehicles with higher life cycle emissions but lower tailpipe emissions are preferred over vehicles with lower total emissions. Kendall and Price (2012) illustrated the risk of such an outcome in a case study of a future hybrid electric vehicle (HEV). Their study showed a future HEV with higher life cycle emissions could be preferred over a vehicle with lower life cycle emissions simply due to the effects of light-weighting materials. Hawkins et al. (2013) arrived at a similar conclusion for BEVs, suggesting some form of life cycle-based emissions standards are required. At the fleet level, BEV incentive and credit programs must also be structured such as not to further erode the potential reductions in emissions through leakage or substitution (Jenn, Azevedo, & Michalek, 2016)

The proposed research would posit lifecycle based policies that include upstream and material-related emissions for the next generation of vehicle technologies, and analyze the economic tradeoffs between LCA and conventional mobile source enforcement programs including with respect to economic costs, implement ability, enforceability, and efficacy. The research would also seek to quantify some of the potential risks and uncertainties of expanding the types of climate mitigation and adaptations actions credited under policy, as well as tradeoffs and burden shifting.

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APPENDICES

A: DATA AND INFORMATION ON LITHIUM DEPOSITS

The following materials provide support and additional documentation for the first chapter:

The section is organized as follows:

- **S1: Full list of Lithium deposits and deposit information**
- **S2: Lithium production cost data**
- **S3: Recycling stock and flow model**

S1 – Identified Lithium Deposits and Available Data

Table S1-1 (below) details the data used to classify available deposits, reserves, and resources:

Table S1-1: Lithium Deposit and Resource Data

Deposit Name	Country	Type	Mineral	LI Grade	Reserve (Mt)	URR (Mt)	Mg/Li Ratio	Prod Model
Bonneville Salt Flats	USA	Brine	Brine	0.004		1.97	100	BW
Great Salt Lake	USA	Brine	Brine	0.006	0.3	0.5	133.33	BW
Searless Lake	USA	Brine	Brine	0.0083		0.03	4.1	BL
Fox Creek	Canada	Brine	Brine	0.01	0.3	0.5	10	BL
Salton Sea	USA	Brine	Brine	0.022	0.5	2	1.27	BL
Silver/Clayton Peak	USA	Brine	Brine	0.03	0.1	0.3	1.33	BL
Qaidam/Qinghai/Taijinaier	China	Brine	Brine	0.03	1	3.3	34	BL
Smackover	USA	Brine	Brine	0.038	0.5	1	20	BL
Rincon	Argentina	Brine	Brine	0.04	1.4	2.8	8.5	BL
Dangxioncuo/DXC	China	Brine	Brine	0.045	0.1	0.2	0.22	BL
Salar del Hombre Muerto	Argentina	Brine	Brine	0.062	0.85	0.9	1.46	BL
Cauchari	Argentina	Brine	Brine	0.062	0.5	0.9	2.84	BL
Olaroz	Argentina	Brine	Brine	0.09	0.2	0.3	2	BH
Maricunga	Chile	Brine	Brine	0.092	0.2	0.4	8	BH
Salar de Uyuni	Bolivia	Brine	Brine	0.096	3.6	10.2	20.83	BL
Lake Zabuye	China	Brine	Brine	0.097	0.8	1.5	0.01	BH
Salar de Atacama	Chile	Brine	Brine	0.14	16.1	35.7	6.4	BH
Dead Sea	Israel	Brine	Brine	0.002	1.9	2	1700	BW
Sua Pan	Botswana	Brine	Brine	0.002		0.3	133.33	BW
Brawley	USA	Brine	Brine	0.005		1	100	BW
Beaverhill Lake	Canada	Brine	Brine	0.005		0.59	10	BL
Diablillos	Argentina	Brine	Brine	0.003		0.9	8	BL

Sal de Vida	Argentina	Brine	Brine	0.035		0.3	2	BL
Taghawkor	Afghanistan	Rock	Spodumene	2.8		0.002		PH
Helmand Basin	Afghanistan	Rock	Spodumene	2.8		0.2		PH
Katawaz Basin	Afghanistan	Rock	Spodumene	1.6		0.01		PH
Parun	Afghanistan	Rock	Spodumene	1.5		0.03		PH
Greenbushes	Australia	Rock	Spodumene	1.9	0.6	0.7		PH
Mt Marion	Australia	Rock	Spodumene	0.65		0.02		PL
Mt Cattlin	Australia	Rock	Spodumene	0.5		0.07		PL
Koralpe	Austria	Rock	Spodumene	0.78	0.1	0.1		PL
Aracuai/Cachoeira	Brazil	Rock	Petalite	0.67		0.023		PL
Deposit Name	**Country**	**Type**	**Mineral**	**LI Grade**	**Reserve (Mt)**	**URR (Mt)**	**Mg/Li Ratio**	**Prod Model**
Big Bird/Curlew	Canada	Rock	Spodumene	1.72		0.2		PH
Moblan	Canada	Rock	Spodumene	1.7		0.04		PH
Bernic Lake/Tanco	Canada	Rock	Spodumene	1.28	0.02	0.14		PH
Wekusko Lake	Canada	Rock	Spodumene	0.79		0.028		PL
Yellowknife	Canada	Rock	Spodumene	0.66	0.1	0.13		PL
Separation Rapids	Canada	Rock	Petalite	0.62		0.072		PL
Barraute/Quebec	Canada	Rock	Spodumene	0.53		0.37		PL
La Corne	Canada	Rock	Spodumene	0.52	0.2	0.4		PL
La Motte	Canada	Rock	Spodumene	0.5		1.023		PL
Snow Lake	Canada	Rock	Pegmatites	0.03		0.026		PW
Niemi Lake	Canada	Rock	Spodumene	0.9625		0.001		PL
Sirmac Lake	Canada	Rock	Pegmatites	0.03		0.003		PW
Nama Creek	Canada	Rock	Pegmatites	0.03		0.01		PW
Violet	Canada	Rock	Pegmatites	0.03		0.01		PW
Moose 2	Canada	Rock	Spodumene	0.9625		0.016		PL

Thor	Canada	Rock	Pegmatites	0.03		0.02		PW
Gods Lake	Canada	Rock	Spodumene	0.9625		0.025		PL
FI	Canada	Rock	Pegmatites	0.03		0.03		PW
James Bay/Lithium One	Canada	Rock	Pegmatites	0.03		0.13		PW
English River Greenstone	Canada	Rock	Spodumene	0.9625		0.13		PL
Yichun	China	Rock	Lepidolite	2	0.2	0.5		PL
Jaijika	China	Rock	Spodumene	0.6	0.2	0.5		PL
Daoxian	China	Rock	Lepidolite	0.55	0.1	0.2		PL
Hupei	China	Rock	Petalite	0.67		0.042		PL
Lijiagou	China	Rock	Petalite	0.67		0.06		PL
Maerkang	China	Rock	Spodumene	0.6	0.2	0.5		PL
Gajika	China	Rock	Spodumene	0.6	0.3	0.6		PL
Jinchuan	China	Rock	Petalite	0.67		0.5		PL
Ningdu	China	Rock	Petalite	0.67		0.5		PL
Kitotolo	Congo	Rock	Spodumene	0.6		0.8		PL
Manono	Congo	Rock	Spodumene	0.6	1.5	3		PL
Läntta	Finland	Rock	Spodumene	0.43	0.35	0.68		PW
Bougouni	Mali	Rock	Amblygonite	1.4		0.03		PL
Karibib	Namibia	Rock	Petalite	1.4		0.15		PL
Barroso	Portugal	Rock	Petalite	0.72		0.01		PL
Tastyg	Russia	Rock	Spodumene	1.86		0.05		PH
Etykinskoe	Russia	Rock	Lepidolite	0.79		0.046		PL
Vishnyakovskoe	Russia	Rock	Pegmatites	0.49		0.21		PW
Goltsovoe	Russia	Rock	Spodumene	0.37		0.29		PW

Deposit Name	**Country**	**Type**	**Mineral**	**LI Grade**	**Reserve (Mt)**	**URR (Mt)**	**Mg/Li Ratio**	**Prod Model**
Zavitinskoe	Russia	Rock	Spodumene	1.115		0.14		PH

Belerechenskoe	Russia	Rock	Spodumene	1.115		0.05	PH
Voznesenskoe	Russia	Rock	Pegmatites	0.49		0.14	PW
Achivansky/Uchastok	Russia	Rock	Pegmatites	0.49		0.05	PW
Pogranichnoe	Russia	Rock	Pegmatites	0.49		0.05	PW
Orlovskoe	Russia	Rock	Lepidolite	0.79		0.05	PL
Urikskoe	Russia	Rock	Spodumene	1.115		0.3	PH
Polmostundrovskoe	Russia	Rock	Pegmatites	0.49		0.4	PW
Ulug-Tanzek	Russia	Rock	Pegmatites	0.49		0.3	PW
Kolmorzerskoe	Russia	Rock	Pegmatites	0.49		0.84	PW
Jadar Valley	Serbia	Rock	Jadarite	0.84	0.5	1	PL
Mina Feli	Spain	Rock	Lepidolite	0.5		0.005	PL
Järkvissle	Sweden	Rock	Spodumene	0.45		0.003	PW
Varuträsk	Sweden	Rock	Spodumene	0.45		0.001	PW
Kings Mountain Belt	USA	Rock	Spodumene	0.68		5.9	PL
Bessemer City	USA	Rock	Pegmatites	0.67		0.42	PL
McDermitt/Kings Valley	USA	Rock	Hectorite	0.53	1.1	2	PL
North Carolina	USA	Rock	Spodumene	0.68	1.6	5.5	PL
Bikita	Zimbabwe	Rock	Spodumene	1.4		0.17	PH
Kamativi	Zimbabwe	Rock	Spodumene	0.28		0.28	PW
Masvingo	Zimbabwe	Rock	Spodumene	0.84		0.057	PL
Barkam	Zimbabwe	Rock	Pegmatites	0.396		0.22	PW

Table S2-1 Lithium Production Cost Data

Country	Grade	Type	Process Model	Cost Estimate ($/ton LCE)	Year of Estimate	Real Costs (2018$USD/ton LCE)	Deposit Name	Source
Argentina	Low	Brine	BL	$2,000	2013	$2,086	Cauchari	*Roskill Lithium
Argentina	Low	Brine	BL	$2,000	2014	$2,071	Cauchari	*Roskill Lithium
Argentina	Low	Brine	BL	$3,300	2015	$3,669	Cauchari	*Roskill Lithium
Argentina	Low	Brine	BL	$3,500	2016	$4,010	Cauchari	*Macquarie Research
Australia	High	Pegmatite	PH	$3,700	2016	$4,239	Greenbushes	*Macquarie Research
Canada	High	Pegmatite	PH	$3,000	2013	$3,129	James Bay	*Roskill Lithium
Canada	High	Pegmatite	PH	$3,000	2014	$3,106	James Bay	*Roskill Lithium
Canada	Low	Pegmatite	PL	$4,500	2016	$5,155	James Bay	*Macquarie Research
Canada	Low	Pegmatite	PL	$4,000	2014	$4,142	La Corne	*Lafierre
Canada	Low	Pegmatite	PL	$3,655	2017	$3,916	La Corne	*Lafierre
China	Low	Brine	BL	$3,000	2013	$3,129	Lake Zabuye	*Roskill Lithium
China	Low	Brine	BL	$3,000	2014	$3,106	Lake Zabuye	*Roskill Lithium
China	Low	Brine	BL	$4,150	2015	$4,614	Lake Zabuye	*Roskill Lithium
China	Low	Brine	BL	$3,300	2016	$3,781	Lake Zabuye	*Macquarie Research
Australia	Low	Pegmatite	PL	$4,500	2016	$5,155	Mt Caitlin	*Macquarie Research
China	Low	Brine	BL	$3,200	2013	$3,337	Qinghai Lake	*Roskill Lithium
China	Low	Brine	BL	$3,200	2014	$3,313	Qinghai Lake	*Roskill Lithium

Country	Grade	Type	Process Model	Cost Estimate ($/ton LCE)	Year of Estimate	Real Costs (2018$USD/ton LCE)	Deposit Name	Source
China	Low	Brine	BL	$5,500	2015	$6,115	Qinghai Lake	*Roskill Lithium
Chile	High	Brine	BH	$2,250	2013	$2,346	Salar de Atacama	*Roskill Lithium
Chile	High	Brine	BH	$2,300	2014	$2,382	Salar de Atacama	*Roskill Lithium
Chile	High	Brine	BH	$3,200	2015	$3,558	Salar de Atacama	*Roskill Lithium
Chile	High	Brine	BH	$2,200	2016	$2,520	Salar de Atacama	*Macquarie Research
Chile	High	Brine	BH	$2,000	2013	$2,086	Salar de Atacama	*Roskill Lithium
Chile	High	Brine	BH	$2,000	2014	$2,071	Salar de Atacama	*Roskill Lithium
Chile	High	Brine	BH	$3,000	2015	$3,336	Salar de Atacama	*Roskill Lithium
Chile	High	Brine	BH	$2,100	2016	$2,406	Salar de Atacama	*Macquarie Research
Argentina	High	Brine	BH	$3,000	2014	$3,106	Salar de Olaroz	*Roskill Lithium
Argentina	High	Brine	BH	$5,100	2015	$5,670	Salar de Olaroz	*Roskill Lithium
Argentina	High	Brine	BH	$2,600	2016	$2,979	Salar de Olaroz	*Macquarie Research
USA	Low	Brine	BL	$4,000	2013	$4,172	Silver/Clayton Peak	*Roskill Lithium
USA	Low	Brine	BL	$4,000	2014	$4,142	Silver/Clayton Peak	*Roskill Lithium
USA	Low	Brine	BL	$4,300	2015	$4,781	Silver/Clayton Peak	*Roskill Lithium
USA	Low	Brine	BL	$2,800	2016	$3,208	Silver/Clayton Peak	*Macquarie Research
China	Low	Pegmatite	PL	$4,300	2014	$4,452	Xinjiang/Ganfeng	*Roskill Lithium

