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FINAL PROJECT REPORT

PLUG-IN ELECTRIC VEHICLE BATTERY RECYCLING SCALE-UP STRATEGIES FOR CALIFORNIA (2015-2050)

Logistics, Life-Cycle Environmental Implications, and Second-Life Potential

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PREFACE

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Plug-in Electric Vehicle Battery Recycling Scale-up Strategies for Califirnia (2015-2050): Logistics, Life-Cycle Environmental Implications, and SecondLlife Applications is the final report for the Strategies for Sustainable and Cost-effective Scale-up of Second-life, Recycling, and Disposal Pathways for PEV Battery Packs project (contract number PIR-12-015), conducted by Lawrence Berkeley National Laboratory. The information from this project contributes to Energy Research and Development Division's Transportation Program.

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ABSTRACT

Plug-in electric vehicle sales, while currently a small fraction of the total light-duty vehicle market, are increasing rapidly because of improving performance, decreasing costs, and incentives aimed at reducing greenhouse gases and reliance on petroleum. California leads the United States, accounting for almost one-third of national PEV sales. However, as these vehicles age, the number of used battery packs requiring end-of-life management will increase dramatically.

This report discusses the challenges and tradeoffs associated with end-of-life management strategies for plug-in electric vehicle batteries and the pace at which new collection, second-life, and recycling infrastructure must be scaled up in California to handle future numbers of retired battery packs. Researchers charted a path for scaling up plug-in electric vehicle battery second-life energy storage and recycling and quantified the economic and environmental tradeoffs of competing strategies by developing scenarios, using logistics and scale-up modeling, and assessing the recycling processes and second-life strategies of PEV batteries.

Results indicate California is likely to reach a sufficient battery pack disposal rate to justify a pilot-scale facility running at full capacity by approximately 2030. However, this rate may not justify a commercial-scale facility until after 2050. If batteries are routed to second life applications, they could play a modest role in achieving the state's stationary energy goals and, if paired with renewables, would reduce greenhouse gas emissions significantly by 2050. The tradeoffs between battery recycling processes are highly relevant to scale-up: while hydrometallurgy recovers a greater fraction of battery materials, pyrometallurgy may prove to be preferable in the face of small battery volumes and uncertain technologies because of its ability to accept a wider range of battery types.

This analysis will help state decision-makers develop long-term infrastructure for managing used batteries.

Keywords: batteries, recycling, second-life, pyrometallurgy, hydrometallurgy, plug-in electric vehicles, energy, greenhouse gas emissions, water, human health, cost, transportation, logistics, scale-up, life-cycle assessment, renewables, electricity, energy storage

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EXECUTIVE SUMMARY

Introduction

Plug-in electric vehicle (PEV) sales, while a small fraction of the light-duty vehicle market, are increasing rapidly because of improving performance, decreasing costs, and incentives aimed at reducing greenhouse gases (GHG) and petroleum use. Currently, batteries used in PEVs have a lifetime of 8-10 years; they still have significant capacity left for less demanding, second-life stationary energy storage applications after their capacity fades below acceptable levels. This second-life battery can be used in California's electricity grid for demand response and frequency regulation to help stabilize the network, or to support residential customers using off-grid solar arrays.

Recycling processes can reduce waste and recover valuable inputs once batteries are no longer suitable for these applications.

Project Purpose and Research

This project charted a path for scaling up PEV battery second-life energy storage and recycling methods, while quantifying the economic and environmental tradeoffs of competing strategies. Researchers developed and evaluated competing strategies for managing PEV batteries once they are no longer suitable for vehicle use. The research focused on four main components:

- Developing scenarios for PEV market adoption and battery disposal
- Infrastructure scale-up and logistics modeling
- Assessing PEV battery recycling processes
- Assessing PEV battery second-life strategies

Researchers developed PEV market adoption and battery disposal scenarios to estimate battery disposal rates by county through 2050 based on expected PEV market adoption rates and battery lifetimes. These scenarios provide reasonable limits for used battery availability for second-life applications and material recovery.

Infrastructure scale-up and logistics modeling used county-level data on used battery availability to determine collection, second-life, dismantling, and recycling locations and facility sizes. The analysis considered rail and road networks, comparing centralized and decentralized approaches to handling post-consumer batteries. Transportation distances and facility sizes are important factors to overall costs, energy inputs, and emissions of infrastructure scale-up.

The recycling process assessment also compared the two main battery recycling processes and includes collection, transportation, recycling inputs and co-products, and capital equipment. Both recycling processes are also compared with the no-recycling strategy for energy use, water use, GHG emissions, and criteria air pollutant emissions. The analysis also highlights the tradeoff between the range of battery types that can be processed in a single facility and the rate of material recovery.

Researchers also explored the net energy and environmental costs and benefits of using PEV batteries for second-life applications before routing them to recycling facilities. The second-life assessment models evaluated energy losses during charging and discharging, energy demand for cooling, energy required to transport batteries to second-life locations, expected energy capacity fade, and the potential net impact of additional energy storage on California's grid. The study identified the role post-consumer PEV batteries can have in achieving California's energy storage and GHG mitigation goals.

Project Results

PEV Adoption and Battery Disposal

- The number of PEV battery packs reaching their end-of-life is projected to show exponential growth through 2050.
- California is likely to reach a battery pack disposal rate sufficient to justify a pilot-scale facility running at full capacity by approximately 2030, but may not reach a level to justify a commercial-scale facility until after 2050.
- The most effective strategy for scaling up recycling may be to build a centralized facility that draws materials from multiple western states, including Oregon and Washington.

Infrastructure Scale-up and Logistics

- Car dealerships are probable candidates for collection locations for used PEV battery packs and will benefit from the ability to conduct basic battery health testing within their maintenance centers. This allows them to correctly diagnose problems and determine whether a battery pack should be sent out for refurbishment or reuse in second-life applications.
- The optimal number of dismantling facilities is two when only PEV batteries are recycled in-state. At these facilities, 50 percent of the battery pack's mass can be diverted to traditional recycling facilities.
- Although out-of-state recycling scenarios, including Arizona and Nevada, increase total transportation distances by a factor of three, the ability to use rail networks results in lower costs and GHG emissions relative to in-state scenarios that rely solely on trucks.
- If batteries are first routed to second-life applications where they are paired with solar and wind farms, the optimal recycling facility location would be nearly equidistant from San Francisco and Los Angeles. If batteries go straight from dealership collection points to recycling, the optimal location is closer to Los Angeles.

PEV Battery Recycling Scenarios and Life-cycle Assessment

- A comparison of hydrometallurgical and pyrometallurgical recycling on the basis of net energy use, criteria air pollutant emissions, GHG emissions, and water use shows that hydrometallurgical is more favorable in most categories, with the exception of water consumption and withdrawals.

- The tradeoffs between recycling processes are highly relevant to scale-up: While hydrometallurgy recovers a greater fraction of battery materials, pyrometallurgy may prove to be preferable in the face of small battery volumes and uncertain technologies because of its ability to accept a wide range of chemistries, including both lithium-ion (Li-Ion) and nickel-metal hydride (NiMH) batteries.
- Human health damages caused by emissions from truck transportation must also be considered. Truck transportation was responsible for the majority of criteria air pollutant-related damages associated with battery recycling: 99 percent of particulate matter (PM) damages; 54 percent of sulfur dioxide (SO_2) damages; and 62 percent of total volatile organic compound (VOC) damages.

Assessment of PEV Battery Second-life Potential

- The contribution of second-life batteries to meet energy storage and GHG mitigation goals is sensitive to the rate at which their capacity degrades. At this time, the late-stage degradation pattern of batteries is not yet quantified.
- Under base-case or initial modeling conditions, second-life use of retired PEV batteries in California has the potential to deliver 15 terawatt-hours per year (TWh/year) in 2050. This is about 5 percent of the 310 TWh/year total anticipated electricity production in 2050, representing a modest role in California's future energy system.
- The battery second-life analysis is projected to support and enable part of the increased production of intermittent renewable power by storing electricity produced during peak generation periods and later delivering it during peak demand periods. Other higher-value storage applications may be possible and should be considered in future work.
- Second-life battery use in California has the potential to reduce GHG emissions by about 7 metric tons of carbon dioxide emissions per year ($MtCO_{2e}$/year) in 2050, by displacing natural gas-fired electricity.

Project Benefits

This project provided new insight into the number of PEV battery packs that may reach their end-of-life through 2050, the location of these batteries, and a set of potential strategies for deriving additional value through second-life applications and material recovery. The analysis produced for this project will help decision-makers weigh the potential economic, energy, climate, and human health costs and benefits of centralized and decentralized strategies for managing used batteries, and plan for the state's long-term infrastructure needs.

CHAPTER 1: Introduction

1.1 Problem Significance

Plug-in electric vehicle (PEV) sales, while still a small fraction of the total light-duty vehicle market, are increasing rapidly because of improving performance, decreasing costs, and incentives aimed at reducing greenhouse gas (GHG) emissions and reliance on petroleum. PEV sales in the United States (US) increased by a factor of more than five between 2011 and 2013, from 18,000 to 100,000 vehicles per year (SAFE, 2014). By 2020, PEV sales are projected to account for 3 percent of total US vehicle sales (Electrification Coalition 2013). A recent report projected that PEVs will compose 30 percent of US light-duty vehicle sales by 2030, and 80 percent by 2050 (National Academy of Sciences, 2013). California leads the US, accounting for almost one-third of national PEV sales (UC Davis, 2014). California also has more than 2,000 public PEV charging stations, more than double the number in any other state and approximately 25 percent of the US total (SAFE, 2014).