Country	Grade	Type	Process Model	Cost Estimate ($/ton LCE)	Year of Estimate	Real Costs (2018$USD/ton LCE)	Deposit Name	Source
China	Low	Pegmatite	PL	$4,500	2013	$4,693	Xinjiang/Ganfeng	*Roskill Lithium
China	Low	Pegmatite	PL	$8,200	2015	$9,117	Xinjiang/Ganfeng	*Roskill Lithium
China	Low	Pegmatite	PL	$4,000	2016	$4,583	Xinjiang/Ganfeng	*Macquarie Research
China	Low	Pegmatite	PW	$5,000	2013	$5,214		*Roskill Lithium
China	Low	Pegmatite	PW	$5,000	2014	$5,177		*Galaxy
Canada	Low	Pegmatite	PL	$4,200	2013	$4,380		*Roskill Lithium
Argentina	Low	Brine	BL	$1,800	2014	$1,864		*Morgan Stanley
Chile	High	Brine	BH	$2,000	2014	$2,071		*Morgan Stanley
Chile	High	Brine	BH	$2,200	2014	$2,278		*Morgan Stanley
China	High	Brine	BH	$3,000	2014	$3,106		*Morgan Stanley
Argentina	High	Brine	BH	$3,000	2014	$3,106		*Morgan Stanley
Canada	High	Pegmatite	PH	$3,000	2014	$3,106		*Morgan Stanley
China	Low	Brine	BL	$3,200	2014	$3,313		*Morgan Stanley
China	Low	Brine	BL	$3,200	2014	$3,313		*Morgan Stanley
China	Low	Pegmatite	PL	$4,000	2014	$4,142		*Morgan Stanley
China	Low	Pegmatite	PW	$4,400	2014	$4,556		*Morgan Stanley
China	Low	Pegmatite	PW	$9,100	2015	$10,118		*Roskill Lithium

Country	Grade	Type	Process Model	Cost Estimate ($/ton LCE)	Year of Estimate	Real Costs (2018$USD/ton LCE)	Deposit Name	Source
China	Low	Pegmatite	PW	$4,300	2016	$4,926		*Macquarie Research
Australia	High	Pegmatite	PH	$4,100	2016	$4,697		*Hatch Consulting
Chile	High	Brine	BH	$2,500	2016	$2,864		*Hatch Consulting
Argentina	High	Brine	BH	$3,100	2016	$3,551		*Hatch Consulting
Argentina	Low	Brine	BL	$3,750	2016	$4,296		*Hatch Consulting
China	Low	Pegmatite	PL	$5,600	2016	$6,416		*Hatch Consulting
China	High	Pegmatite	PH	$5,800	2016	$6,645		*Hatch Consulting
China	Low	Brine	BL	$4,300	2016	$4,926		*Hatch Consulting
Canada	Low	Pegmatite	PL	$2,700	2016	$3,093		*Hatch Consulting
Canada	High	Pegmatite	PH	$3,260	2016	$3,735		*Hatch Consulting
USA	Low	Brine	BW	$6,400	2016	$7,332		*Hatch Consulting
USA	Low	Pegmatite	PL	$3,900	2016	$4,468		*Hatch Consulting
Canada	High	Pegmatite	PH	$4,930	2017	$5,282		*McKinsey
China	Low	Pegmatite	PW	$8,500	2017	$9,108		*McKinsey
China	Low	Pegmatite	PL	$6,100	2017	$6,536		*McKinsey
China	Low	Brine	BW	$3,300	2017	$3,536		*McKinsey
Australia	High	Pegmatite	PH	$4,300	2017	$4,607		*McKinsey
Australia	Low	Pegmatite	PL	$5,800	2017	$6,215		*McKinsey
Chile	High	Brine	BH	$2,100	2017	$2,250		*McKinsey

Country	Grade	Type	Process Model	Cost Estimate ($/ton LCE)	Year of Estimate	Real Costs (2018$USD/ton LCE)	Deposit Name	Source
Argentina	High	Brine	BH	$2,400	2017	$2,572		*McKinsey

The production cost model was estimated as a multilevel or random effects model. The model in simplified form can be expressed as:

$$Production\ Cost = N(\mu, \sigma)$$
$$\mu = \alpha_{grade,type}$$
$$\sigma = \sigma_{type}$$

Where we estimate the average production cost for each combination of grade-type levels, with the standard deviation associated with deposit type. The summary of the model coefficient estimates, standard error on the mean estimates, and significance test values are listed below.

The model coefficients are listed in table S2-2.

Table S2-2 Production Cost Model Coefficients

	Estimate	Std. Error	t value	Pr(>|t|)
High Grade Brine	2869.4	291.8	9.834	1.26e-14 ***
Low Grade Brine	3745.7	291.8	12.837	< 2e-16 ***
Unfavorable Brine	5434.0	922.7	5.889	1.38e-07 ***
High Grade Pegmatite	4283.0	435.0	9.846	1.20e-14 ***
Low Grade Pegmatite	5079.7	326.2	15.571	< 2e-16 ***
Unfavorable pegmatite	6516.5	532.7	12.232	< 2e-16 ***

Residual standard error: 1305 on 67 degrees of freedom

Multiple R-squared: 0.9214, Adjusted R-squared: 0.9143

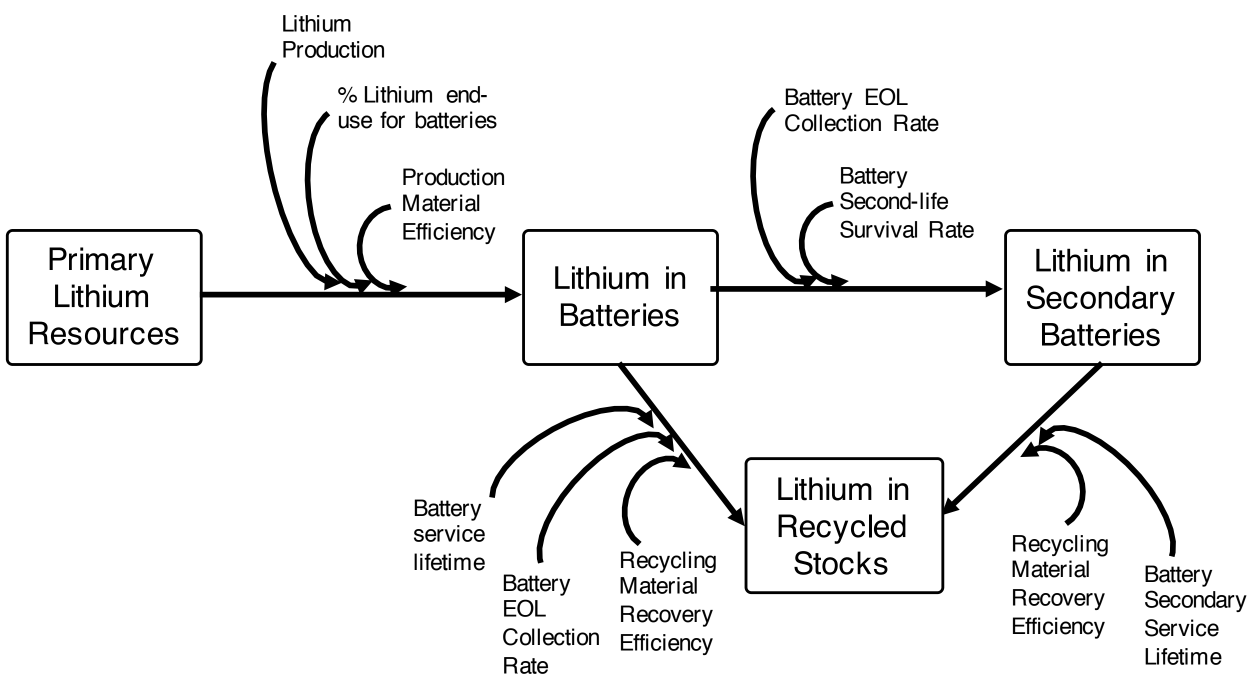
F-statistic: 130.9 on 6 and 67 DF, p-value: < 2.2e-16

S3 Lithium recycling stock and flow model

The potential for recycled lithium from batteries was investigated via a simplified stock and flow model of the lithium production system (Figure S8-1). We track four stocks: lithium in primary resources, lithium in batteries, lithium in secondary resources, and lithium in waste stocks awaiting recycling.

Figure S3-1 provides a visual description of the stock and flow model

Figure S3-1 Recycling Stock and Flow Model



The flows between these stocks are mitigated by several factors, including:

- Production rate – global production of LCE
- % of End-use Lithium in Batteries – share of total lithium market for large-format LIBs
- Battery Material production efficiency – the inverse of material losses during production
- Battery Service Lifetime – years in primary application
- Battery EOL Collection Rate – the rate which batteries are collected for recycling or second-life when retired
- Battery Second-life Survival Rate – the percentage of retired batteries that can be repurposed to serve economically in a secondary application
- Battery Secondary Service Lifetime – years in secondary application
- Recycling Material Recovery Efficiency – percentage of material recovered from recycled batteries

The recovery process consists of three stages modelled off the critical review by Zheng et al. (2014). The first stage is pretreatment which primarily consists of mechanical shredding and sorting of plastic fluff; minimal material is lost during pre-treatment. Secondary treatment involves separating the cathode from the collector foil, with NMP solvent for instance. As much as 20% of the potential cathode material is lost during secondary treatment. The final step, deep recovery, involves dissolution of the cathode materials through leaching or electrolytic reactions. The average material efficiencies assumed are shown in table S3-1.

Table S3-1 Recycling Material Balance

	Input	Material Recovered
Pretreatment	100 %	98%
Secondary Treatment	98 %	78%
Deep Recovery	78 %	50.6%

Table S3-2 shows the estimated recovery of materials from a 100 g LiCo2 cell based on the assumed recycling process described above.

Table S3-2 Estimated Material Recovery for Sample LIB Cell (Zeng et al., 2014)

LIB Cell (100g initial weight)	Material Recovered (g)
Iron	18
Copper	9
Aluminum	3
Plastics	7
Cobalt	12
Lithium	1.5
Nickel	0.1

The results of the recycling stock and flow model were then fed back into the lithium production model. In this displacement scenario, recovered lithium from recycled batteries is assumed to displace primary lithium demand, essentially decreasing the annual demand for primary lithium production. The displacement scenario was only evaluated for the optimistic demand case, given the significantly slower development of recycled battery stock under the conservative model. Figure S3-2 shows the annual global production of primary lithium under the displacement scenario by country of origin, and Figure S3-3 the results by production pathway.

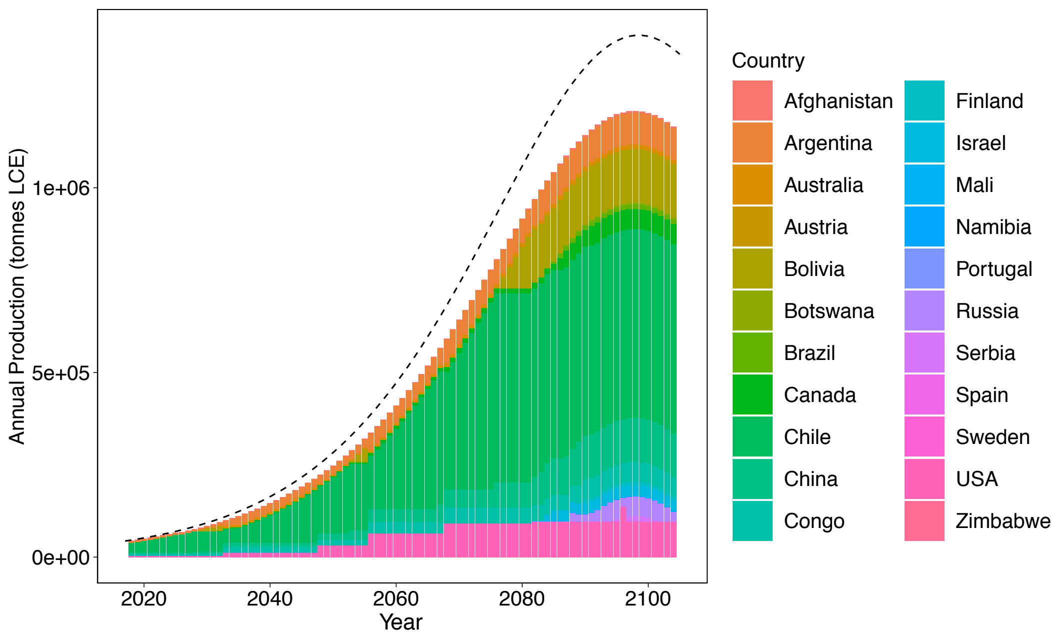


Figure S3-2 Recycling Stock and Flow Model

Figures S3-2 and 3 indicate the potential for recovered lithium to displace primary production. Given the continued development of lithium and other critical energy materials in degraded and potentially recyclable devices, there is good reason to consider the future value of these resources, as well as when and where recycled stocks will develop. Another potential consideration is delaying or avoiding the expansion of production capacity from low grade and unfavorable mineral resources with disproportionate local environmental impacts.

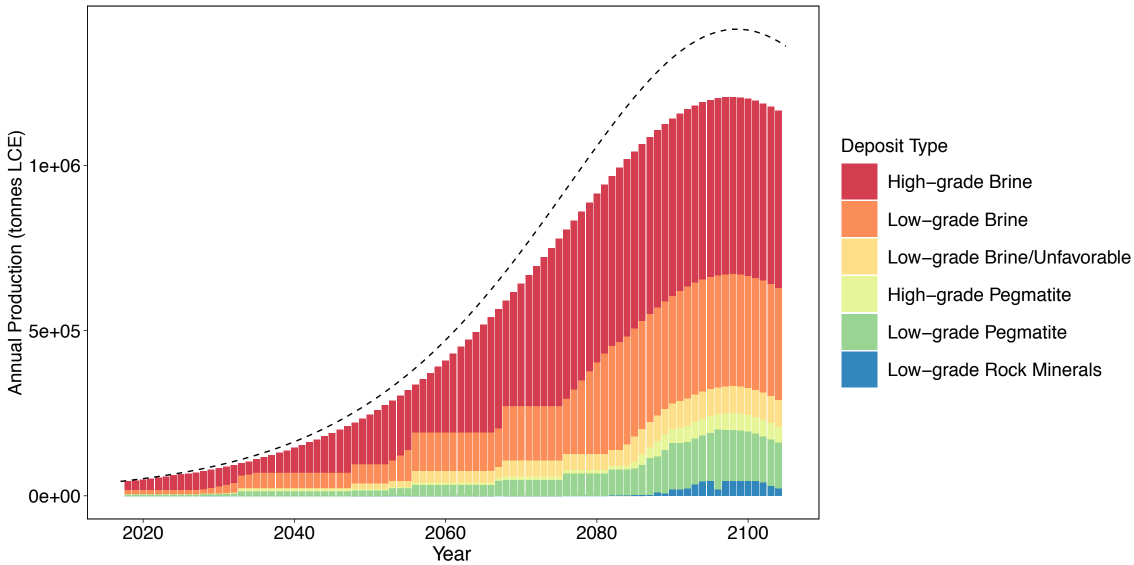


Figure S3-1 Recycling Stock and Flow Model

B. INVENTORY AND IMPACT ASSESSMENT DATA FOR LITHIUM

The section is organized as follows:

- **S1: Life cycle inventory model description and data**
- **S2: Impact Assessment Description**
- **S3: Expanded Results**

S1: Life cycle inventory model description and data

The LCI model is based on a generic process model of production for rock and brine resources respectively. This section provides graphical representations of the lithium production process, as well as a full description of the life cycle inventory data used in the study.

For pegmatites and other lithium containing minerals, numerous processing stages require energy inputs (Figure S1-1). Mechanical separation and comminution processes require between 150 and over 1000 kWh per ton of lithium carbonate. High temperatures are also used during beneficiation processes, which can result in significant inputs of fossil energy.

For brines, the processes usually begins with pumping of the lithium brine; the power requirements vary based on the depth, size, and number of bore, while the initial concentration of brines can vary an order of magnitude (Figure S1-1).   The concentrated brine is harvested and transported to the processing facility. The key energy inputs in conventional or favorable processing conditions are during pumping, pre-heating the slurry before treatment addition of soda ash, and heating during the thickening and drying. Additional fossil or electrical energy inputs can occur when additional processing is required for concentrating the brine, removing impurities, or transportation between site locations.

Figure S1-1 Key Inputs and Processes for Lithium Minerals

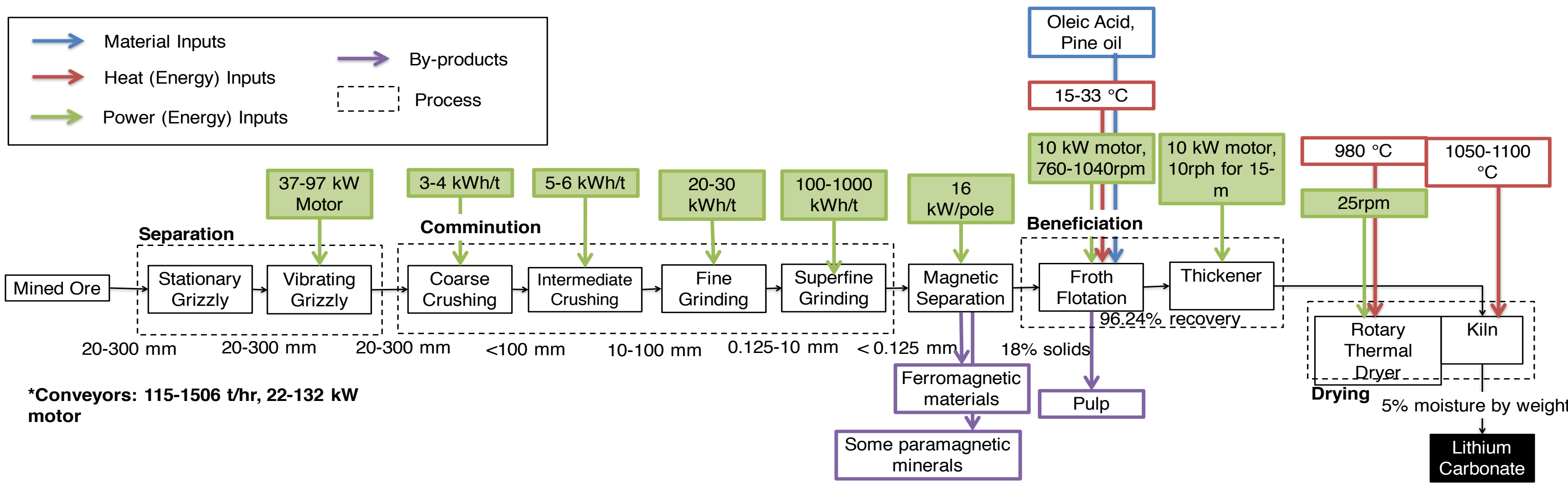
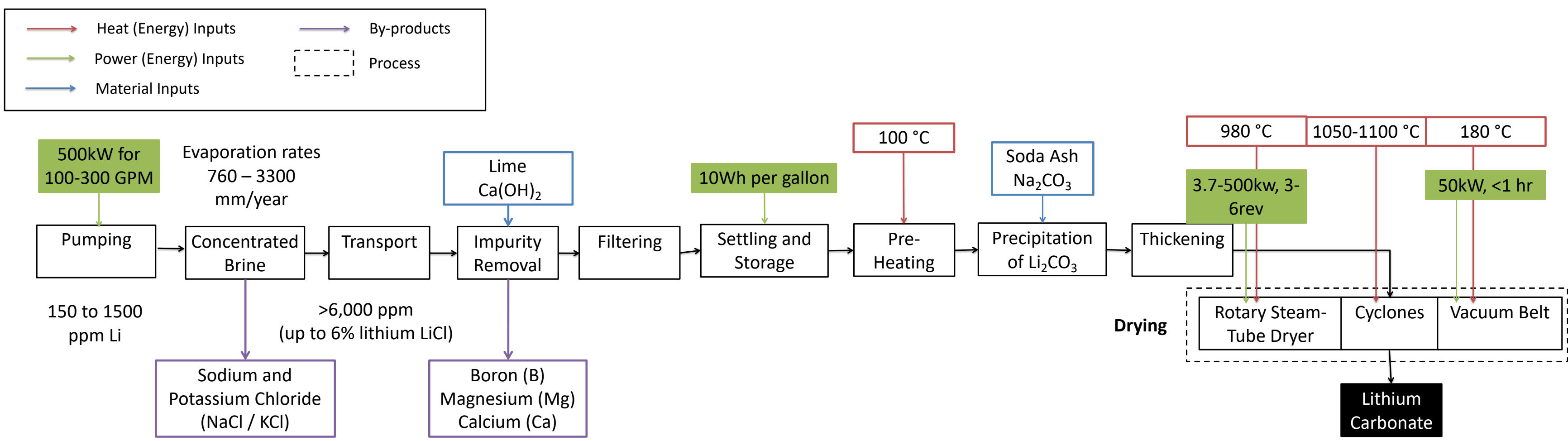
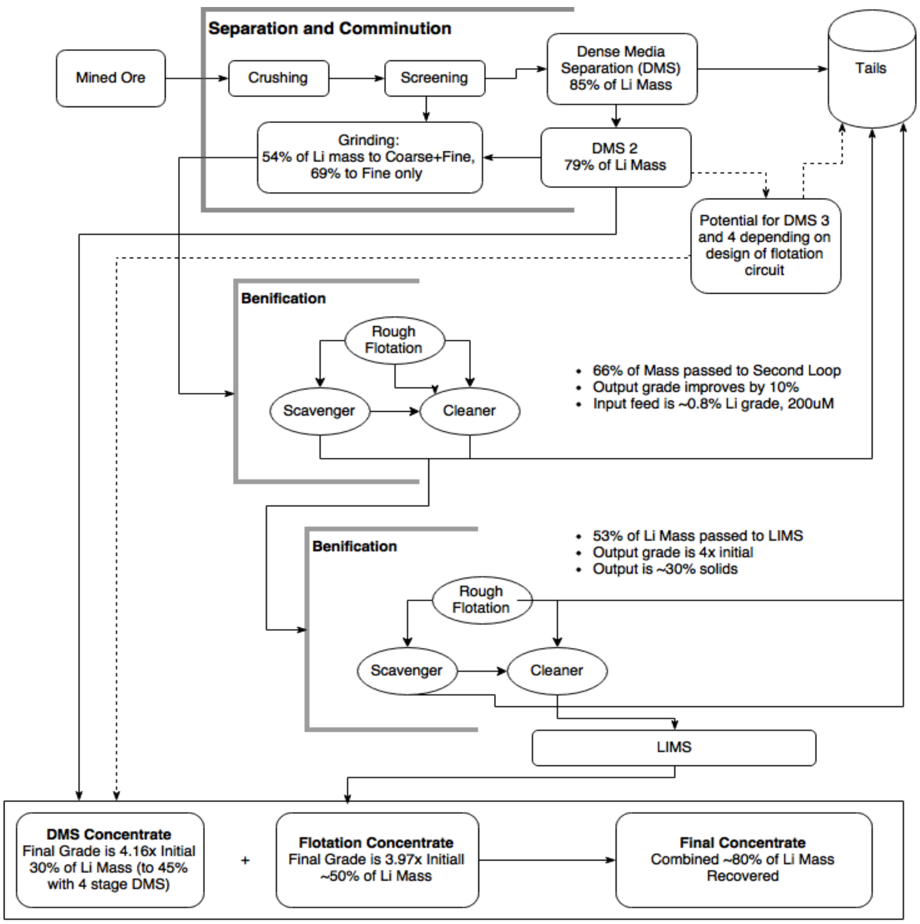


Figure S1-2 Key Inputs and Processes for Lithium Brines



Another uncertainty in estimating material and energy inputs into lithium processing is the design of the production circuit. After recovery, raw ore is processed through one or more additional circuits: dry material separation and recovery , heavy liquid material separation including froth flotation (FF), and hydrometallurgical recovery (HMR). Depending on ore grades, increased processing and beneficiation increases requirements of energy and consumable reagents, increases material loses to tailings, and results in increased generation of overburden and other mining wastes. Figure S2-2 illustrates the impacts on the rate of material recovery from beneficiation of lower grade ores.

Figure S1-3 Processing and recovery stages for pegmatites



The resulting material and energy flows in the life cycle inventory model are described in Table S1-1. To facilitate the design of the engineering model, processing machinery and inputs are grouped into 19 categories for which a reference LCI was obtained or estimated.

Reference LCI data was obtained from the Ecoinvent database (Ecoinvent Centre, 2017). As no LCI data was available for the collector agents used in HMR concentration, two proxy LCI models were estimated using material safety data from the manufacturer. In addition, ten inventories for utility provided electricity were also obtained to estimate impacts from regional electricity generation. For Argentina and Bolivia, the Chilean electricity inventory is used. For other Asian and developing countries without electricity inventory data, the Oceania inventory is used. The resulting list of 38 reference LCIs is described in Table S1-2.

Table S1-1 Summary of Life Cycle Inventory Models for Lithium Production Processes

Process Model Description	High-grade Pegmatite	Low-grade Pegmatite	Low-grade Lithium Minerals	High-grade Brine	Low-grade Brine	Low-Grade Brine/Unfavorable Conditions	HMR Concentration
Large Machine (steady state hours)	1.32E-03	2.20E-03	3.68E-03	3.00E-02	3.39E-02	3.39E-02	
Average Machine (high load hours)	2.93E-03	4.87E-03	8.09E-03				
Small Machine (steady state hours)	8.79E-03	1.46E-02	2.42E-02				
Blasting (kg)	1.40E-04	2.33E-04	3.86E-04				
Butanol (kg)	1.47E-02	1.47E-02	1.47E-02				
CollectorC (kg)							4.30E-02
CollectorL (kg)							7.70E-01
Dispersant (kg)							3.74E-02
Fatty Acid (kg)							4.14E-02
Ferrosilicon (kg)	3.23E-02	5.36E-02	8.89E-02				
Filtering Earth Bentonite (kg)	6.12E-04	1.02E-03	1.71E-03				
Heat, Natural Gas (MJ)					1.92E-01	4.47E-01	
Mining Truck (tkm)	4.57E-03	4.57E-03	7.59E-03	2.75E-03	3.11E-03	4.86E-03	
Quicklime (kg)						5.30E-01	
Soda Ash (kg)							1.10E-01
Sodium Hydroxide (kg)							1.89E-01
Sulfuric Acid (kg)							1.44E-03
Unspecified Lorry (kg)				2.00E-03	2.66E-03	2.66E-03	4.00E-03
Electricity (kWh)	1.74E-02	2.88E-02	4.79E-02	7.14E-03	9.50E-03	9.50E-03	1.83E-02
Source	***Stamp (2013)***	***Laferriere (2012)***	***Laferriere (2012)***	***Stamp (2012)***	***Stamp (2012)***	***An (2012)***	***Laferriere (2012)***

Table S2-2: Reference LCIs used in this study

Ecoinvent Average Machine, high load
Ecoinvent Butanol
Ecoinvent Carbonate from Brine
Ecoinvent Carbonate from Spodumene
Ecoinvent Concentrated Lithium Brine
Ecoinvent Fatty Acid
Ecoinvent Filtering Earth Bentonite
Ecoinvent HCL Acid at Gate
Ecoinvent HCL Acid Market
Ecoinvent Heat, Natural Gas, CN
Ecoinvent Heat, Natural Gas, Low-NOx, CN
Ecoinvent Heat, Natural Gas, Low-NOx, RER
Ecoinvent Heat, Natural Gas, RER
Ecoinvent Hydroxide from Brine
Ecoinvent Large Machine, steady state
Ecoinvent Small Machine, steady state
Ecoinvent Soda Ash
Ecoinvent Sulfuric Acid
EcoInvent Unspecified Lorry
Ecoinvent, Blasting, RER
Ecoinvent, Carbonate from Brine
Ecoinvent, Estimated CollectorC
Ecoinvent, Estimated CollectorL
Ecoinvent, GLO Market for Ferrosilicon
Ecoinvent, GLO market for sodium hydroxide, without water, in 50% solution state
Ecoinvent, Generic Mining Truck (on-site

Ecoinvent, GLO market for Quicklime

Ecoinvent, Market for medium voltage Australia

Ecoinvent, Market for medium voltage Brazil

Ecoinvent, Market for medium voltage Canada

Ecoinvent, Market for medium voltage Chile

Ecoinvent, Market for medium voltage China

Ecoinvent, Market for medium voltage Europe

Ecoinvent, Market for medium voltage Germany

Ecoinvent, Market for medium voltage Oceania

Ecoinvent, Market for medium voltage Spain

Ecoinvent, Market for medium voltage USA

S2: Description of Impact Assessment Categories

Global warming potential (GWP)	Carbon dioxide (CO_2) equivalent emissions to air with the potential to contribute to global warming, combining emissions of CO_2, N_2O, CH_4, and other potent GHG emissions based on their relative contribution to radiative forcing on a 100-year time horizon (Updated to AR5, IPCC 5^{th} Assessment).
Acidification potential	Emissions that contribute to acidic pollution expressed as equivalent hydrogen ions (H_+) from nitrogen and sulfur emissions to soil and water
Ozone depletion potential	Substances released to air that could deplete stratospheric ozone reported in chlorofluorocarbon-11 equivalents
Eutrophication potential	Emissions to air and water that can enrich freshwater and coastal water bodies with nitrates or phosphates represented in nitrogen equivalents. These pollutants can accelerate biological productivity (growth of algae and weeds) and deplete oxygen in aquatic ecosystems
Photochemical smog formation potential	Air emissions of NO_x, VOCs, and other ground level ozone forming chemicals reported in units of ozone equivalence. TRACI uses the maximum incremental reactivity method to estimate the likely tropospheric ozone smog formation potential from VOCs, which have several chemical fate pathways
Human health - particulate	Human health - particulate – Air pollution emissions including particulate matter consisting of inhalable coarse particles between 2.5 and 10 microns (PM_{10}) & fine particles less than or equal to 2.5 microns ($PM_{2.5}$) and their precursors
Human health - cancer	Cancer comparative toxicity unit (CTU_{cancer}), human health non-cancer comparative toxicity unit ($CTU_{non\text{-}cancer}$), and Ecotoxicity comparative toxicity unit (CTU_{eco}) – metrics that represent the emissions of known carcinogens and toxics to urban air, nonurban air, freshwater, seawater, natural soil, and agricultural soil based on a chemical fate model. Human health cancer aims to provide information about emissions known to cause human cancer. Human health non-cancer represents contributions to other kinds of toxicity.