Much of the prior research focused on PEV deployment is related to reducing battery upfront costs, facilitating PEV integration with the grid, and maximizing the net energy, carbon, and other environmental benefits during vehicle operation. Less attention has been paid to the fate of the batteries after they leave the vehicles. If the current California vehicle fleet were fully electrified, the resulting post-consumer battery flow would total roughly 900,000 metric tons per year, reversing progress that many California cities have made towards achieving strategic "zero waste" goals (Hendrickson et al., 2015; Zaman & Lehmann, 2013). Recent publications suggest that PEV batteries can be used in second-life stationary energy storage applications after their capacity fades below levels acceptable to drivers and, once batteries are no longer suitable for stationary applications, recycling processes can reduce waste and recover valuable inputs (Cready et al., 2003; Hendrickson et al., 2015; Dunn et al., 2015). However, little research has been devoted to understanding the challenges and tradeoffs associated with end-of-life management strategies for PEV batteries, and the pace at which new collection, second life, and recycling infrastructure must be scaled up.

1.2 Project Overview

This project mapped a path to scaling up PEV battery second-life energy storage and recycling, and quantifying the economic and environmental tradeoffs of competing strategies. The project focused on quantitative insight, and combines geographic information systems (GIS) and life-cycle assessment (LCA) to develop and evaluate competing strategies for managing PEV batteries once they are no longer suitable for use in vehicles. The research assessed four main components:

- PEV market adoption and battery disposal scenario development (Chapter 2)
- Infrastructure scale-up and logistics modeling (Chapter 3)

- Assessment of PEV battery recycling strategies (Chapter 4)
- Assessment of PEV battery second life potential (Chapter 5)

The PEV market adoption and battery disposal scenarios (Chapter 2) are formulated to provide projected battery disposal rates in California by county, based on expected PEV market adoption rates and battery lifetimes. These scenarios, while not meant to be predictive, provide reasonable bounds for expected used battery availability for second life applications and material recovery.

Infrastructure scale-up and logistics modeling utilizes county-level used battery availability data to determine collection, second life, dismantling, and recycling locations and facility sizes. The analysis presented in Chapter 3 compares centralized and decentralized approaches to handling post-consumer batteries using both rail and road networks, and reveals the importance of transportation distances and facility sizes for overall costs, energy inputs, and emissions.

Chapter 4 compares pyrometallurgical and hydrometallurgical recycling processes, including collection, transportation, recycling inputs and co-products, and capital equipment. These processes are also compared with a no-recycling strategy on the basis of energy use, water use, GHG emissions, and criteria air pollutant emissions. The analysis also highlights the tradeoff between flexibility in chemistries that can be processed in a single facility, and the rate of material recovery.

Chapter 5 explores the net energy and environmental costs and benefits of utilizing PEV batteries for second life applications before ultimately routing them to recycling facilities. By modeling energy losses during charging and discharging, cooling energy demand, energy required to deliver batteries to second life locations, expected capacity fade, and the potential net impact of energy storage on California's grid mix, this task quantifies the potential role that post-consumer PEV batteries can play in reaching California's energy storage and GHG mitigation goals.

1.3 Literature Review

1.3.1 PEV Market Adoption and Battery Disposal

Market adoption curves are widely used to predict growing market shares of new technologies, including pure electric and plug-in hybrid electric vehicles (McManus & Senter, 2009). Although many organizations make conservative linear projections for market growth (EIA, 2013), consumer choice modeling and past data generally indicates that new technologies generally follow an "s" or sigmoid curve, in which slow growth is followed by more rapid growth once critical mass is reached, followed by a slowing of growth as the market reaches saturation (Sullivan et al., 2014). This curve is the basis for the market adoption scenarios.

Fleet turnover models are also useful for a wide variety of applications including estimates of energy use, air quality impacts, and demands on road infrastructure. Fleet models also play a major role in the scenarios. Rather than track data collected on vehicles on the road, this project tracks vehicles as they are newly purchased, beginning with historical data from the 1970's and

extending to future sales projections through 2050. A set of governing equations can be employed to estimate the fraction of vehicles of a particular model year that are retired each year and the annual vehicle-miles traveled by vehicle age. The VISION model by Argonne National Laboratory is an excellent example of such a model, and many of the governing equations are based on those used in the VISION model (ANL, 2014a). However, existing fleet turnover models lack geospatial specificity; the focus has been almost exclusively on US national totals. This leaves a pressing need for state- and county-level estimates for purposes of charging, battery collection, and recycling infrastructure planning.

1.3.2 Infrastructure Scale-up and Logistics

GIS tools have been implemented in various applications in the past; for example, previous work has been done in the areas of resource assessment and facility location choice for analyzing bioenergy systems (Western's Governors Association, 2008; Graham et al., 2000; Kaylen et al., 2000). Location-allocation models have also been used as a tool for public facilities planning with the goal of minimizing transportation distances (Yeh & Chow, 1997). Corbett et al. prepared a Geospatial Intermodal Freight Transportation (GIFT) model for the California Air Resources Board and the California Environmental Protection Agency that describes the energy and environmental impacts of goods movement through California's intermodal transportation systems (Corbett, 2010). This analysis builds on the previous GIS optimization work by adding the capability to estimate the corresponding economic costs, energy use and GHG emissions, and county-level human health damages.

1.3.3 PEV Battery Recycling

Researchers used LCA to quantify the environmental impacts of lithium-ion battery (LIB) production and recycling. LCA is a holistic approach for analyzing all aspects of product or process's lifetime to fully determine the associated environmental implications. This method has been used often in the related LIB production and recycling literature, which is summarized in Table 1.

Table 1: Related Literature on LCA of LIB

Reference	Chemistries	Description
Samaras & Mesterling (2008)	NMC	Assessed and compared GHG emissions of four different plug-in/standard hybrid electric vehicles. Cradle-to-gate emissions for Li-ion battery manufacturing were taken from (Rydh & Sandén, 2005). PHEVs were found to reduce emissions by 32% when used in place of typical internal combustion vehicles. Batteries were found to contribute .01-.1% of total vehicle emissions.
Dewulf et al. (2010)	NMC	Compared differences in production of rechargable lithium-ion batteries from virgin materials and pyrometallurgically recycled materials, where material and exergy flow for recycling and production are deatiled. LCA results revealed that 140 MJ of exergy were saved in 1 kg of cathode production from recycled materials.
Dunn et al. (2012)	$LiMn_2O_4$	Examined the effects of three different vehicle battery recycling techniques (hydrometallurgy, indirect physical, direct physical) on energy consumption in battery production. It was found that significant reductions in consumption could be achieved using all three technqiues, but closed-loop recycling achieved the greatest savings in battery and cathode production.
Notter et al. (2010)	$LiMn_2O_4$	Developed a process-based model for assessing several environmental metrics of battery electric vehicles, focusing on cradle-to-gate contributions of vehicle batteries. Battery manufacturing was found to contribute 7-10% of energy demand and GHG emissions, where the active cathode materials accounted for roughly 20% of these impacts.
Majeau-Bettez et al. (2011)	NMC, LFP	This study assessed nickel metal hydride (NiMH) and Li-ion vehicle battery production. Life-cycle production numbers for Li-ion batteries were based on the same data source as Samaras and Mesterling (2008).LFP cathodes were found to have less environmental impacts based on 13 different metrics. The results for NCM batteries were significantly higher than those of Notter et al. (2010) and Dunn et al. (2012).
Ellingsen et al. (2014)	NMC	Assessed NCM Li-ion batter with a focus on using primary data from manufacturers and transparency in life-cycle inventory. Primary data was taken from Miljobil Grenland (EU li-ion battery manufacturer) for battery structure and production processes, where data gaps were filled from existing studies (Majeau-Bettez, Notter). Results were closer to those of Majeau-Bettez and Zackrisson than process-level studies of Notter and Dunn.

Reference	Chemistries	Description
EPA (2013)	$LiMn_2O_4$, LFP	Incorporated primary data from battery manufacturers and recycling centers, which was coupled with data from existing studies. Assessed the cradle-to-gate impacts of carbon nanotubes in anode production. Results were aggregated for three recycling technologies in order to protect propreitory data provided by industry representatives. Cradle to gate emissions are similar to those of Notter and Dunn.
Li et al. (2014)	NMC	Compared cradle-to-grave Li-ion vehicle battery impacts for eight different environmental metrics for graphite and silicon nanowire anodes. Recycling processes assumed no materials could be reused in batteries, where data was accessed from existing studies in a combination of physical, hydrometallurgy, and pyrometallurgy. Primary data for battery production was taken from laboratories and prototyping facilities. Results for GHG emissions and energy use in battery production were approximately double of that of Notter et al. (2010) for the graphite anode case.

Source: Lawrence Berkeley National Laboratory
Battery Chemistries are Denoted as $LiMn_2O_4$ (LMO), $LiFePO_4$ (LFP), $LiNi_4Mn_4Co_2O_2$ (NMC).