Ecotoxicity	Freshwater or marine toxicity or damage.

S3: Expanded Results

Section 3 provides some additional results. Table S3-1 contains the average impact assessment scores for each production pathway and the baseline values from Ecoinvent. For electricity, the weighted average region for each production pathway is used. The impacts of HMR processing is also provided for comparison.

Table S3-1 Impact assessment results for each production pathway (all per kg LCE)

TRACI Category	High-grade Pegmatite	Low-grade Pegmatite	Low-grade Rock Minerals	High-grade Brine	Low-grade Brine	Low-grade Brine/Unfavorable Conditions	Rock Baseline	Brine Baseline	HMR Concentration
ETP	15.80	16.58	17.88	6.69	11.91	16.82	19.88	15.48	14.61
HHC	11.71	13.44	16.31	9.06	12.96	15.98	13.74	24.06	9.08
HHNC	5.32	5.65	6.19	2.69	4.47	6.59	8.72	6.44	4.82
GWP	2.28	2.67	3.32	3.06	3.97	5.28	2.06	2.23	1.66
HHP	5.58	6.84	8.94	2.47	3.88	5.47	12.43	2.94	3.66
ODP	5.32	5.80	6.60	7.45	9.83	11.46	2.76	2.92	4.60
SFP	1.85	2.20	2.80	3.84	4.73	5.36	1.78	2.22	1.29
AP	15.78	17.79	21.15	16.73	22.72	29.60	23.78	17.93	12.62
EP	16.30	17.16	18.60	7.09	12.48	17.47	9.03	20.86	14.98

(ETP = Ecotoxicity Potential in CTUe; HHC = Human health cancer in CTUh×10^9; HHNC = Human health non-cancer in CTUh×10^7; GWP = Global Warming Potential in kg CO_2-eq; HHP = Human health particulate in g×10^7 $PM_{2.5}$; ODP = Ozone depletion potential in mg×10^7 CFC-11-eq; SFP = Smog formation potential in kg×10 O_3e-eq; AP = Acidification potential in g SO_3-EQ; EP = Eutrophication potential in g N-eq)

While the average intensity of lithium carbonate production changes only moderately over the study period, the total impacts of the global production system do increase with increasing demand (Figure S3-2).

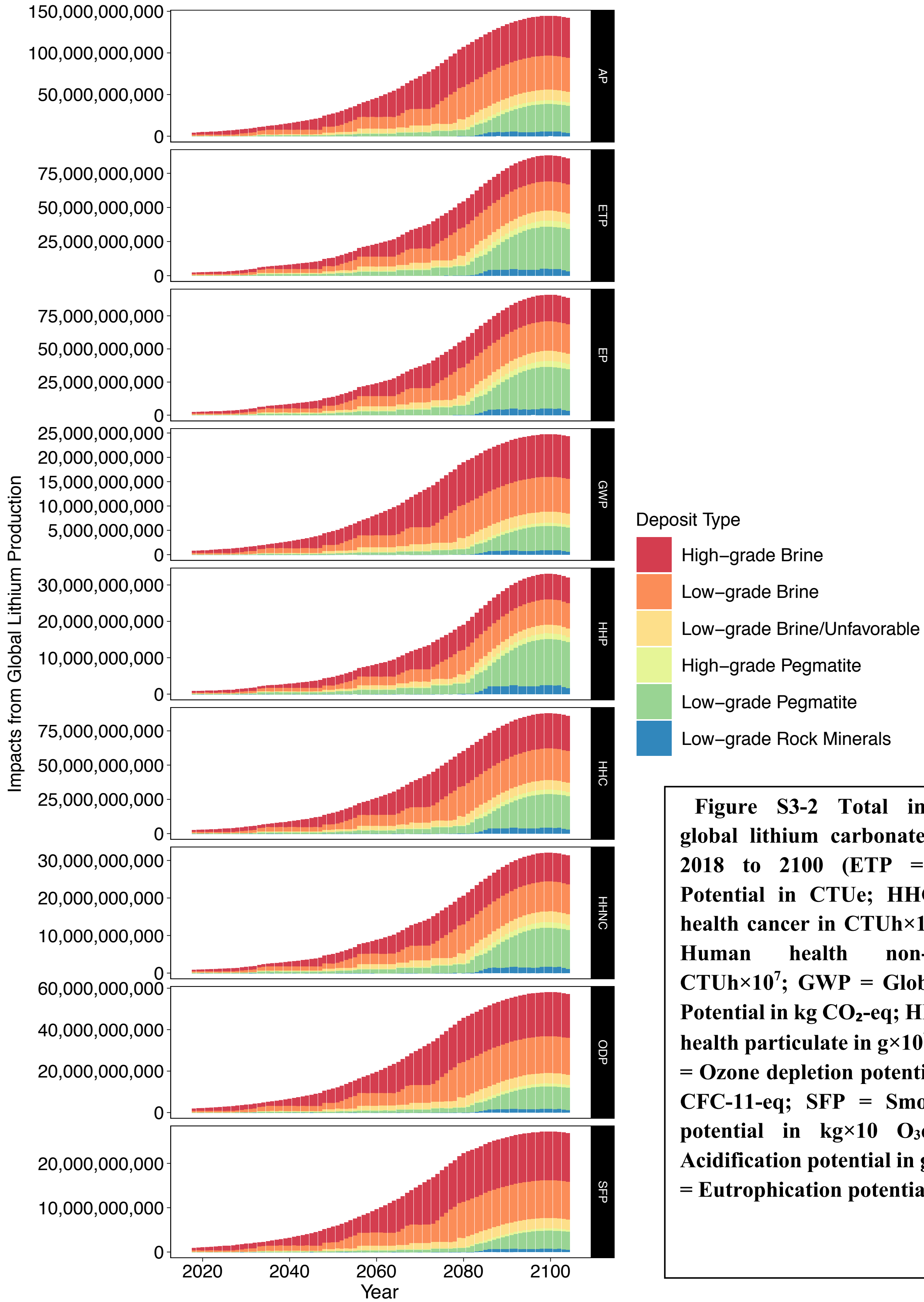


Figure S3-2 Total impacts from global lithium carbonate production, 2018 to 2100 (ETP = Ecotoxicity Potential in CTUe; HHC = Human health cancer in CTUh×10^9; HHNC = Human health non-cancer in CTUh×10^7; GWP = Global Warming Potential in kg CO_2-eq; HHP = Human health particulate in g×10^7 $PM_{2.5}$; ODP = Ozone depletion potential in mg×10^7 CFC-11-eq; SFP = Smog formation potential in kg×10 O_3e-eq; AP = Acidification potential in g SO_3-EQ; EP = Eutrophication potential in g N-eq)

Finally, Figure S3-3 compares the average production impacts for average periods, 2020 to 2040 and 2080 to 2100. We can observe with the significant increase in production from low grade pegmatite and brine resources, there are moderate increases in environmental impacts. Impacts to water, emissions of toxics and aerosol particulate matter increased by over 11%. Global warming impacts per kilogram of lithium carbonate equivalent increase by 3% from 3.23 to 3.33 kg CO2e/kgLi2CO3e. Overall, these changes to impacts from increasing production of unfavorable or unconventional resources were minor.

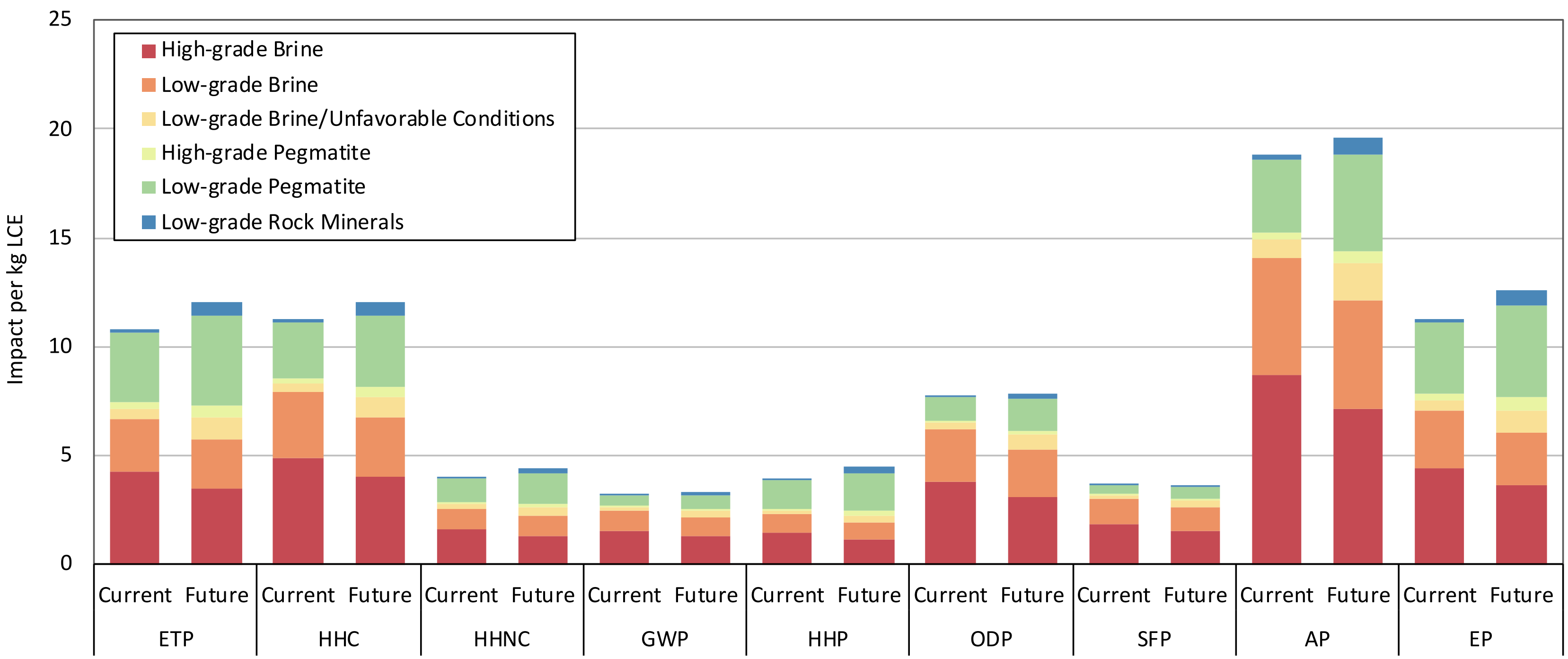


Figure S3-3 Comparing impacts per ton for current vs future LCE supply (ETP = Ecotoxicity Potential in CTUe; HHC = Human health cancer in CTUh×10^9; HHNC = Human health non-cancer in CTUh×10^7; GWP = Global Warming Potential in kg CO_2-eq; HHP = Human health particulate in g×10^7 $PM_{2.5}$; ODP = Ozone depletion potential in mg×10^7 CFC-11-eq; SFP = Smog formation potential in kg×10 O_3e-eq; AP = Acidification potential in g SO_3-EQ; EP = Eutrophication potential in g N-eq)

In Part 1 of this work (Resource Model), the author's also considered a conservative projection for lithium demand. This conservative projection sought to investigate the effects of slowed growth in the demand for lithium from batteries post 2050 and lower estimated primary resource availability. Estimating the logistic growth model for the resource requires information about both historic and current demand as well as the total recoverable resource (i.e.URR). Based on identified deposits and prior published estimates, there is a wide range of potential URR, from 55 Mt to 99 Mt of lithium as Li metal, or 293 to 527 Mt of LCE. This span of resource estimates is used to estimate a low-demand, or conservative, scenario and a high-demand, or optimistic, scenario. In addition, the study used a short term forecast of lithium demand to expand the historical record of lithium production based primarily on expected increases in global lithium battery manufacturing between now and 2030.

The conservative demand scenario reflects decreased development of low grade minerals in the later part of this century. This is due to the comparably higher costs of expanding production from these sources, lower yields, and sufficient supply potential from larger brine sources to meet increasing demand. This result in a 48% – 64% reduction in sector-wide environmental impacts from global LCE production in 2100 compared with the optimistic demand scenario (S3-4). The most significant reductions occur in the categories of ecotoxicity, eutrophication, and human exposure to particulates.

In addition, significant increases in the average impacts on per kg of LCE after 2080 did not occur (Figure S3-5). The average impact value estimated per kg of LCE was 18-23% lower by 2100 for the same three impact categories (e.g. ecotoxicity, eutrophication, and human exposure to particulates). Under the conservative scenario, development of low grade pegmatite resources occurs far slower and we do not see the decline in the supply of LCE from low grade pegmatite resources towards the end of 2100.