1.3.4 PEV Battery Second Life

Various authors have explored different aspects of second-life PEV battery use, especially economic issues. In a pioneering study, Cready et al. (2003) considered the techno-economic potentials of using retired PEV batteries for a variety of second-life applications, identifying 4 promising candidates: transmission support, light commercial load following, residential load following, and distributed node telecommunications backup power. They observed that major uncertainties exist regarding the performance and life span of used PEV batteries. Narula et al. (2011) conducted an economic analysis of PEV batteries used for a variety of second-life applications, assuming a fixed (either 5- or 10-year) service life. They found marginal economic benefits for single-use applications, through results improved with multiple simultaneous applications, e.g. area regulation; transmission and distribution upgrade deferral; and energy time shifting. Neubauer & Pesaran (2011) assessed the economic impact that second-life battery use may have on initial PEV costs. They found the benefits to be relatively minor, and strongly dependent on the battery degradation profile and on the specific second-life application. Williams & Lipman (2012) analyzed the potential economic impacts of second-life battery use, finding modest but positive economic benefits of second-life battery use. The benefits were strongly affected by the extent to which multiple services (e.g. area regulation, and transmission and distribution upgrade deferral) could be obtained from the batteries, and by costs associated with potential power-conditioning requirements. Heymans et al. (2014) studied the economics of second-life battery storage in the context of the Canadian electricity supply system, finding marginal feasibility without economic policy incentives. Ambrose et al. (2014) considered the potential for retired PEV batteries to provide electricity storage for rural micro-grids in

developing regions, concluding that second-life lithium-ion batteries may be price competitive with new lead-acid batteries, while potentially delivering improved performance.

Fewer studies have considered the environmental or energetic implications of second-life battery use. Ahmadi et al. (2014) estimated the potential CO_2 emission reduction of using repurposed vehicle batteries to store off-peak electricity in Canada, thus avoiding natural gas-fired peak generation. Faria et al. (2014) conducted an environmental assessment of second-life PEV battery use for electricity peak shaving and load shifting, based on grid characteristics of several European countries. Both studies found that GHG emission reduction from second-life use depends strongly on the emission intensity of the electricity sources involved. However, the studies assumed fixed values for uncertain system parameters including battery degradation and capacity thresholds of first- and second-life use, and did not comprehensively explore the sensitivity of the results to potential variation of these parameters.

CHAPTER 2:
PEV Adoption and Battery Disposal

2.1 Background and Objectives

Recovering some Li-ion battery components, and even remanufacturing or refurbishing used batteries for reuse in automotive or stationary applications, can slow the disposal of batteries and generate additional value for vehicle owners and utilities. Developing a roadmap for building the infrastructure necessary to process used batteries and divert them to appropriate uses requires some information about expected PEV market adoption and battery disposal rates in coming decades. Market adoption of PEVs is arguably the greatest source of uncertainty in projections of transportation-related electricity demand, battery recycling needs, and availability of PEV batteries for second life applications. External factors such as gas prices, high-occupancy vehicle (HOV) lane access, tax rebates, vehicle purchase costs, and availability of charging infrastructure all play a role in determining which consumers will choose to purchase a PEV. Researchers applied a fleet turnover model, combined with sigmoid market adoption curves, to estimate low, mid, and high cases for PEV adoption and resulting used battery generation. This analysis developed a range of possible quantities of used batteries generated annually across California and in individual counties.

2.2 Methods

The fleet turnover model combines vehicle sales in California, beginning with historical data and ultimately shifting to market projections, with vehicle retirement curves to determine the number and age of automobiles on the road at any given time. This base case scenario is then combined with sigmoid PEV adoption curves that predict sales in terms of the share of overall automobile sales in California. Although previous studies use a sigmoid curve to model the total number of PEVs sold, this approach prevents the model from ever assuming PEV sales exceed total automobile sales. Using PEV sales and retirements, researchers are able to track battery packs through their lifetime in vehicles and project the number of batteries requiring end-of-life management each year.

2.2.1 Adoption and Disposal Curves

Automobile sales data and projections are provided by US census region and vehicle type in the Energy Information Administration's (EIA) 2013 Annual Energy Outlook. US census regions are comprised of collections of states; California belongs to the Pacific region, which also includes Washington, Oregon, Hawaii, and Alaska. Sales were allocated to individual counties based on county-level population projections (Zarnoch et al., 2010). The downside of this approach is that differences in vehicle ownership (and thus sales) among counties are not accounted for. However, because the model is entirely sales-based, county-by-county differences in vehicle ownership could not be accounted for without county-level sales data.

Researchers applied the PEV adoption curve to the entire California market, and then distributed sales among counties based on characteristics such as high-occupancy vehicle

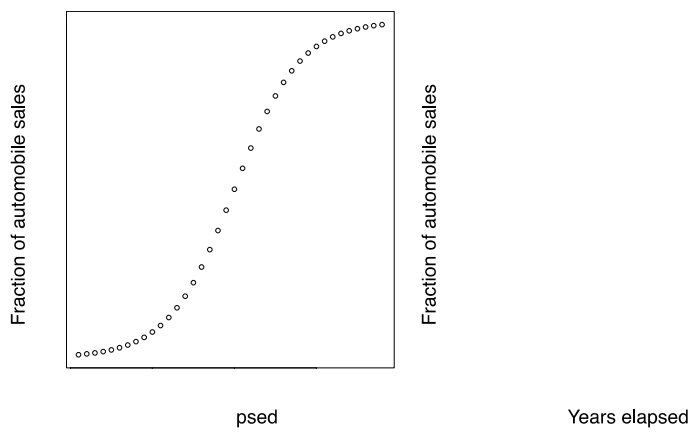
(HOV) lane access, charging infrastructure, and affluence. Equation 1 is used to approximate the proportion of California passenger car sales that are PEVs between 2014 and 2050. To avoid allowing small fractions of vehicles to survive indefinitely on the road, all cars from a particular model year are assumed to have retired after 36 years. This assumption also prevents the scenario from requiring sales data from years too early for reliable data collection. With a 36-year maximum lifetime, sales data incorporated into the scenario begins in 1978.

Equation 1: PEV Sales Penetration

$$P(t) = \frac{1}{1.41(1 + e^{-0.25t+5})}$$

where P = the fraction of automobile sales comprised of PEVs and t = years elapsed since 2014.

Figure 1: Low, Mid, and High PEV Market Adoption Curves



Source: Lawrence Berkeley National Laboratory

As vehicles are retired due to age, collisions, or other failures, new vehicles enter the passenger car fleet. Equation 2 presents the model that defines the fraction of new vehicles purchased during a particular year that remain on the road after a given number of years. This model is based on conventional passenger cars, but is applied to all cars in the scenario, including PEVs and flex-fuel vehicles. The functional life of LIBs that are used in PEVs is not well understood. Battery replacement was assumed to be more cost-effective than full vehicle replacement. replacement batteries are expected to be comparable to the vehicle's original battery, and, aside from the possible need for battery replacement, PEVs are not expected to have substantially different lifetimes than conventional vehicles. Regional variations in vehicle retirement rates were not accounted for. Across California, these differences are unlikely to be important, but harsh winters in some parts of the US might result in substantially different vehicle lifetimes.

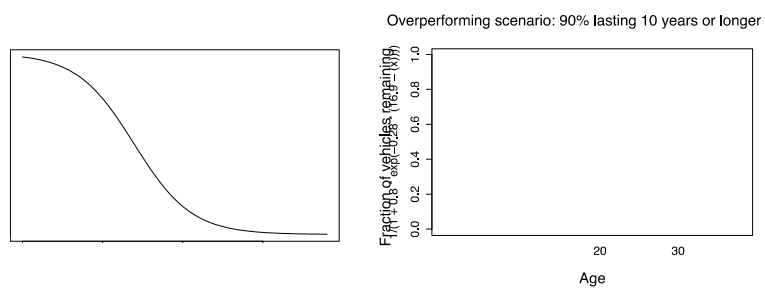
Equation 2: Fraction of Vehicles Remaining on the Road (FVR)

$$FVR(a) = \frac{1}{1 + e^{-0.28(16.9-a)}}$$

where a = vehicle age in years (Scown et al., 2013).

The next crucial step in the project was to translate market adoption scenarios into battery disposal estimates. Researchers used logistic curves to represent the fraction of batteries remaining after a given numbers of years beyond its initial purchase date; these curves are simply scaled versions of Equation 2. In the default scenario, 75 percent of batteries last 10 years or longer. The "underperforming" scenario has only 60 percent of batteries lasting 10 years or longer, and the "overperforming" scenario has 90 percent of batteries lasting 10 years or longer. Cars, however, may outlast their batteries, so new batteries were assumed to be purchased for cars that remain on the road, but whose batteries have reached their end-of-life. However, cars within 2 years of their end-of-life were assumed to retire early rather than have a new battery installed. It is possible that older batteries can be refurbished to last only a few years for a lower price than a new battery, which would make it possible to further extend the life of such cars.

Figure 2: Battery Disposal Curves for PEVs - Underperforming, Default Scenario, and Overperforming



Source: Lawrence Berkeley National Laboratory

2.2.2 County-level Projections

On a national level, California is an early-adopter state for a number of reasons: the state has aggressive zero emission vehicle (ZEV) sales goals, a relatively large network of charging stations, and progressive environmental policies (McManus & Senter, 2009). Within California, regional variations in PEV adoption can also be expected because of differences in affluence, charging infrastructure, incentives, and driving behavior. Appendix A shows the categorization for each county in California, such that adoption group 1 is comprised of the earliest PEV adopters while adoption group 5 are the latest adopters. As discussed in Scown et al. (2013), the results of such a categorization are largely consistent with the regional differences in hybrid electric vehicle (HEV) adoption.