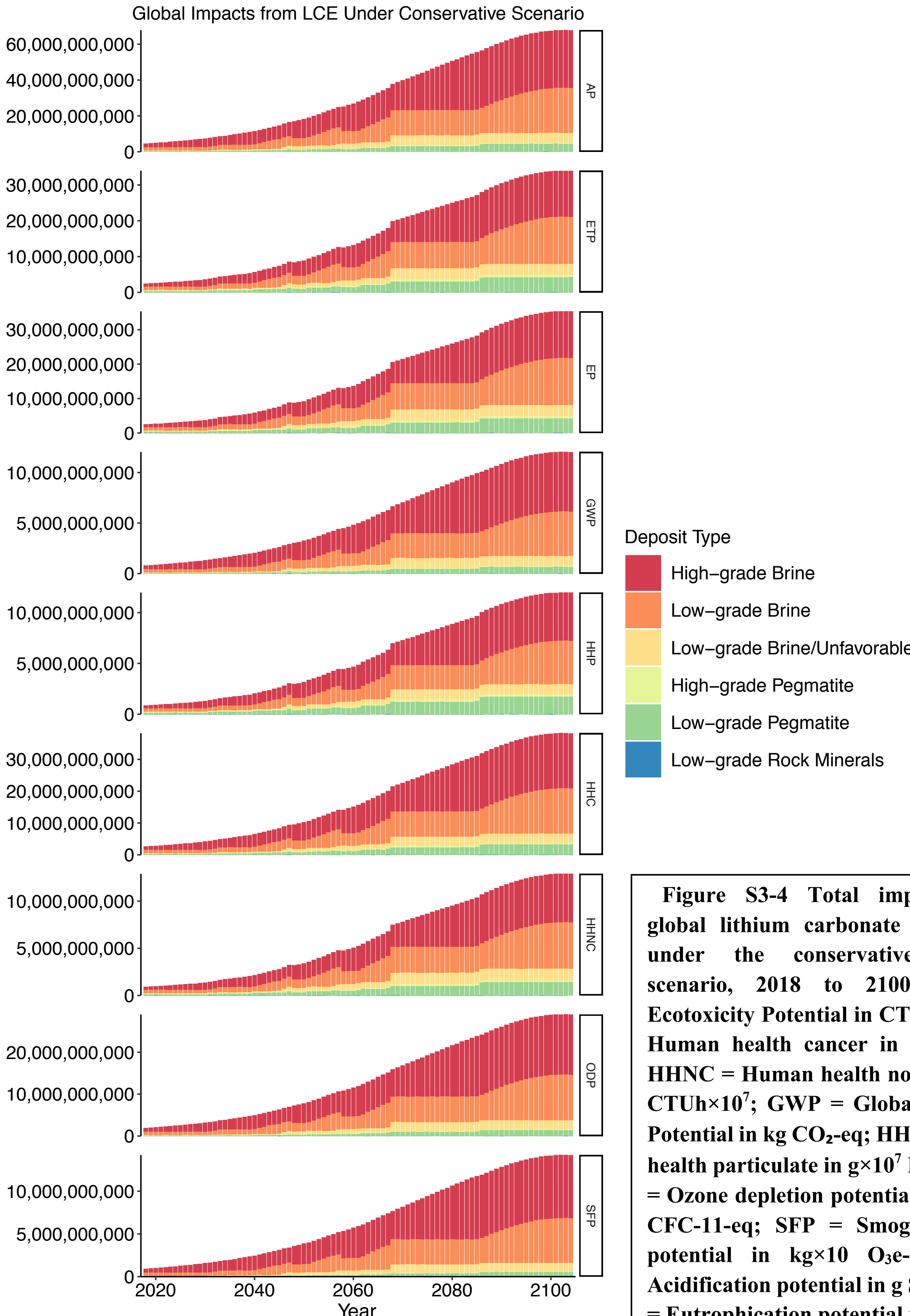


Figure S3-4 Total impacts from global lithium carbonate production under the conservative demand scenario, 2018 to 2100 (ETP = Ecotoxicity Potential in CTUe; HHC = Human health cancer in CTUh×10^9; HHNC = Human health non-cancer in CTUh×10^7; GWP = Global Warming Potential in kg CO_2-eq; HHP = Human health particulate in g×10^7 $PM_{2.5}$; ODP = Ozone depletion potential in mg×10^7 CFC-11-eq; SFP = Smog formation potential in kg×10 O_3e-eq; AP = Acidification potential in g SO_3-EQ; EP = Eutrophication potential in g N-eq)

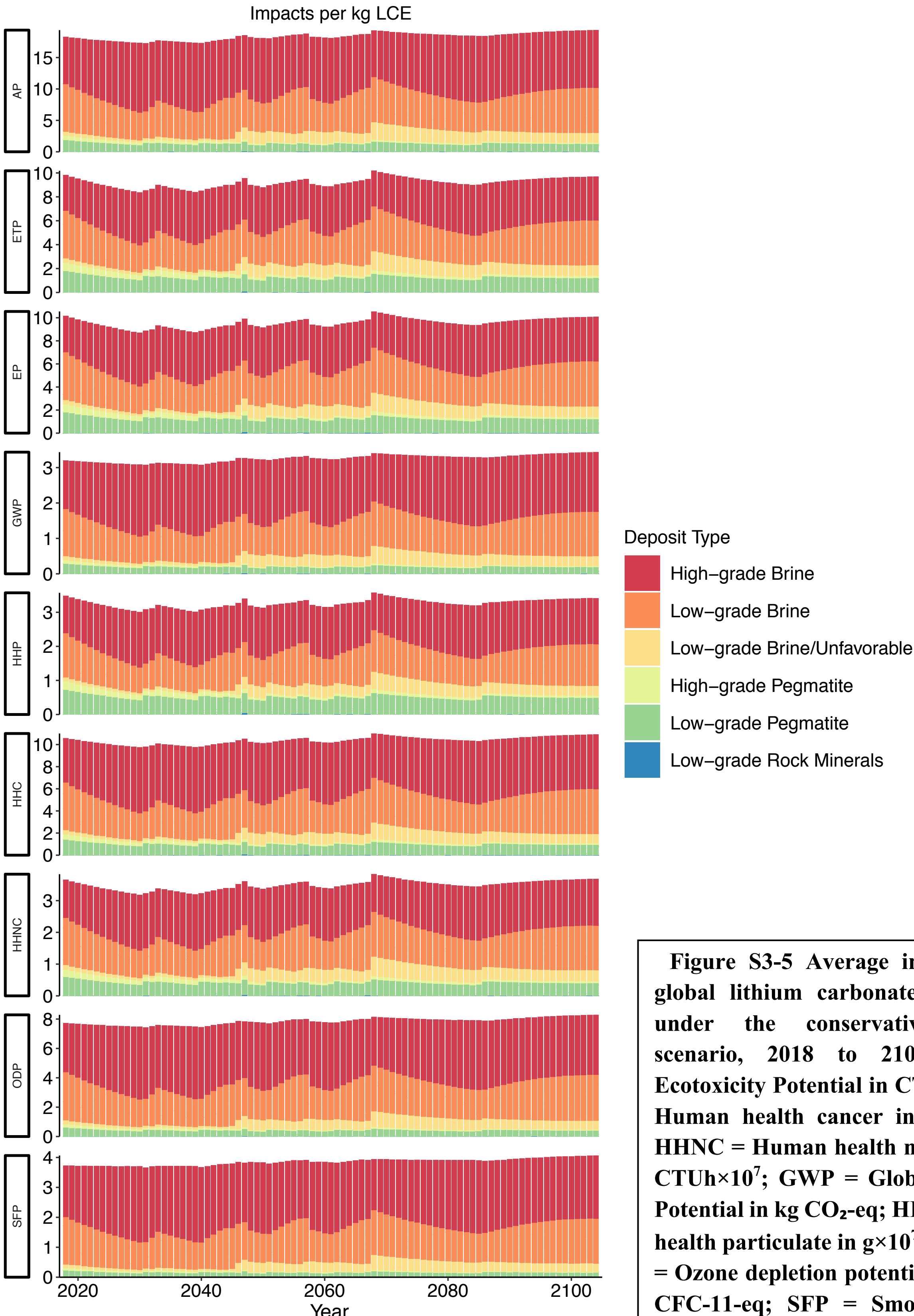


Figure S3-5 Average impacts from global lithium carbonate production under the conservative demand scenario, 2018 to 2100 (ETP = Ecotoxicity Potential in CTUe; HHC = Human health cancer in CTUh×10^9; HHNC = Human health non-cancer in CTUh×10^7; GWP = Global Warming Potential in kg CO_2-eq; HHP = Human health particulate in g×10^7 $PM_{2.5}$; ODP = Ozone depletion potential in mg×10^7 CFC-11-eq; SFP = Smog formation potential in kg×10 O_3e-eq; AP = Acidification potential in g SO_3-EQ; EP = Eutrophication potential in g N-eq)

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C. SUPPORTING INFORMATION FOR CHAPTER 5

Table A. Vehicle battery scenarios, representative models, and US sales volume [1]

Battery Scenario	PEV Type	Vehicle Model	US Sales (Up to 4/2015)
Short-range PHEV	**PHEV 15**	Toyota Prius Plug-in Hybrid	39600
		Honda ACCORD Plug-in Hybrid	1025
		BMW I8	1163
		Ford FUSION Energi Plug-in Hybrid	20166
		Ford C-MAX Energi Plug-In Hybrid	20122
Mid-range PHEV	**PHEV 40**	Chevrolet Volt	68139
		Cadillac ELR	1731
Short-range BEV	**EV 40**	Scion iQ EV	0
		Mitsubishi Motors Corporation i-MiEV	1844
		Mercedes-Benz Smart fortwo EV	4104
Mid-range BEV (Low Power)	**EV 80**	Nissan Leaf	68267
		Kia Soul Electric	612
		FIAT 500e	7993
		Volkswagen e-Golf	1172
		Honda FIT	1122
Mid-range BEV (High Power)	**EV 80**	Chevrolet SPARK EV	2981
		Ford Focus Electric FWD	4879
		Mercedes-Benz B-Class Electric	1426
Long-range BEV	**EV 100**	Toyota RAV4 EV	2432
		Tesla Motors Model S	45371

Table B. Battery Cell Test data literature. Abbreviations: d = discharge, ch = charge, E = empirical, M = modeling, MP = manufacturer predicted, DOD = depth of discharge, RPT = reference performance test, CC-CV = constant current, constant voltage, EVPC = Electric Vehicle Power Characterization.

Lead Author and reference	Chemistry: cathode/anode	Manufacturer	Brand	Shape	C Rate	d/ch	Cycles	DOD (%)	Capacity Fade (%)	Resistance Inc. (%)	Test	Temp (C)	E/M/MP
Omar [2]	LFP/C	-	-		1C	d	3221	80	20	126	cycle life	room	E
Omar [2]	LFP/C	-	-		1C	d	1600	80	20	127	cycle life	40	E
Omar [2]	LFP/C	-	-		10C	d	1100	80	20	156	cycle life	55	E
Omar [2]	LFP/C	-	-		15C	d	559	80	20	140	cycle life	55	E
Kim [3]	LFP/C	-	-	Pouch	4C	d	3000	85	15	-	cycle life	room	E
Song [4]	LFP/C	-	18650	Cylinder	3C	d	600	95	5	-	cycle life	25	E
Song [4]	LFP/C	-	18650	Cylinder	3C	d	600	70	30	-	cycle life	55	E
Song [4]	LFP/C	-	18650	Cylinder	3C	d	250	80	20	-	cycle life	55	E
Zheng [5]	LFP/C	Tianjin Lishen Battery Joint-Stock Co., Ltd.	18650	Cylinder	1C	d	600	98	2	0	cycle life	25	E
Zheng [5]	LFP/C	Tianjin Lishen Battery Joint-Stock Co., Ltd.	18650	Cylinder	10C	d	600	86	14	9	cycle life	25	E
Zheng [5]	LFP/C	Tianjin Lishen Battery Joint-Stock Co., Ltd.	18650	Cylinder	10C	d	600	73	27	13	cycle life	55	E
Ouyang [6]	LFP/C	-	-	-	1/2C	ch	50	96	4	-	cycle life, RPT	-10	E
Ouyang [6]	LFP/C	-	-	-	1/2C	ch	50	81	19	-	cycle life, RPT	-10	E
Ouyang [6]	LFP/C	-	-	-	1/2C	ch	50	73	27	-	cycle life, RPT	-10	E

Lead Author and reference	Chemistry: cathode/anode	Manufacturer	Brand	Shape	C Rate	d/ch	Cycles	DOD (%)	Capacity Fade (%)	Resistance Inc. (%)	Test	Temp (C)	E/M/MP
Zhang [7]	LCO/C	Sony US	18650S	Cylinder	1/2C	ch, d	800	68	32	747	Arbin battery	-	E
Ramadass [8]	LCO/C	Sony	18650	Cylinder	C/9-1C	d	800	69	31	58	CC-CV, discharge	room	E
					C/9-1C	d	800	64	36	83	CC-CV, discharge	45	E
Li [9]	LCO/C	Sanyo	UF653467	Prismatic	1C	ch, d	286	70	30	-37	cycle life	room	E
Ning [10]	LCO/C	Sony US	18650	Cylinder	1C	d	300	91	10	12	cycle life, Arbin battery	ambient	E
					3C	d	300	83	17	18	cycle life, Arbin battery	ambient	E
Shirk [11]	LMO/C	2012 Nissan Leaf		Prismatic	ACL2	ch	685	25	75	31	LPP, EVPC	~20-40	E
					DCFC	ch	685	30	70	33	LPP, EVPC	~20-40	E
Erdas [12]	Spinel LTO	-	CR2016	Coin	1C	d	100	59	41	-	cycle life	-	E
					1C	d	30	80	20	-	cycle life	-	E
	Spinel Ag-LTO	-	CR2016	Coin	1C	d	100	98	2	-	cycle life	-	E
Yu [13]	Spinel LTO	-	CR2025	Coin	5C	d	400	94	6	-	cycle life	25	E
		-	CR2025	Coin	5C	d	400	88	12	-	cycle life	25	E

Lead Author and reference	Chemistry: cathode/anode	Manufacturer	Brand	Shape	C Rate	d/ch	Cycles	DOD (%)	Capacity Fade (%)	Resistance Inc. (%)	Test	Temp (C)	E/M/MP
	Spinel V-LTO				2C	d	1713	98	2	-	cycle life	25	E
Yang [14]	LFMP-C/V-LTO	-	CR2032	Coin	3C	d	400	98	2	-	cycle life	room	E
Morales [15]	LFP/LTO	-	-	Coin	4C	d	2500	83	17	-	cycle life	room	E
Burke [16]	NMO/LTO	Altairnano	24V, 50Ah	Prismatic	4C&C/2	ch, d	1000	99	1	-	cycle life	40	E
					4C&C/3	ch, d	16647	80	20	-	cycle life	40	M
Yi [17]	Spinel LTO	-	CR2026	Coin	10 C	ch, d	200	87	13	-	cycle life	-	E
	LTO-LLTO	-	CR2025	Coin	10 C	ch, d	200	82	18	-	cycle life	-	E
Burke [18]	NCM/C	EIG	-	-	-	-	2000-3000	80	20	-	cycle life	-	E
	Mn Spinel/C	-	-	-	-	-	1000	80	20	-	cycle life	-	E
	NCA/C	-	-	-	-	-	2000-3000	80	20	-	cycle life	-	E
	LFP/C	EIG	-	-	-	-	>3000	80	20	-	cycle life	-	E
	Mn Spinel/LTO	Altairnano	-	-	-	-	>5000	80	20	-	cycle life	-	E
Wong [19]	NCA/C	-	-	-	1C	d	400	100	0	-	cycle life	-	E
					25C	d	400	80	20	-	pulse	50	E
					83C	d	400	94	6	-	continuous	34	E