Researchers matched counties with metropolitan statistical areas (MSAs). Some cities have instituted local policies such as HOV lane access for PEVs and initiatives for constructing charging stations; these cities are categorized as "early-adopter MSAs" and are put in adoption

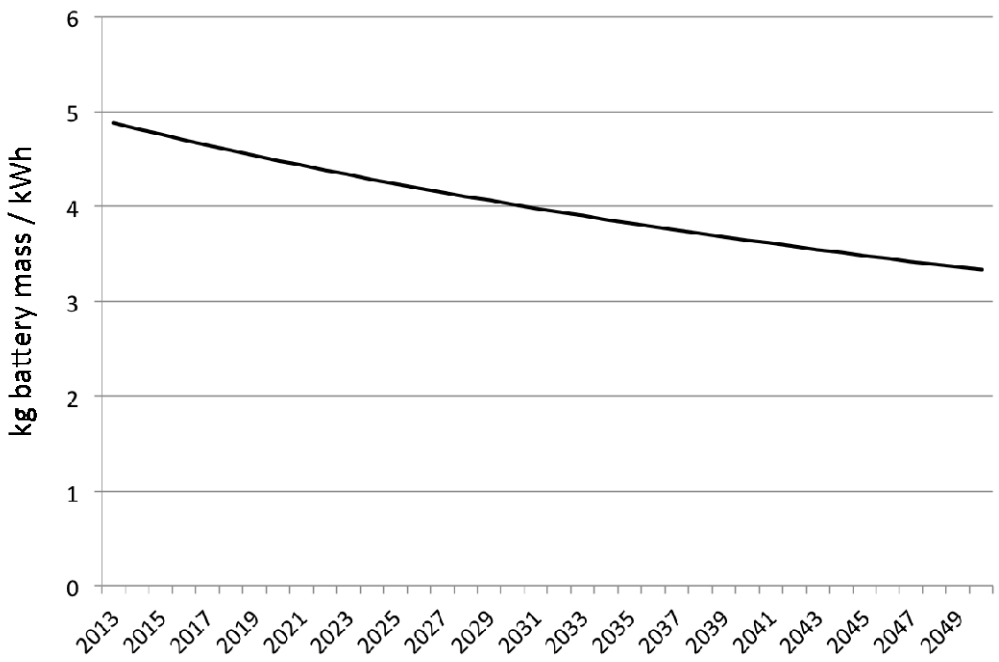
group 1; they are responsible for the majority of very early growth in PEV sales. Although affluence is not taken into account, these tend to include either large and/or very affluent cities. Alameda, Contra Costa, Los Angeles, Marin, San Francisco, and San Diego Counties, for example, are all within early-adopter MSAs. Because of the higher upfront cost associated with PEVs, and the advantages of living in a home with access to charging (either in a garage or other dedicated parking spot), affluence is expected to be major factor in determining where PEVs are adopted early on. Counties in the 80th percentile or above nationally in terms of median income are categorized as adoption group 2, if they have not already been included in group 1. Most of California's affluent counties are already included in group 1, so group 2 includes a small collection of counties such as Santa Clara, Napa, and Solano. Counties with a median income in the 70th percentile nationally or greater are categorized as group 3, if they have not already been included in previous groups. Sonoma, Yolo, Santa Cruz, and San Benito Counties, for example, fall into this group. Counties between the 50th and 70th national median income percentile fall into adoption group 4, and those below the 50th percentile are in group 5, which consists primarily of rural/agricultural counties.

The year in which each adoption group enters the PEV market is largely arbitrary and acts as a parameter that can be used for sensitivity analysis. Currently, group 1 begins purchasing new PEVs in 2014 (current year), group 2 begins purchasing PEVs in 2020, group 3 joins the market in 2022, group 4 joins in 2025, and group 5 joins in 2035. Upon reaching the year in which the group joins the PEV market, its share of sales growth is proportional to its population during that year. Allocating new sales growth, rather than total new sales, by population prevents the projection of decreases in PEV sales in earlier-adopting counties when new counties begin purchasing PEVs.

2.2.3 Vehicle Range and Battery Technology Projections

There are two additional factors that must be accounted for to estimate the total mass and energy storage capacity available from used batteries disposed each year: expected PEV battery storage capacity projections and the energy density of those batteries. (Kassakian et al., 2013) project modest decreases in mass of battery required per kWh of energy storage capacity between now and 2050, reaching around 3.3 kg/kWh by 2050 down from nearly 5 kg/kWh currently (see Figure 3). Battery range estimates were taken from Scown et al. (2013).

Figure 3: Energy Density Projections for PEV Batteries

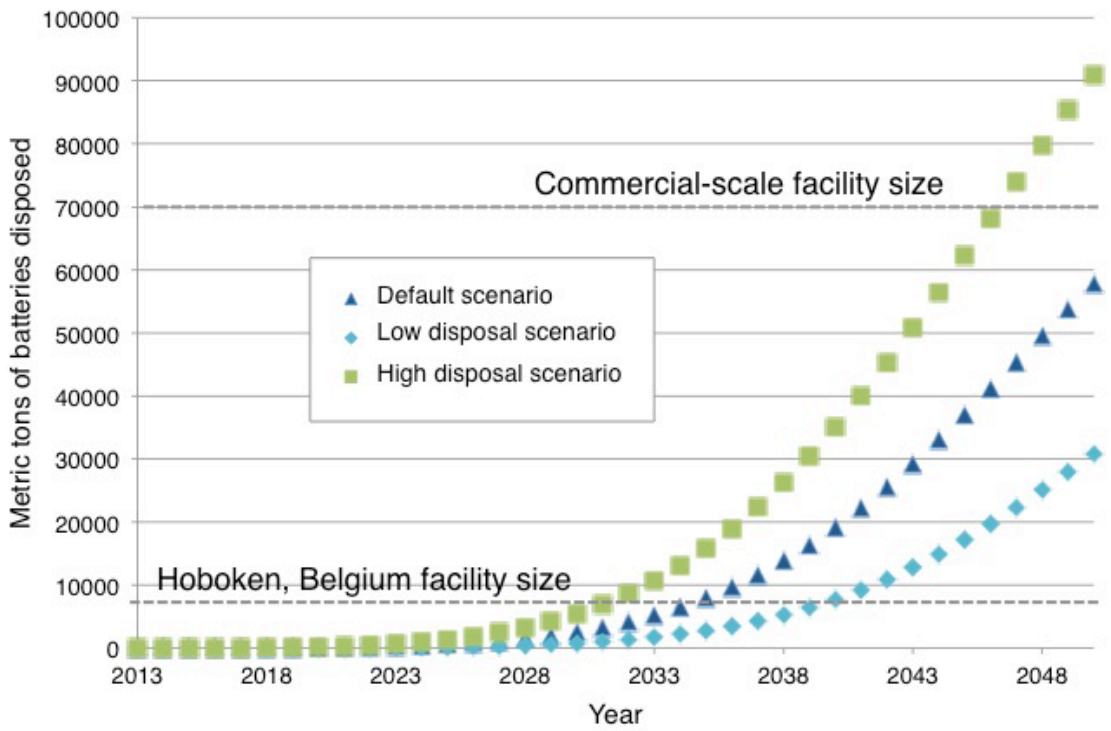


Data source: Kassakian et al. (2013)

2.3 Results and Discussion

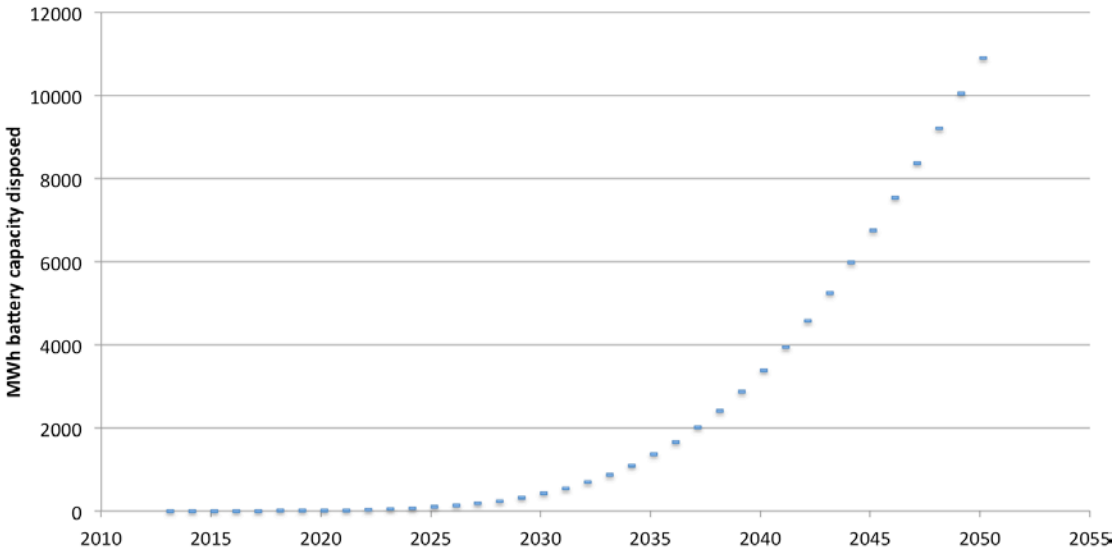
The results for the mass of batteries disposed each year through 2050 are shown in Figure 4. Umicore has provided two recycling facility benchmarks: a 7,000 annual metric ton pilot facility (with their Hoboken, Belgium facility as an example) and a 70,000 annual metric ton facility as the commercial-scale goal. The results indicate that California will reach a disposal rate sufficient to justify a pilot-scale facility running at full capacity by approximately 2030, but may not reach 70,000 metric tons per year until after 2050. This implies that the most effective strategy for scaling up recycling may be to build a centralized facility that draws from multiple western states, including Oregon and Washington.