Lead Author and reference	Chemistry: cathode/anode	Manufacturer	Brand	Shape	C Rate	d/ch	Cycles	DOD (%)	Capacity Fade (%)	Resistance Inc. (%)	Test	Temp (C)	E/M/MP
Watanabe [20]	NCA/C	-	-	Cylinder	1C	ch, d	~1000	80	20	-	cycle life	25	E
					1C	ch, d	~300	80	20	1540	cycle life	60	E
Bodenes [21]	NCM/C	-	-	Cylinder	C/5	d	26	93	8	100	cycle life	85	E
					C/5	d	29	78	22	1115	cycle life	120	E

Table C. Battery OEMs and their Automotive Partners

Cell Producer	Vehicle	Chemistry	Capacity (Ah)	Configuration	Specific Energy (kWh/kg)
AESC	Nissan Leaf	LMO	33	Pouch	155
LG CHEM Li-Tec	Renault Zoe	NMC	36	Pouch	157
Li-Tec	Daimler Smart	NMC	52	Pouch	152
Li Energy Japan	Mitsubishi i-MiEV	LMO	50	Prismatic	109
Samsung	Fiat 500e	NMC	64	Prismatic	132
Lishen Tianjin	Coda	LFP	16	Prismatic	116
Toshiba	Honda Fit	LTO-NMC	20	Prismatic	89
Panasonic	Tesla Model S	NCA	3.1	Cylindrical	248
Sanyo	--	--	22	Prismatic	112
LEJ	--	--	21	Prismatic	108

Table D. Plug-in Electric Vehicle and Battery Warranties [22-27]

Manufacturer	Standard Vehicle Warranty		Powertrain/Battery/Hybrid Unique Component				
	Years	Miles	Years	Miles	Capacity Fade	Battery Specific	Comments
Nissan	8	100000	5	60000	30%	Yes	
Ford	8	100000	8	100000	Not Specified	No	
Tesla (65)	4	50000	8	125000	Not Specified	Yes	*Excessive capacity loss covered, but not specified
Tesla (85)	4	50000	8	Unlimited	Not Specified	Yes	*Excessive capacity loss covered, but not specified
Honda	3	36000	5	60000	Not Specified	No	*Excessive capacity loss covered, but not specified
Fiat/Chrysler	4	50000	8	100000	Not Specified	Yes	
BMW	4	50000	8	100000	30%	Yes	

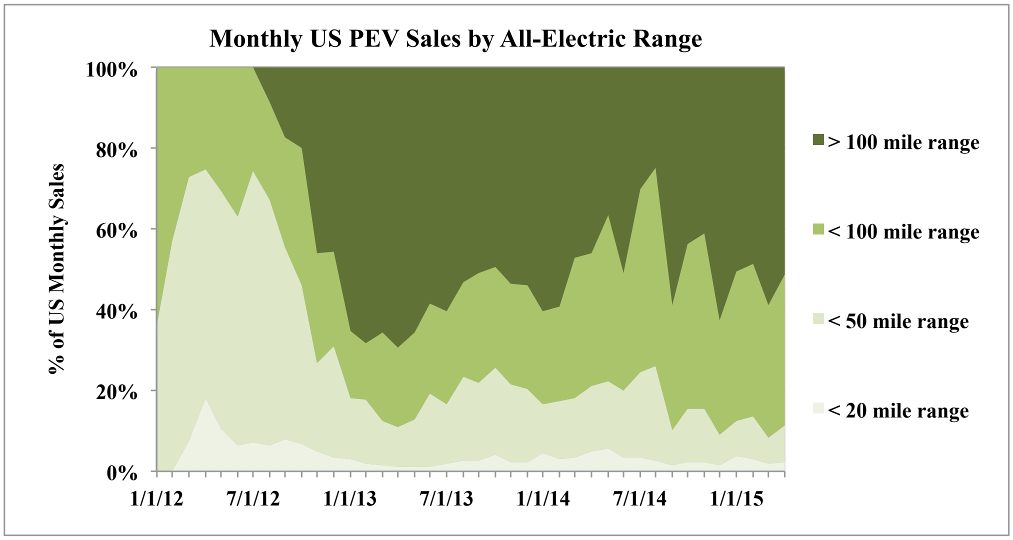

Figure A. US sales of PEVs shows move toward longer-range vehicles [1]

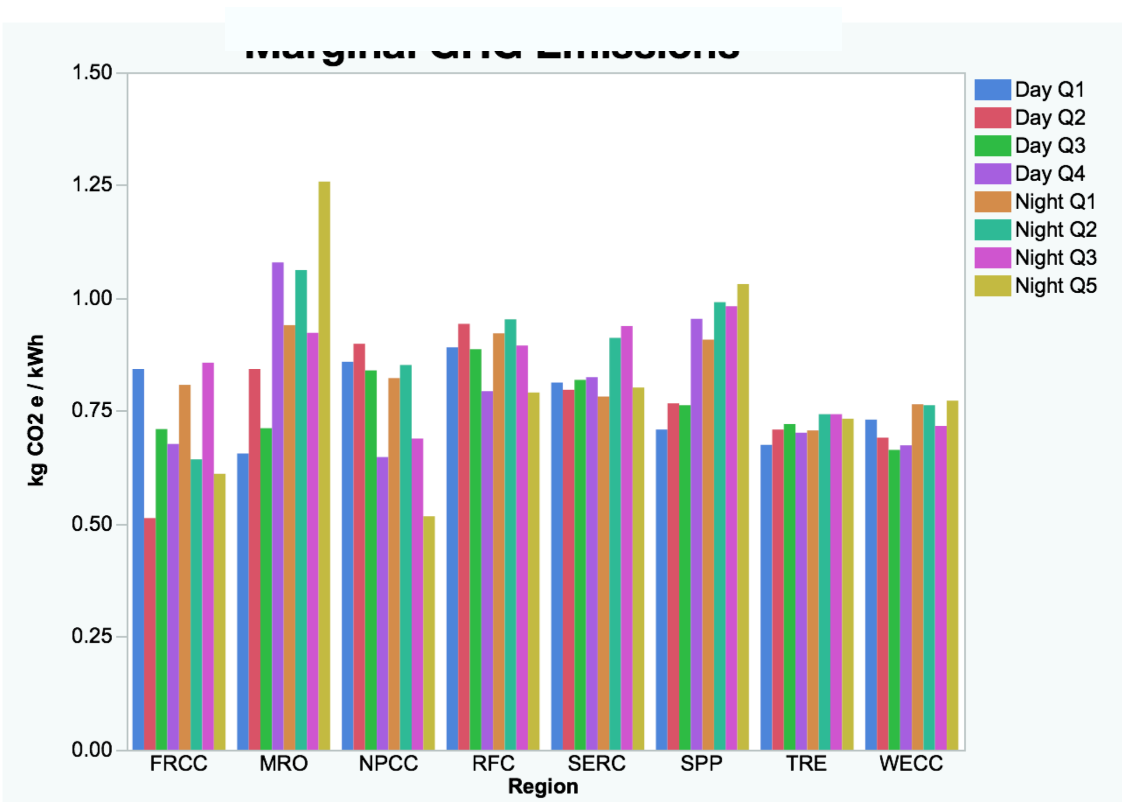

Figure B. Marginal US National Electricity Reliability Corporation (NERC) region marginal grid emissions intensities used in this study [28]

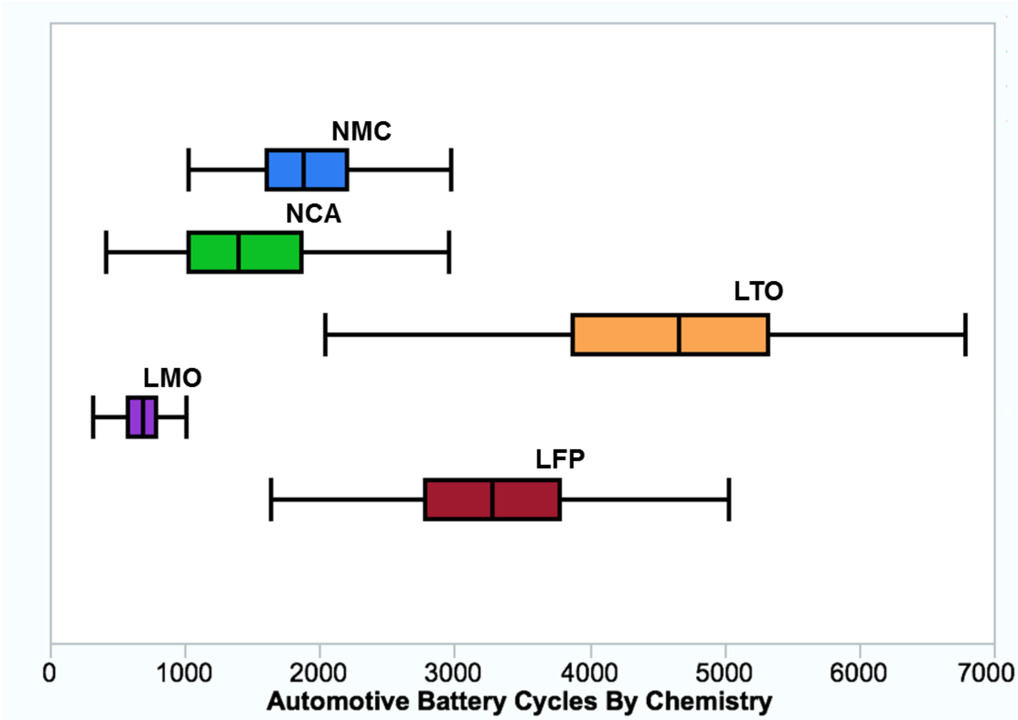

Figure C. Battery cycles by chemistry. Abbreviations: Lithium Manganese Oxide = LMO, Lithium Nickel Manganese Cobalt Oxide = NMC, Lithium Nickel Cobalt Aluminum Oxide = NCA, Lithium Iron Phosphate = LFP, Lithium Manganese with Titanate Oxide Anode = LTO

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D. Supporting information on EV LCA

These supporting materials provides summary tables used to generate all figures in the main text. The supporting material also contains sections with additional calculations and data as described in the main text. The SM is organized as follows:

- Section S1. Literature survey for Life Cycle GHG Emissions from Battery Electric (BEV), Internal Combustion Engine (ICEVs) and Hybrid Electric Vehicles (HEVs)
- Section S2. US Battery Electric Vehicle Sales, 2012 to 2019
- Section S3. Vehicle Production
- Section S4. Battery Production
- Section S5. Vehicle Energy Demands
- Section S6. Annual Vehicle Miles Travelled
- Section S7. Electricity Generation
- Section S8. Full Results

Section S1. Literature survey for Life Cycle GHG Emissions from Battery Electric (BEV), Internal Combustion Engine (ICEVs) and Hybrid Electric Vehicles (HEVs)

Table 1 in the main text summarizes some of the key findings of prior studies examining the life cycle greenhouse gas emissions of light duty vehicles, and provides comparison with both pure gasoline vehicles with a hybrid electric powertrain, and conventional gasoline ICEVs. Table S1.1 provides a full list of the studies included, referenced, or used for calculations in Table 1.

Table S1.1 Summary of Studies Examining the Life Cycle GHG Emissions of BEVs, ICEVs, and HEVs (Archsmith et al., 2015; Bandivadekar, 2008; Burnham et al., 2006; Dunn et al., 2012; Ellingsen et al., 2014; Graff Zivin et al., 2014; Hawkins et al., 2013; Kendall and Price, 2012; Kim et al., 2016; MacLean and Lave, 2003; Majeau-Bettez et al., 2011; Mercedes, 2008; Miotti et al., 2016; Notter et al., 2010; Samaras and Meisterling, 2008; Tamayao et al., 2015)

Study	Vehicle Type	Battery Capacity (kWh)	Vehicle + Battery Production (kg CO_2e)	Battery Production (g CO_2e/km)	Vehicle + Battery Production (g CO_2e/km)	Vehicle Operation (g CO_2e/km)
Samaras and Meisterling (2008)	PHEV	20.1	7903	10	41	40
Notter et al. (2010)	BEV	34.2	6253	7	32	101
Majeau-Bettez et al. (2011)	BEV	24	7396	19	48	
Dunn et al. (2012)	BEV	28	7039	4	32	
Hawkins et al. (2013)	BEV	24	7934	18	50	
Ellingsen et al. (2014)	BEV	26.6		26	26	
Graff Zivin et al. (2014)	BEV	24				69 - 293

Study	Vehicle Type	Battery Capacity (kWh)	Vehicle + Battery Production (kg CO_2e)	Battery Production (g CO_2e/km)	Vehicle + Battery Production (g CO_2e/km)	Vehicle Operation (g CO_2e/km)
Miotti et al. (2016)	BEV	19 - 60	7389	4	34	120 - 185
Tamayao et al. (2015)	BEV	24	2616			41 - 144
Kim et al. (2016)	BEV	24	7640	14	44	
Archsmith et al. (2016)	BEV	28	7765	6	37	124 - 194
Maclean and Lave (2003)	ICEV		9600		38	285
Samaras and Meisterling (2008)	ICEV		8500		34	
Burnham et al. (2006), in Hawkins et al. (2012)	ICEV		7600		30	
Burnham et al. (2006), in Hawkins et al. (2012)	ICEV		7000		28	
Notter et al. (2010)	ICEV		6370		25	121
Hawkins et al. (2013)	ICEV		6566		26	
Miotti et al. (2016)	ICEV		8178		33	282
Archsmith et al. (2016)	ICEV		7207		29	248
Kim et al. (2016)	ICEV		6200		25	
Kim et al. (2016)	ICEV		7200		29	
Kim et al. (2016)	ICEV		7000		28	
Kim et al. (2016)	ICEV		7500		30	

Study	Vehicle Type	Battery Capacity (kWh)	Vehicle + Battery Production (kg CO_2e)	Battery Production (g CO_2e/km)	Vehicle + Battery Production (g CO_2e/km)	Vehicle Operation (g CO_2e/km)
Burnham et al. (2006), in Hawkins et al. (2012)	HEV		9200		46	
Bandivadekar (2008)	HEV		10800		54	
Samaras and Meisterling (2008)	HEV		8800		44	
Mercedes (2008), in Hawkins et al. (2012)	HEV		10600		53	
Kendall and Price (2012)	HEV		9900		40	139
Kendall and Price (2012)	HEV		17300		69	131
Miotti et al. (2016)	HEV		9200		46	242

Section S2. Battery Electric Vehicle Sales in the US

Table S2.1 summarizes the monthly sales data used to create Figure 1 in the main text. The monthly vehicle sales data was obtained from the Inside EVs Monthly Sales Scorecard (Loveday, 2019). The estimated average vehicle battery pack capacity was obtained from the EPA vehicle fuel economy data file.