Figure 4: Mass of Lithium-ion Batteries Projected to be Available for Recycling/Disposal by Year in California



The disposal scenarios also provide researcgers with insight into the potential for battery second life energy storage. By 2050, Californians alone may be generating more than 10 GWh-worth of energy storage capacity, after accounting for the degradation of batteries during their life in automobiles (see Figure 5). The key to understanding the value of this storage is a better understanding of how Li-ion batteries degrade over time with different cycling, such as the cycling required for peak-shaving or other grid services. This is an area of ongoing work, and one that requires additional time and expertise to fully address.

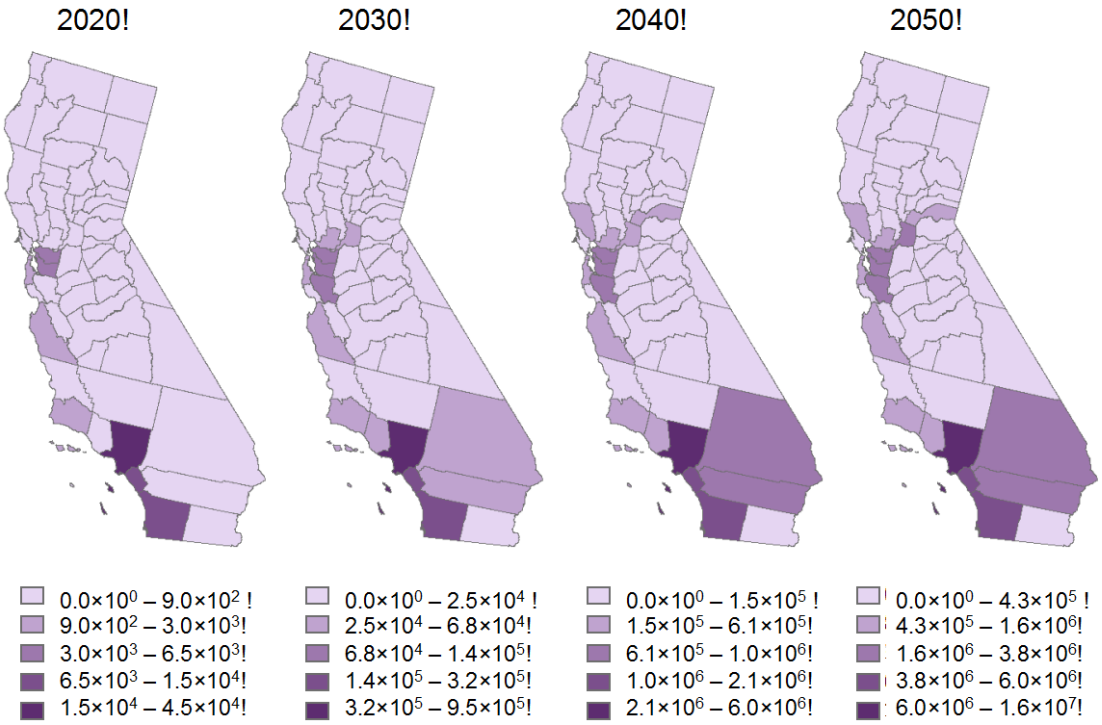
Figure 5: Quantity of PEV Batteries Projected to Reach Their End-of-Life Annually by Remaining Energy MWh Storage Capacity (default scenario)



Source: Lawrence Berkeley National Laboratory

Results of these scenarios by county for 2020, 2030, 2040, and 2050 are shown in Figure 6. Although the San Francisco Bay Area is responsible for a large proportion of early PEV sales, the difference in population between the Bay Area and Los Angeles result in more PEVs sold in Southern California. The Central Valley, including Sacramento, gains a substantial share of PEV sales by 2040.

Figure 6: Distribution of PEV Batteries Disposed Annually in California (number of batteries)



Source: Lawrence Berkeley National Laboratory

CHAPTER 3:
Infrastructure Scale-up and Logistics

3.1 Background and Objectives

As PEV adoption increases, there are concerns about the amount of waste generated at the end-of-life stage. Battery recycling has energy and economic incentives as it can contribute to a 48 percent reduction on the overall energy intensity of Li-ion battery production (Dunn et al., 2012). The environmental impacts of the transportation processes are only now beginning to be evaluated in a systematic way that values their importance. Freight transport and supply chain logistics should be evaluated holistically based on the economic and environmental costs using a life cycle assessment. New analytical methods that include data management techniques and computing need to be developed in order to improve planning and decision making for new industries that rely on efficient logistics (Corbett et al., 2010). Geospatial models allow the decision makers to quantify the environmental costs of the freight transport, compare alternatives and evaluate the impacts of their decisions.

This report addresses the task of understanding potential strategies for scaling up the battery recycling industry in California, given the projected market adoption and the disposal rates of the batteries. From the analysis, it is clear that the process of collecting and transporting the disposed batteries contributes substantially to the overall costs and GHG footprint of battery recycling. It is particularly important to accurately estimate the transportation impacts and to be able to calculate the total embodied distance across the supply chain. The battery recycling logistics need to be evaluated based on the spatial distribution of the facilities and capital costs, allowing the identification of optimal strategies for minimizing the GHG emissions and costs of the battery recycling industry.

This project's purpose is to develop geospatial freight transportation models to simulate the transportation between battery collection, disassembly, reuse and recycling sites and optimize the transportation logistics procedure. The project utilizes California-specific data and inputs for calculating the economic costs and GHG emissions associated with batteries movement through California's highway, and rail systems. The project is implemented in Geographical Information System (GIS) that integrates different modal networks (railway and highways) and contributes to improved decision making associated with the recycling process of batteries of EVs at a state level. Specifically, the model evaluates:

- GHG footprint and economic costs associated with the transport and processing of Li-ion automotive batteries during their second life applications and end-of-life in California and,
- Optimal locations and sizes of dismantling and recycling infrastructure.

This project develops a methodology that combines optimization methods and spatial analysis tools available through GIS into several integrated models for the transportation of PEV batteries during their recycling process. The desired outcome is a transportation cost-

minimizing system that enables users to analyze both cost and environmental impacts of the battery movement during end-of-life. The models use geographic data to locate the optimal infrastructure sites and the best routing option for the transportation sector. The corresponding outcomes are described by the location, size and types of required infrastructure as well as the most appropriate means of transportation regarding each available scenario.

3.2 Methods

The GIS modeling methodology was designed to estimate the economic costs, GHG emissions, and human health impacts associated with the supply chain of the PEV batteries during their end-of-life. Recognizing the value of other GIS-based freight analysis tools, this project integrated economic and environmental attributes into network analysis in GIS (Corbett, 2010). This study developed an algorithm for geospatial optimization using a location-allocation methodology in GIS that integrated economic and environmental performance measures associated with current freight flows into the segments of the network. The optimization process was based on the minimization of the total ton-kilometers transported between the collection points and the final recycling destination. This is the appropriate objective function to minimize, as the economic and environmental costs correspond to the total distance traveled by applying specific metrics and emission factors.

Two alternative scenarios were developed to illustrate the end-of-life options after the batteries have reached the threshold point of not being able to be used in vehicles. The first scenario considered direct recycling of their batteries after their first use whereas the second one included possible second life applications of the batteries before their final recycling.

To model the supply chain, researchers created a network dataset in an ArcGIS software environment to calculate the transportation distances and corresponding costs. Data on California's highway network, railway network, and other required data such as locations of major cities and train stations, and borders of counties and census tracts, were sourced from federal sources including the US Department of Commerce and the US Census Bureau (US Census Bureau, 2013). Geographically explicit car dealership locations were acquired from the Data Lists website (Data Lists, 2014).

The optimization models consider the spatial distributions of the collecting, dismantling, reuse and recycling facilities and find the best design for the recycling supply chain. The goal of the models is to optimize the facility locations in order to minimize the total transportation costs associated with battery dismantling and recycling. The models calculate both economic (total miles driven for fuel efficiency cost) and environmental (GHG emissions from the transportation) metrics for transportation. The collection points of the batteries were assumed to be car dealerships, as these locations are currently used for battery testing and take-back (Smith, 2014). For the facility optimization process, all California county centroids were considered as candidate locations, serving as approximation for the purposes of this analysis (Vidovic et al., 2011). This is a generalization of the available location points, but serves as a useful approximation for the purposes of these models. An important feature of the model is that it allows the user to set the preferred distance of the recycling facility from big city centers;

placing facilities far away can minimize the health impacts from on-site emissions, while placing facilities within big cities may improve access to qualified labor force and critical infrastructure. The disposed battery mass was assumed to be equally distributed among the car dealerships in each county to avoid market projections and the total battery mass per county was based on future demand projection scenarios (Scown et al., 2013).

3.2.1 Recycling Logistics

This scenario illustrates the case where the PEV batteries are recycled directly after their first life. From the collection points, the batteries are transported to dismantling facilities for the second stage of the recycling process, where the separation of the non-hazardous materials for traditional recycling takes place. At this stage, approximately 50 percent of the battery mass is diverted to traditional recycling facilities, since only the hazardous components of the batteries must be sent to a centralized battery recycling facility (Spiers, 2014). Two main scenarios were selected as the most realistic versions of the recycling industry structure, in-state or out-of-state recycling. In-state recycling assumes that the recycling facility is located inside the state and can handle the amount of batteries disposed in the state. In the out-of-state recycling case the recycling facility is assumed to be in a different state to allow for more centralized recycling applications. In-state recycling can offer greater independence to the system and decrease the distance the batteries would need to travel for recycling. On the other hand, having out-of state recycling facilities would allow for larger centralized facilities with economies of scale and easier access to batteries and markets for recovered materials beyond the West Coast. The model performs an optimization for each scenario, in order to provide the optimal spatial distribution of the required infrastructure and calculates the associated transportation costs. Using a location-allocation network analysis in GIS, researchers located the optimal locations for the facilities. The distances are weighted by the mass of the batteries transported in order to provide reliable results for the entire system.

3.2.2 Second Life Logistics

In this scenario, the second life of the PEV batteries is taken into consideration before the final recycling. This scenario takes into account the need for energy storage, especially in areas with high renewable energy generation (solar and wind). The supply chain for this scenario follows the described flow. From the initial collection points the batteries are transported to the dismantling facilities to go through the first processing stage, where 10 percent of the battery mass is assumed to be diverted to traditional recycling (Spiers, 2014). The batteries are then transported to their final second life application locations, and at the end of their second life they are sent to the centralized battery recycling facility. Three alternative logistics scenarios for battery second-life use were modeled: decentralized solar, decentralized wind, and centralized wind/solar. The centralized scenario assumes that all the batteries are used in a single large facility in Kern County where the average solar and wind intensities are both greatest of all California counties. The decentralized solar and wind scenarios assume that quantities of second-life batteries are distributed to different counties in proportion to each county's resource intensity for solar and wind, respectively. The total resource intensity of each county was calculated according to the IPCC Report based on the Direct Normal Irradiance (DNI) (IPCC, 2011). Solar and wind intensity data were sourced from NREL (NREL, 2014a).

3.2.3 Human Health Impacts

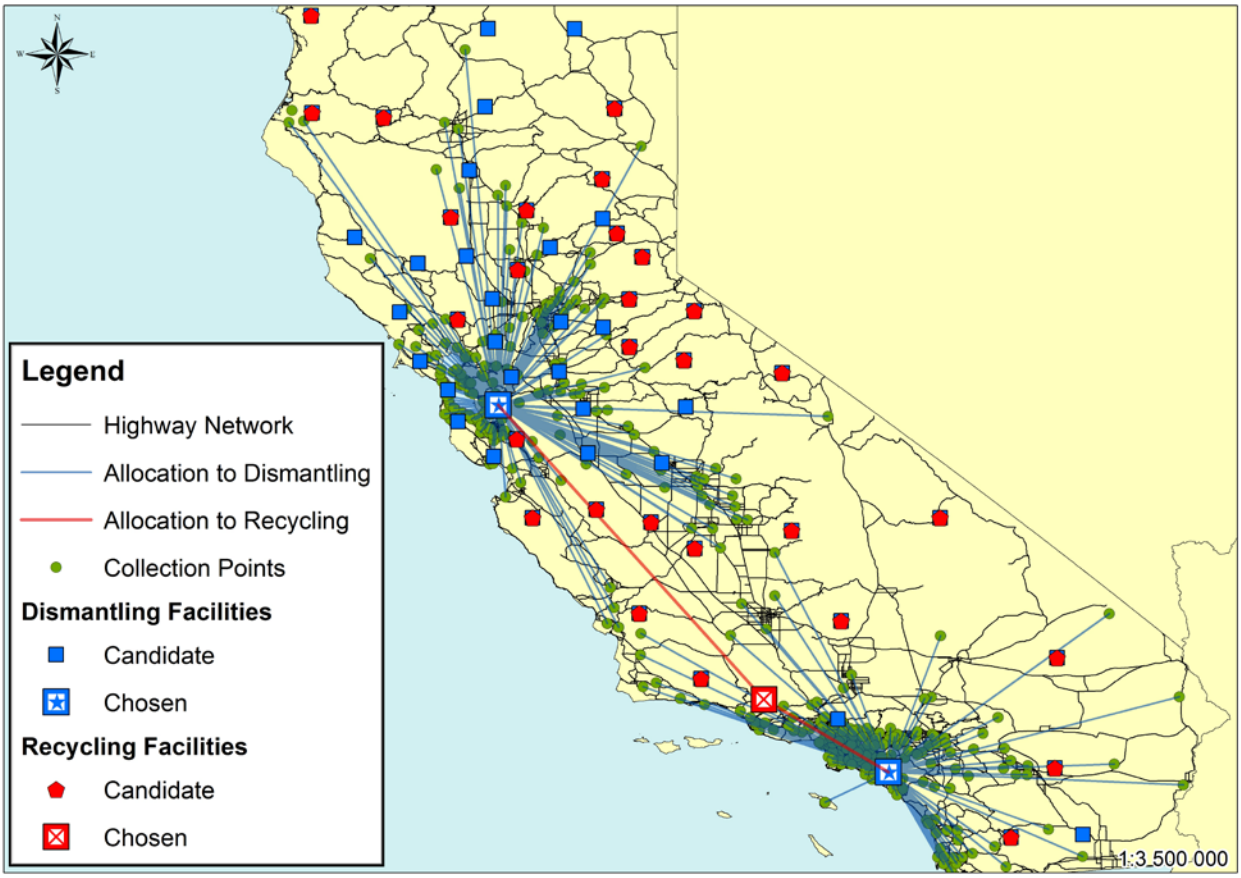
The results from the modeling process of the above scenarios were combined with the Air Pollution Emission Experiments and Policy model (APEEP) to determine the human health implications of the supply chain of the battery recycling process (Muller & Mendelsohn, 2006). The APEEP model estimates the health damages that occur from the emissions of SO_2, NOx, particulate matter (PM) and volatile organic compounds (VOCs). The air pollutant emissions that were taken into consideration were associated with the trucking and rail transportation from the GIS model, and the electricity consumption and on-site emissions of the pyrometallurgy facilities from the LCA model. Air pollutant emission factors for rail and truck transportation were taken from Carnegie Mellon's economic input-output LCA tool (EIO-LCA) (CMU, 2014). The emissions of the corresponding power plants that are responsible for the electricity production in California were also taken into consideration for the estimation of the health impacts. Ground-level emission sources were assumed for the calculations.

3.3 Results and Discussion

3.3.1 Optimal Infrastructure Scale-up

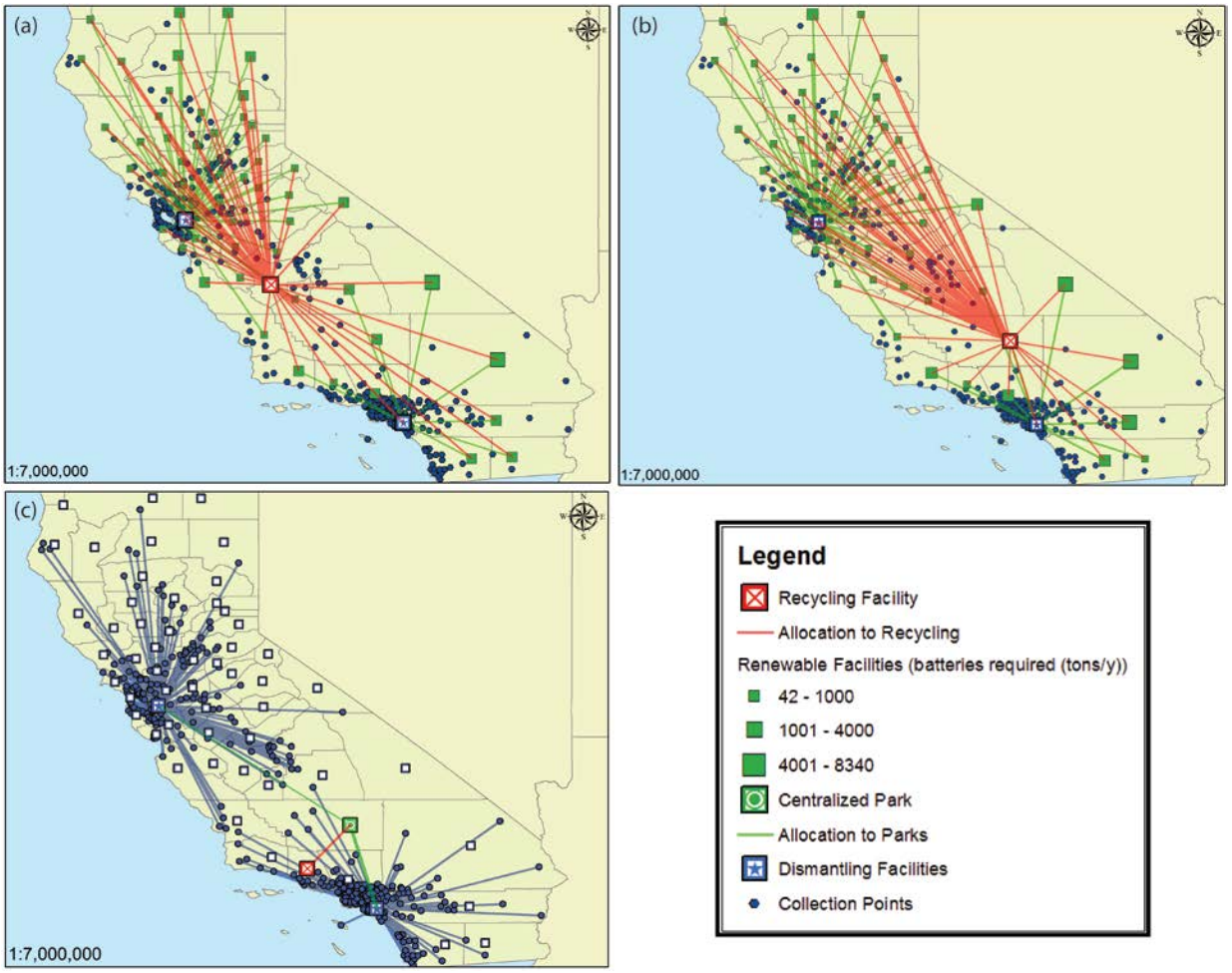
Using California-specific data, researchers calculated the optimal facility locations and the corresponding total ton-kilometers traveled for both direct recycling and second life applications scenarios. Figure 7 shows the candidate and chosen locations for dismantling and recycling facilities that were estimated by an algorithm developed by the researchers for direct recycling using only truck transportation. Figure 8 shows the candidate and chosen locations for dismantling and recycling facilities for the second life application scenario using truck transportation. The optimization model sited the facilities in close proximity to the clusters of the collection points, which is intuitive, as the objective function of the optimization was the minimization of total ton-kilometers transported from all collection points. The sensitivity analysis indicated that the economics are most favorable for two dismantling facilities and as expected, the model optimally located them close to San Francisco and Los Angeles, the state's two largest population centers. If a third dismantling facility is added, the model recalculates the transportation distances and divides the collection points into three clusters (San Francisco, Los Angeles, and Central Valley) in order to satisfy the new system optimal facility locations. The algorithms take into account the battery mass allocation at the collection points, which is why the optimal recycling facility is located closer to the cluster with the greatest number of dealerships and is not equidistant from both dismantling facilities. The allocation of battery mass at the collection points, the system-wide travel time minimization, and the siting criteria are some of the most important parameters that define the optimal locations of the facilities and allow for the calculation of the emissions and economic costs of the transportation system.