Table S2.1 US Battery electric vehicle sales

Model	Average Battery Pack Capacity	2012	2013	2014	2015	2016	2017	2018
BMW I3 BEV	33	0	0	6092	11024	7625	6276	6119
FIAT 500e	24	0	260	5132	6194	5330	5380	2740
Ford Focus	33.5	683	1738	1964	1582	901	1817	558
Chevrolet Bolt EV	60	0	0	0	0	579	23297	16674
Honda Clarity BEV	25.5	0	0	0	0	0	1121	1133
Hyundai IONIQ EV	28	0	0	0	0	0	432	204
Kia Soul Electric	30	0	0	359	1015	1728	2157	1113
Mercedes B250e	28	0	0	774	1906	632	744	89
Mercedes Smart fortwo ED	17.6	137	923	2594	1387	657	544	467
Mitsubishi i-MiEV	16	588	1029	196	115	94	6	0
Nissan LEAF	24	9819	22610	30200	17269	14006	11230	13388
Tesla Model 3	75	0	0	0	0	0	1772	131382
Tesla Model S	85	2171	19000	17800	25202	28896	27060	22445
Tesla Model X	100	0	0	0	214	18223	21315	19150
Volkswagen e-Golf	24.2	0	0	357	4232	3937	3534	1026

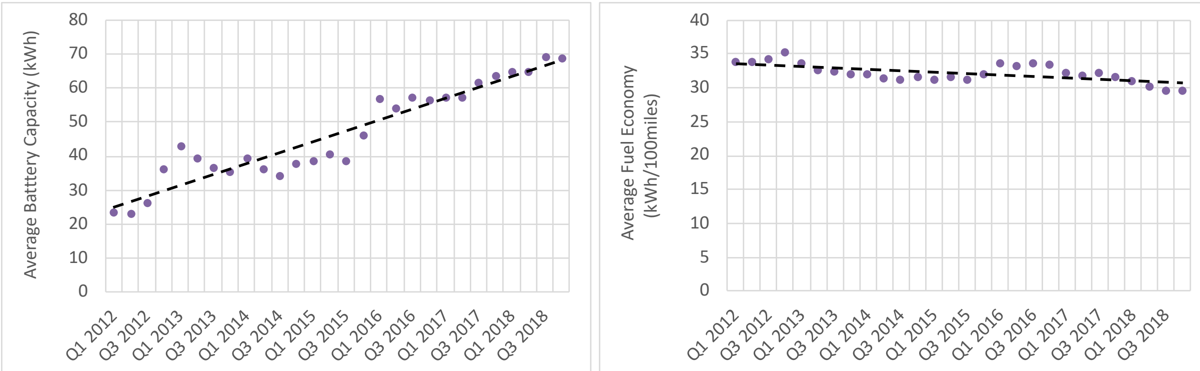

Figure S2.2 Average, Sales-Weighted Battery Capacity (Left) and Fuel Economy (Right)

Section S3. Vehicle Production

To model the emissions of the glider production, the material composition of the glider and its mass along with life cycle inventory of those materials is required. The life cycle inventory used to model LCGHG emissions associated with vehicle production, assembly, and disposal was acquired from the GREET 2 model. Their data on material acquisition and transformation, vehicle assembly, and vehicle disposal was combined with glider mass and composition to estimate emissions. In this study, the battery system was modelled separately from the rest of the vehicle, referred to as the glider. Hence the glider mass is calculated by subtracting battery mass from the curb weight. The material compositions for the Leaf (2012), PLS and the PSUV vehicle scenarios are based on material composition used in a similar study (UCS 2015) which builds off of material data used in GREET 2 model. The material composition for the EOV scenario is from the vehicle teardown performed on Chevrolet Bolt by Munro associates.

The material composition of the glider and mass used for each of the four modeled vehicle scenarios can be seen in Table S2.1.

Table S2.1 Average Glider Composition and Mass by Vehicle Group

	EOV	**PLS**	**PSUV**	**Leaf (2012)**
Steel	54.25%	21.0%	21.0%	66.0%
Cast Iron	4.24%	3.0%	3.0%	2.0%
Wrought Aluminum	2.12%	26.0%	26.0%	1.5%
Cast Aluminum	8.50%	17.0%	17.0%	5.0%

Copper/Brass	7.63%	6.0%	6.0%	5.5%
Glass	4.24%	4.0%	4.0%	3.0%
Average Plastic	13.56%	15.0%	15.0%	12.0%
Rubber	2.54%	2.6%	2.6%	2.0%
Glass Fiber-Reinforced Plastic	0.00%	2.5%	2.5%	0.0%
Others	3.0%	2.9%	2.9%	3.0%
Glider Mass (lbs)	2,609	3,505	4,043	2,785

Additional considerations included material transformation, fluid use, assembly, and disposal, which were also acquired from GREET 2 model. Fluids are included in the body and powertrain material life cycle stage of this study's model, and in EVs include brake fluids, powertrain coolant, and windshield fluid; sedans and SUVs were assigned different sets of lifetime fluid use, with the latter having higher fluids use. All vehicles were given identical assembly and disposal impacts, where the energy use was 11.57 mmBTU and 3.26 mmBTU respectively. Note that the modeled emissions may underestimate true impacts, as the life cycle emissions of the approximately 3% of "other" materials was not accounted for. Additionally, since electricity does not play a major role in this phase, time dependence of the electric grid was not included.

Section S4. Battery Production

The battery production model examined the cradle to gate of the battery life cycle, which included emissions from raw material extraction and refining, production, and assembly. An existing tool, the Battery Performance and Cost Model (BatPaC) constructed by Argonne National Laboratory, was used as the basis for the battery production model. BatPaC is based on a robust study of the material properties of LIB electrode and packaging materials, as well as battery pack design and production. BatPaC estimates the cost and composition of the LIB pack systems; in prior work (Ambrose, 2016), we connected these these outputs to material life cycle inventory data to estimate the GHG intensity of battery production processes. BatPaC offers the capabilities to compare the performance of different LIB cathode materials, however nickel rich cathode compounds NMC (e.g. 622 and 811), are being predicted to dominate light duty automotive applications (Curry, 2017). Table S3.1 summarizes the key parametric assumptions relating to the battery pack design, i.e. pack size, mass, power output, and cell and module capacity. The scenarios were developed based publicly available data on current models of archetypal vehicles described in main text.

Table S4.1 Battery Pack Configuration Detail

	Leaf	EOV	PLS	PSUV	2025 EOV	2025 PLS	2025 PSUV	2025 LR-EOV	2025 LR-PLS	2025 LR-PSUV
Pack Capacity (kWh)	24	60	100	100	60	100	100	100	125	175
Pack Mass (kg)	295	434	723	723	288	481	481	481	601	841
Battery power, kW	100	170	386	568	170	386	568	170	386	568
Battery energy kWh	24	60	100	100	60	100	100	100	125	175
Number of cells per module	8	29	516	516	29	516	516	48	648	906
Number of cells in parallel	2	3	6	6	3	6	6	3	6	6
Number of modules in row	24	2	2	2	2	2	2	2	2	2
Number of rows of modules per pack	2	5	8	8	5	8	8	5	8	8
Number of modules in parallel	1	1	1	1	1	1	1	1	1	1
Battery Cathode Chemistry	LMO	NMC	NMC	NMC	NMC	NMC	NMC	NMC	NMC	NMC

The resulting breakdown of key materials are summarized in Table 32.2. Material LCIs were then obtained from the GREET 2017 model, and used to estimate the total energy and global warming potential for battery material production (measured in CO2 equivalents, or GHGs). We also conducted a sensitivity analysis on assumptions about battery assembly energy requirements (as measured by the kWh of energy input per kWh of usable storage) and pack energy density for the future vehicle case (Table S2.2). .

Table S4.2 Battery Material Composition by Scenario

	Leaf	EOV	PLS	PSUV	2025 EOV	2025 PLS	2025 PSUV	2025 LR-EOV	2025 LR-PLS	2025 LR-PSUV

Aluminum (%)	32%	22%	32%	33%	22%	32%	33%	28%	24%	24%
Graphite (%)	12%	20%	14%	13%	20%	14%	13%	27%	12%	12%
PVDF (%)	2%	2%	2%	1%	2%	2%	1%	3%	1%	1%
Binder (%)	2%	2%	2%	1%	2%	2%	1%	3%	1%	1%
Copper (%)	11%	12%	17%	20%	12%	17%	20%	4%	6%	6%
Electrolyte (%)	2%	11%	9%	9%	11%	9%	9%	5%	34%	34%
Steel (%)	9%	3%	0%	0%	3%	0%	0%	2%	4%	4%
Coolant (%)	0%	1%	4%	3%	1%	4%	3%	2%	4%	4%
Plastics	2%	2%	2%	3%	2%	2%	3%	3%	2%	2%
BMS	1%	0%	1%	1%	0%	1%	1%	0%	1%	1%
Cathode Active Material (%)	27%	24%	17%	15%	24%	17%	15%	23%	11%	11%

Table S2.3 and S2.4 show the results of the scenario based sensitivity analysis of battery production energy and GHG emissions. Under the high assembly energy scenario, total energy requirements and GHG emissions more than doubled. While the efficiency of production processes increases significantly, those gains are not sufficient to offset the increases in battery capacity.

Table S4.3 Battery Scenarios Sensitivity Analysis for 2025

	Leaf	**EOV**	**PLS**	**PSUV**	**2025 EOV**	**2025 PLS**	**2025 PSUV**	**2025 LR-EOV**	**2025 LR-PLS**	**2025 LR-PSUV**
Assembly Energy Low (kWh)	804	2,118	3,530	3,530	2,118	3,530	3,530	3,530	4,413	6,178
Assembly Energy High (100 kWh/kWh)	2,374	5,904	9,876	9,912	5,904	9,876	9,912	9,801	12,305	17,229
Assembly Low GHGs (kg)	420	1,108	1,847	1,847	1,033	1,722	1,722	1,722	2,152	3,013
Assembly High GHGs (kg)	1,242	3,089	5,167	5,186	2,879	4,816	4,834	4,780	6,001	8,402

Material GHGs	1,481	3,080	5,133	5,133	2,048	3,414	3,414	3,381	4,226	5,916

Energy inputs and GHG emissions from battery assembly are primarily attributable to environmental controls and formation cycling. We assumed a constant inventory for battery assembly energy based on electricity generation for industrial purposes in South Korea. If the primary energy source for battery assembly was changed, this could significantly impact the emissions attributable to battery assembly energy inputs.

Section S5. Vehicle Energy Demands

FASTSim is a system analysis tool by NREL to compare the drivetrain performance. The model was first verified by modifying the inputs for three vehicles of our focus and cross checking the resulting fuel economy values with the 2018 values reported by the EPA. The vehicle parameter inputs are provided in Table S3.1

Table S5.1 Vehicle Input Parameters for FASTSim

	2018				2025			2025 LR		
	PLS	**PSUV**	**EOV**	**Leaf (2012)**	**PLS**	**PSUV**	**EOV**	**PLS**	**PSUV**	**EOV**
Drag coefficient	0.24	0.25	0.308	0.315	0.24	0.25	0.308	0.24	0.25	0.308
Frontal area (m^2)	2.341	2.59	2.816	2.755	2.341	2.59	2.816	2.341	2.59	2.816
Curb weight (lbs) input to fastsim	4883	5421	3570	3433	4254	4792	3192	4784	5851	3616
Curb (kg)	2215	2459	1619	1557	1929	2173	1448	2170	2654	1640
Vehicle glider mass (kg)	510	723	503	763	630	844	575	535	652	498
Battery mass	766	766	460	290	481	481	288	601	841	481
Motor power (kW)	285	311	60	80	285	311	60	285	311	60
Battery power (kW)	300	327	160	86	300	327	160	325	350	200

Battery energy (kWh)	100	100	60	24	100	100	60	125	175	100

Section S6. Annual Vehicle Miles Travelled (VMT)

Two sets of scenarios for vehicle travel were developed: one, representing primary use in a personal passenger vehicle application (US Department of Transportation).; and two, representing use in a shared on-demand or potentially automated ride-hailing fleet. In all scenarios, annual VMT decreases as the vehicles age due to a variety of factors. Table S4.1 shows the assumed annual mileage for each scenario.

Table S6.1 Annual VMT by Vehicle Scenario

Vehicle Age	Gas Car	Gas SUV	HEV	EV Car	EV SUV
0	13467	14026	14199	12135	12638
1	13596	14227	13981	12251	12820
2	12092	12790	12953	10895	11525
3	12774	13594	13255	11510	12249
4	12896	13367	13448	11620	12044
5	12254	12974	12161	11042	11691
6	11860	12446	13809	10686	11214
7	11356	12445	11145	10232	11214
8	12345	12572	12185	11123	11328
9	11655	12799	12383	10502	11532
10	10319	11560	11490	9299	10417
11	10160	11506	11598	9155	10368
12	10624	10548	12733	9573	9505
13	9419	9863	9326	8488	8887
14	9195	11801	7593	8285	10633
15	8590	9783	12789	7740	8815
16	8817	8972	7993	7944	8085
17	8421	10245	7729	7588	9231
18	9133	9590	3002	8230	8641

19	8329	10004	4009	7505	9015
20	8072	9803	9547	7273	8833

Section S7. Electricity Generation

This section provides the complete results of the electricity generation analysis and the resulting forecast for grid carbon intensity. The study considered two regional scenarios: the California subset of the WECC region (CAMX) and a US national average. The study also considered two policy scenarios: a business as usual case and a carbon tax scenario with a $25 dollar per ton cost of carbon. The Annual Energy Outlook 2018 defines the Reference case in which: population (including armed forces overseas) grows by an average rate of 0.6%/year, nonfarm employment by 0.7%/year, and productivity by 1.6%/year from 2017 to 2050. The real gross domestic product increases by 2.0%/year from 2017 through 2050, and growth in real disposable income per capita averages 2.2%/year (U.S. Energy Information Administration, 2018).

For all scenarios, the study considered a time horizon from 2018 to 2050. Data on the net electricity generation by year by fuel source was obtained from the Annual Energy Outlook created by the Energy Information Administration. The AEO forecast is based on outputs of the National Energy Model, a large scale economic equilibrium model of energy supply and disposition (Gabriel et al., 2001).

The average net generation by fuel source is provided for a subset of years in Table S5.2.

Table S7.1 Average Net Generation by Fuel Source for Residential and Commercial End Uses

Scenario	Region	Fuel Source	2016	2020	2025	2030	2035	2040
Reference case	US-AVG	Coal	30%	28%	27%	26%	25%	24%
		Petroleum	1%	0%	0%	0%	0%	0%
		Natural Gas	34%	32%	33%	34%	34%	34%
		Nuclear	20%	18%	16%	15%	14%	14%
		Renewable Sources	15%	20%	22%	23%	26%	28%
		Other	0%	1%	1%	1%	1%	0%
	WECC-CAMX	Coal	5%	4%	0%	0%	0%	0%
		Petroleum	0%	0%	0%	0%	0%	0%
		Natural Gas	45%	33%	30%	27%	22%	20%
		Nuclear	10%	10%	5%	0%	0%	0%
		Renewables	40%	53%	65%	73%	78%	80%
$25 carbon allow	US-AVG	Coal	30%	20%	9%	3%	1%	1%

	Petroleum	1%	0%	0%	0%	0%	0%
	Natural Gas	34%	40%	40%	42%	42%	39%
	Nuclear	20%	18%	18%	17%	16%	16%
	Renewable Sources	15%	22%	32%	37%	40%	43%
	Other	0%	1%	1%	1%	1%	0%
WECC-CAMX	Coal	5%	0%	0%	0%	0%	0%
	Petroleum	0%	0%	0%	0%	0%	0%
	Natural Gas	45%	45%	30%	19%	14%	14%
	Nuclear	10%	9%	5%	0%	0%	0%
	Renewables	40%	45%	66%	81%	86%	86%

The average generation by fuel source data was combined with the life cycle emissions inventory data to estimate the emissions rates by year. For each fuel source, a regionally representative LCI was estimated using data from the GREET 1 model. Table S6.2 shows the estimated LCIs by fuel source and scenario. The final row of the table shows the estimated total greenhouse gas emissions of each kilowatt hour provided in carbon dioxide equivalents. A 100 year global warming potential is assumed, with characterization factors taken from the IPCC AR5.

Table S7.2 Life Cycle Inventory by Fuel Source and Regional Scenario

Flow	California (CAMX)				National Average (US-AVG)				Unit
	Coal	**Oil**	**Natural Gas**	**Nuclear**	**Coal**	**Oil**	**Natural Gas**	**Nuclear**	
Total energy	10751.1	12251.1	8402.1	3806.2	11560.4	12251.1	10246.5	3806.2	btu/kWh
Fossil fuels	10740.3	12178.1	8392.7	123.9	11548.7	12178.1	10234.9	123.9	btu/kWh
Coal	10527.7	38.7	3.9	13.8	11320.2	38.7	4.8	13.8	btu/kWh
Natural gas	43.2	832.2	8356.1	96.6	46.4	832.2	10190.3	96.6	btu/kWh
Petroleum	169.4	11307.3	32.6	13.6	182.1	11307.3	39.8	13.6	btu/kWh

VOC	0.1	0.1	0.1	0.0	0.1	0.1	0.1	0.0	g/kWh
CO	0.2	1.2	0.5	0.0	0.2	1.2	0.6	0.0	g/kWh
NOx	1.4	7.2	0.5	0.0	1.5	7.2	0.6	0.0	g/kWh
PM10	0.4	0.3	0.0	0.0	0.4	0.3	0.0	0.0	g/kWh
PM2.5	0.2	0.2	0.0	0.0	0.2	0.2	0.0	0.0	g/kWh
SOx	3.5	6.7	0.1	0.0	3.8	6.7	0.1	0.0	g/kWh
CH4	1.6	1.2	1.6	0.0	1.7	1.2	1.9	0.0	g/kWh
N2O	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	g/kWh
CO2	1069.2	1030.8	500.9	8.3	1149.7	1030.8	610.8	8.3	g/kWh
CO2 (w/ C in VOC & CO)	1069.8	1033.0	501.9	8.3	1150.3	1033.0	612.1	8.3	g/kWh
GHGs (CO_2e)	1114.0	1064.8	545.4	9.0	1197.9	1064.8	665.1	9.0	g/kWh

Finally, the estimated average carbon intensity of electricity generation for each year is provided in Table S6.3.

Table S7.3 Average Carbon Intensity of Electricity Generation by Year and Scenario

Year	California (CAMX)	US (Average)	CA ($25 C-tax)	US ($25 C-tax)
2017	296.7	525.1	297.4	522.2
2018	308.4	523.2	306.3	521.7
2019	297.1	506.5	299.5	502.1
2020	228.0	496.3	248.6	438.1
2021	216.5	485.5	220.4	408.3
2022	190.0	477.4	175.1	378.4

2023	160.3	479.6	167.6	356.2
2024	149.8	484.7	154.8	338.7
2025	166.0	487.7	163.5	322.1
2026	180.4	489.7	174.4	305.6
2027	174.7	488.1	155.0	288.7
2028	168.5	486.3	140.3	281.8
2029	161.1	485.8	125.2	278.0
2030	149.3	484.4	101.0	269.1
2031	135.0	480.8	85.2	263.9
2032	127.4	476.6	84.3	259.0
2033	123.2	473.0	82.2	254.6
2034	123.8	471.0	78.8	250.2
2035	120.8	467.0	77.8	246.7
2036	117.9	465.7	77.0	243.3
2037	114.7	463.3	77.0	240.1
2038	112.4	460.5	77.1	235.1
2039	112.8	458.3	75.2	231.0
2040	109.3	456.0	73.7	225.6
2041	108.8	454.1	72.4	220.0
2042	108.4	451.3	69.8	214.0
2043	107.2	449.3	69.8	211.4
2044	105.7	448.3	69.5	208.2
2045	104.0	445.9	69.6	204.7
2046	98.7	442.3	70.1	200.4
2047	97.1	440.0	70.5	196.3

2048	96.3	437.9	70.7	191.5
2049	96.7	437.0	70.4	185.5
2050	94.8	436.6	70.9	184.0

Section S8: Full Results

This section provides a table view of the complete results of the final GHG estimates.

Beginning on the next page, table S6.1 contains per mile GHG emissions attributable to vehicle and battery for each vehicle design scenario. The phase column corresponds with the key categories of emissions in producing the vehicle and battery system.

Table S6.2 shows the use-phase GHG emissions per mile for each vehicle and grid scenario. In addition to the results in the previous table, S6.2 adds the pre mile emissions rates for the three SAV scenarios. Use-phase emissions were estimated as a function of vehicle energy demands and electricity generation. The emissions rate decreases as the vehicle life decreases as the service life increases due to the (generally) decreasing carbon intensity of the grid. But the extent of this effect diminishes with the decreasing annual mileage.

Table S6.3 provides the total results, which are the sum of the vehicle and battery emissions with the use phase emissions. As such, the total results are presented by grid scenario and service life in years. Table S6.3 makes clear the key trend, namely the increasing share of production emissions in life cycle emissions and per mile emissions for passenger vehicles.

Table S8.1 Battery and Vehicle GHG Emissions (g CO_2-e / mile) by Vehicle and Utilization Scenario

	ICE LDV	ICE SUV	HEV	Leaf (2012)	EOV	PLS	PSUV	2025 EOV	2025 PLS	2025 PSUV	2025 LR-EOV	2025 LR-PLS	2025 LR-PSUV	SAV ICE-SUV	SAV HEV	SAV LR-EOV	SAV LR-PLS	SAV LR-PSUV
Body and Powertrain Materials	32.7	34.3	27.4	28.5	29.6	53.0	57.9	29.6	53.0	57.9	26.7	47.8	52.2	7.1	5.6	5.2	9.3	10.7
Glider Assembly	4.8	4.5	4.5	5.3	5.3	5.3	5.0	5.3	5.3	5.0	4.8	4.8	4.5	0.9	0.9	0.9	0.9	0.9
End of Life	1.4	1.4	1.4	1.6	1.6	1.6	1.5	1.6	1.6	1.5	1.4	1.4	1.4	0.3	0.3	0.3	0.3	0.3
Battery Materials	0.3	0.4	1.5	10.6	23.3	36.8	33.8	15.5	24.5	22.5	22.5	32.4	42.8	0.1	0.3	11.3	16.3	20.5
Battery Production				3.0	7.9	13.2	12.4	7.9	13.2	12.4	11.9	14.9	19.6			6.0	7.4	9.4
Use (12 years - USAVG)	420.9	462.5	301.2	169.9	161.0	206.9	218.4	150.4	167.1	195.0	156.0	189.4	222.8	462.5	301.2	176.9	219.2	257.6
Use (12 years - CAMX)	420.9	462.5	301.2	72.5	68.7	88.3	93.1	45.5	50.6	58.9	47.2	57.3	67.4	462.5	301.2	47.2	57.3	67.4

Table S8.2 Battery and Vehicle GHG Emissions (g CO_2-e / mile) by Vehicle and Utilization Scenario

	Grid Scenario	EOV	PLS	PSUV
2018	Average US Grid	255 - 215	360 - 295	374 - 306
	Average US Grid with $25 C-tax	231 - 173	329 - 241	341 - 249
	Average California Grid	167 - 119	246 - 171	254 - 175
	Average California Grid with $25 C-tax	168 - 115	247 - 166	255 - 170
2025	Average US Grid	235 - 198	303 - 245	335 - 273
	Average US Grid with $25 C-tax	171 - 131	233 - 171	253 - 187
	Average California Grid	131 - 92	189 - 128	201 - 136
	Average California Grid with $25 C-tax	122 - 82	178 - 116	189 - 122
2025 Long Range	Average US Grid	250 - 209	331 - 270	393 - 318
	Average US Grid with $25 C-tax	184 - 140	251 - 186	298 - 219
	Average California Grid	143 - 100	201 - 137	240 - 161
	Average California Grid with $25 C-tax	134 - 89	189 - 124	226 - 145

Table S8.3 Use-phase GHG Emissions by Grid and Vehicle Scenario

Grid Scenario	Service Life (Years)	Leaf (2012)	EOV	PLS	PSUV	2025 EOV	2025 PLS	2025 PSUV	2025 LR-EOV	2025 LR-PLS	2025 LR-PSUV	SAV LR-EOV	SAV LR-PLS	SAV LR-PSUV	Unit
CAMX	8	75.5	75.7	88.5	104.3	50.6	56.7	64.1	57.8	62.1	71.4	57.7	62.0	71.2	g CO2e/mile
CAMX	12	70.6	70.8	82.7	97.6	47.5	53.3	60.2	54.3	58.3	67.1	54.0	58.0	66.6	g CO2e/mile
CAMX	16	65.8	65.9	77.1	91.2	45.4	50.9	57.7	51.9	55.7	64.3	51.4	55.2	63.4	g CO2e/mile
CAMX	20	62.2	62.4	73.0	86.5	44.0	49.3	55.9	50.2	53.9	62.3	49.5	53.2	61.1	g CO2e/mile
USAVG	8	165.2	165.6	193.6	227.6	157.9	177.0	199.6	180.4	193.6	222.4	180.3	193.6	222.4	g CO2e/mile
USAVG	12	164.3	164.8	192.6	226.4	156.4	175.3	197.7	178.7	191.8	220.4	178.5	191.7	220.2	g CO2e/mile
USAVG	16	163.3	163.8	191.5	225.1	155.1	173.8	196.1	177.1	190.1	218.6	176.9	189.9	218.1	g CO2e/mile
USAVG	20	162.2	162.7	190.2	223.7	153.9	172.5	194.7	175.8	188.7	217.0	175.3	188.2	216.2	g CO2e/mile
CAMX-$25C	8	76.3	76.5	89.4	105.4	41.0	45.9	52.0	46.8	50.3	57.9	46.7	50.1	57.5	g CO2e/mile
CAMX-$25C	12	69.2	69.4	81.1	95.8	36.8	41.3	46.8	42.1	45.2	52.2	41.7	44.8	51.4	g CO2e/mile
CAMX-$25C	16	61.8	62.0	72.5	86.0	34.5	38.7	44.0	39.4	42.3	49.0	38.8	41.7	47.9	g CO2e/mile
CAMX-$25C	20	56.9	57.1	66.8	79.5	32.9	36.9	42.0	37.6	40.4	46.8	36.8	39.5	45.4	g CO2e/mile
USAVG-$25C	8	141.4	141.8	165.8	195.2	91.9	103.0	116.2	105.0	112.7	129.5	104.9	112.6	129.3	g CO2e/mile
USAVG-$25C	12	129.3	129.7	151.6	178.9	88.7	99.4	112.3	101.3	108.8	125.2	101.1	108.5	124.7	g CO2e/mile
USAVG-$25C	16	121.5	121.8	142.4	168.4	86.1	96.5	109.1	98.3	105.5	121.6	97.8	105.0	120.6	g CO2e/mile
USAVG-$25C	20	116.1	116.4	136.0	161.2	83.7	93.8	106.2	95.6	102.6	118.3	94.7	101.6	116.7	g CO2e/mile

Table S8.4 Total GHG Emissions by Grid and Vehicle Scenario

Grid Scenario	Service Life (Years)	Leaf (2012)	EOV	PLS	PSUV	2025 EOV	2025 PLS	2025 PSUV	2025 LR-EOV	2025 LR-PLS	2025 LR-PSUV	SAV LR-EOV	SAV LR-PLS	SAV LR-PSUV	Unit
CAMX	8	145	167	246	254	131	189	201	143	201	240	79	103	120	g CO2e/mile
CAMX	12	122	136	198	204	105	148	158	115	159	188	68	87	102	g CO2e/mile
CAMX	16	107	119	171	175	92	128	136	100	137	161	62	78	92	g CO2e/mile
CAMX	20	97	107	153	155	83	114	121	90	123	143	57	72	85	g CO2e/mile
USAVG	8	238	255	360	374	235	303	335	250	331	393	187	233	273	g CO2e/mile
USAVG	12	219	229	317	329	210	265	294	223	291	343	177	219	258	g CO2e/mile
USAVG	16	209	215	295	306	198	245	273	209	270	318	171	211	248	g CO2e/mile
USAVG	20	201	206	280	290	189	232	258	200	256	300	167	206	242	g CO2e/mile
CAMX-$25C	8	146	168	247	255	122	178	189	134	189	226	70	91	106	g CO2e/mile
CAMX-$25C	12	120	135	196	202	95	137	145	104	146	172	57	74	87	g CO2e/mile
CAMX-$25C	16	103	115	166	170	82	116	122	89	124	145	51	65	76	g CO2e/mile
CAMX-$25C	20	92	102	146	148	73	102	107	79	109	127	46	59	69	g CO2e/mile
USAVG-$25C	8	213	231	329	341	171	233	253	184	251	298	121	153	179	g CO2e/mile
USAVG-$25C	12	182	194	272	281	145	192	210	156	209	247	109	137	161	g CO2e/mile
USAVG-$25C	16	165	173	241	249	131	171	187	140	186	219	102	127	150	g CO2e/mile
USAVG-$25C	20	153	159	220	226	121	156	170	129	171	199	97	120	141	g CO2e/mile

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