Figure 7: Candidate and Chosen Locations for In-state Direct Recycling Using Truck Transportation



Source: Lawrence Berkeley National Laboratory

Figure 8: GIS-Results for Three Different Second-life Application Scenarios: (a) Decentralized Solar, (b) Decentralized Wind, (c) Centralized Renewable



Source: Lawrence Berkeley National Laboratory

The energy and emissions intensities of transporting batteries to and from their locations of second-life use are shown in Table 2, based on results of the GIS analysis. This includes collection of the batteries from dealerships, distribution of batteries to the second-life site, and final transport from the second-life site to a recycling facility. The centralized renewable scenario requires the least energy use and emits the least GHGs, per ton of battery used in second-life applications. The decentralized solar scenario is most intensive, while the decentralized wind scenario is medium intensity. This has to do with the distribution of the batteries in each county based on the resource intensity of each.

Table 2: Energy and Emission Intensities of Transporting Batteries in Three Second-life Applications Logistics Scenarios

	Energy Use (MJ_p per ton of batteries)	Emissions ($kgCO_{2e}$ per ton of batteries)
Decentralized Solar		
Collection	151	11.2
Distribution	454	33.8
Recycling	639	47.6
Total	**1,243**	**92.6**
Decentralized Wind		
Collection	151	11.2
Distribution	423	31.5
Recycling	484	36.1
Total	**1,058**	**78.8**
Centralized Renewable		
Collection	151	11.2
Distribution	469	34.9
Recycling	260	19.4
Total	**880**	**65.5**

Source: Lawrence Berkeley National Laboratory

3.3.2 Cost and Emissions Calculations for Direct Recycling

Based on analysis of the in-state versus out-of-state recycling scenarios for direct recycling, the detailed results of the transportation costs and GHG emissions are shown in Figure 9. Two dismantling facilities were assumed for all the different scenarios and the optimal locations for all the facilities that were estimated from the model were used. The optimal locations for the dismantling facilities were the same in all scenarios, as the collection locations and their corresponding battery mass disposed were kept constant while the optimal location for the recycling facility was estimated for each scenario separately. For the rail transportation scenarios the locations of the freight railway stations were taken into account when estimating the optimal facility locations in order to accurately calculate the distance traveled by rail. In the out-of-state scenarios the recycling facility location was assumed to be the railway station that was closer to the state centroid in order to account for other parameters that would affect the siting decisions, such as imports from other states, which is outside of the scope of this paper.

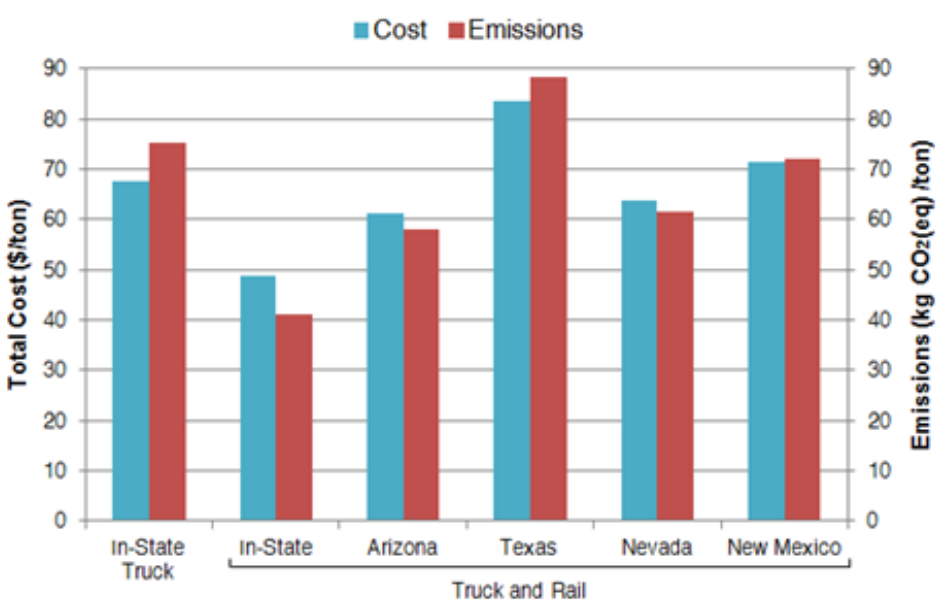
The capital cost of the facilities is estimated by scaling the original cost using an appropriate scaling factor (NREL, 2011), according to Equation 3. The applied scaling factor corresponds to the infrastructure scaling as capacity increases (Moore, 1959). This method, widely used in the literature, allows for a quick estimation of the capital cost, but has limitations considering the accuracy of the applied scaling factor (NETL, 2013). The cost estimate of the scaled facility is determined by the cost of the original facility using a scaling factor that corresponds to the category of the facility (NETL, 2013).

Equation 3: Capital Cost Scaling

$$New\ Cost = Base\ Cost * \left(\frac{Size(New)}{Size(Base)}\right)^{0.6}$$

The costs for loading and unloading, considered as bulk solids, were estimated to be $5/ton (Western Governors' Association, 2008). The distance-dependent costs were estimated at $0.21/ton-km for trucking and $0.03/ton-km for rail transportation (US DOT, 2014). The economic input-output life-cycle assessment model (EIO-LCA) is used as a data source as it provides a comprehensive LCA assessment for trucking emissions. The emission factors, used both in the GIS and LCA models, were assumed to be 294 gCO_{2e}/ton-km for trucking and 43 gCO_{2e}/ton-km for rail transportation (CMU, 2014). The effect of rail transportation was significant in the results as the overall costs and GHG emissions for in-state transportation decrease by 12 percent and 45 percent respectively when rail was considered. This effect is substantial in the transport to Arizona or Nevada in out-of-state scenarios, as the costs remain the same and the emissions decrease by 23 percent compared to the in-state trucking option, even though the total miles traveled are 3 times higher when traveling to Arizona or Nevada.

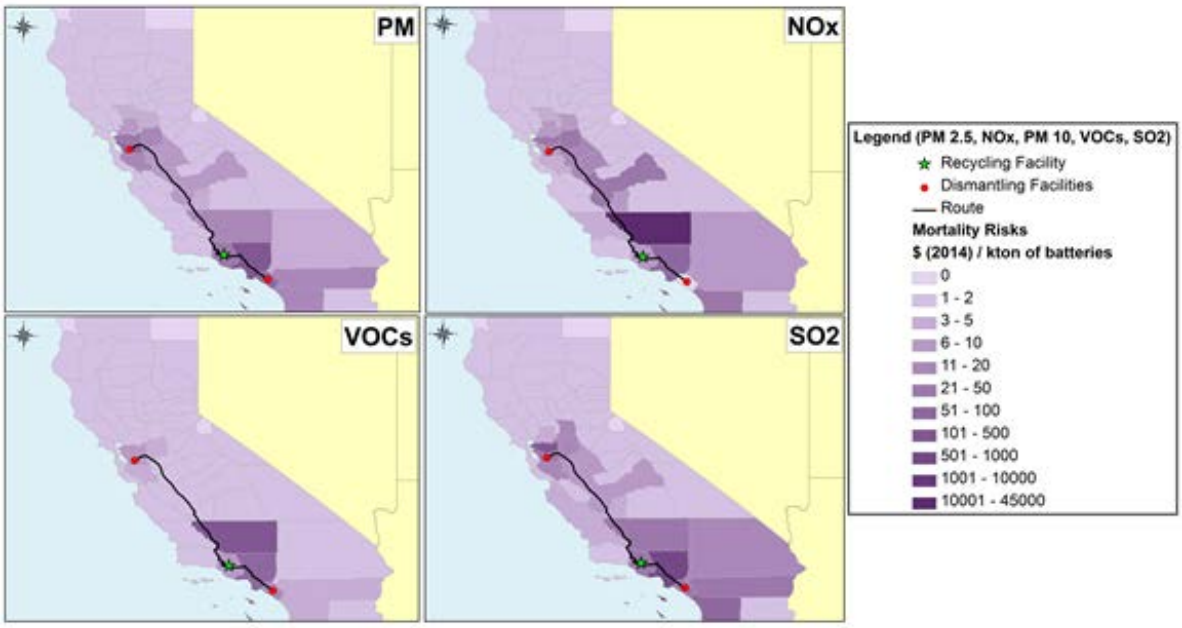
Figure 9: Transportation Costs and GHG Emission Metrics for In-state and Out-of-state Scenarios



3.3.3 Human Health Impact Results

By combining the transportation distances from the GIS model with the air pollutant on-site emissions and electricity use from the LCA modeling, researchers calculated the health impacts using the APEEP model. The APEEP model estimates the mortality risk, which is referred to as the value of statistical life (VSL), and assigns an economic value to each county to represent that effect (Muller & Mendelsohn, 2006). The results shown in Figure 10 are based on the optimal facilities locations and truck transportation routes for the direct recycling scenario. For the in-state scenario, freight trucks were the main source of PM, SO_2 and VOCs, which were consequently highest in counties along the shipping routes for used LIBs. NO_x emissions, which were mainly attributable to the pyrometallurgy facility, peaked in counties around the location of the facility. Air pollutants from the electricity generation were assigned to the existing power plant locations distributed throughout the state and their effect is based on each county's mortality risk parameters. Currently, trucks provide the primary mode of transportation for used batteries, so the corresponding health impacts were estimated assuming a business as usual (BAU) case (Spiers, 2014). As illustrated in Figure 10, most health impacts occur in Kern and Los Angeles counties because of their higher population density, topography, and large share of total distance traveled. Aside from NO_x health damages, which were mostly attributable to the pyrometallurgy facility (96 percent of total), truck transportation was responsible for the majority of criteria air pollutants: 99 percent of PM damages, 54 percent of SO_2 damages, and 62 percent of total VOC damages. The pyrometallurgy facility was responsible for 37 percent of the total VOC health damages and the electricity generated for pyrometallurgy processing accounted for the bulk of remaining SO_2 health damages (45 percent). The pyrometallurgy recycling process emitted a negligible amount of SO_2 on-site as a lime-scrubbing process controls these emissions.

Figure 10: Spatial Distribution of Human Health Impacts of In-state Recycling for Trucking Transportation



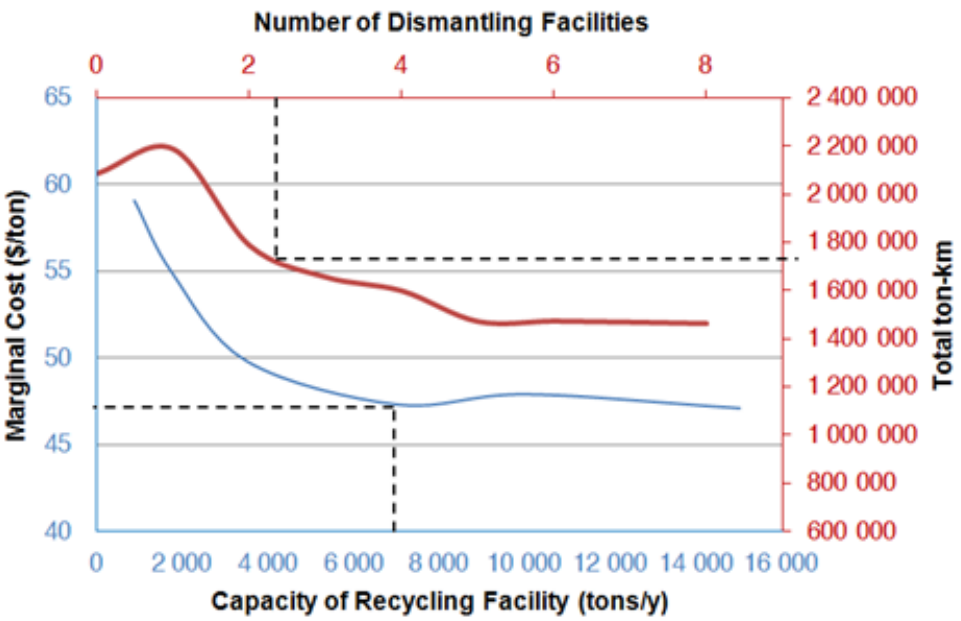
Source: Lawrence Berkeley National Laboratory

3.4 Sensitivity Analysis

Intuitively, more collection and recycling points in a system would yield greater transportation cost savings as the total ton-kilometers traveled are minimized. However, an increased number of facilities lead to greater capital costs. Considering such a tradeoff, it is important to examine the connections between capital and transportation costs.

Sensitivity analysis can provide insights into the tradeoffs between transportation cost savings and capital expenditures, yielding an optimal number of facilities (NETL, 2013). The relationship between transportation costs and the number of dismantling facilities is highlighted in Figure 11. There is a drop-off in the total ton-kilometers traveled when two dismantling facilities exist in the system. Beyond that point, the curve reflects a flatter relationship with the transportation distances. Similar curves were found for out-of-state recycling scenarios as well. A sensitivity analysis was also used to determine the effect of the battery mass transported in relation to the marginal cost for the industry (Figure 11). That analysis gave an exponential curve with the optimal recycling facility size of 7,000 tons/yr, which translated to a marginal cost of $34/ton (includes capital and transportation cost). The battery mass used in this study (7,000 tons/yr) was validated by the industry as it is the capacity of Umicore's facility (Caffarey, 2014) and it was used in the rest of the analysis to calculate the corresponding costs and emissions.

Figure 11: Sensitivity Analysis of Relation between the Number of Dismantling Facilities and Total Ton-kilometers Traveled (Red Curve), and between Capacity of Recycling Facility and Marginal Cost (Blue Curve), for In-State Recycling Using Truck Transportation

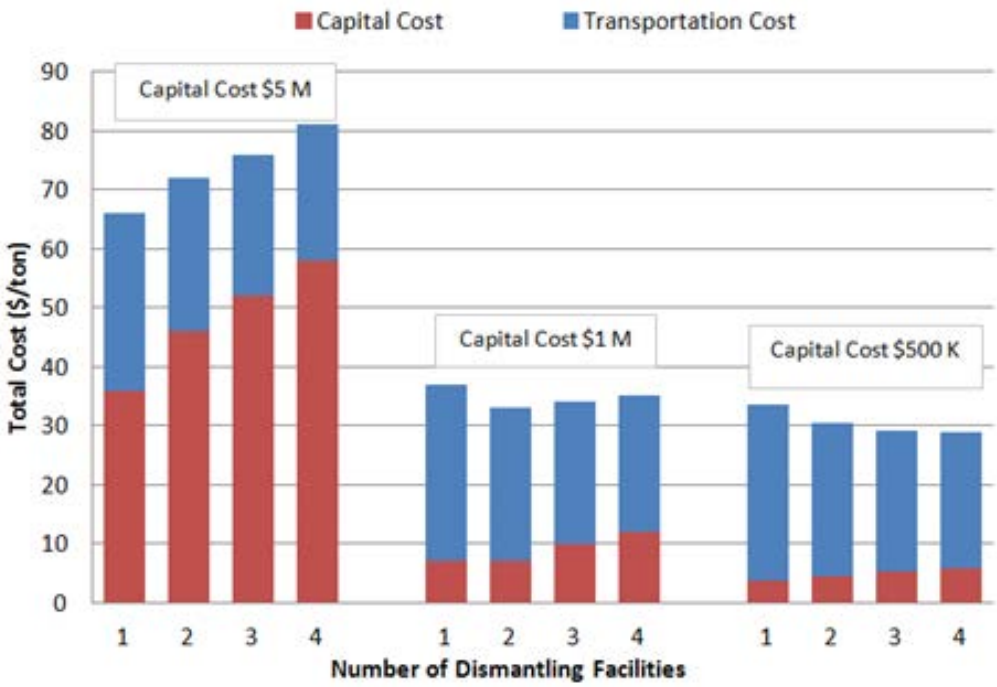


Source: Lawrence Berkeley National Laboratory

The capital cost of the facilities was calculated based on a facility's original cost and capacity by applying an appropriate scaling factor to vary the cost by size. This factor approximates the effects of economies of scale (Moore, 1959). In this case a scaling factor of 0.6 was used reflecting the use of the facilities. This general method, widely used in the literature, allows for a quick estimation of the capital cost, but contributes a degree of uncertainty to the results because it is not tailored specifically to the investments required for battery recycling (NETL, 2013). Two other cost components were taken into consideration: a loading/unloading cost and a distance-dependent travel cost.

Because the capital cost of the infrastructure is uncertain, a sensitivity analysis was run to determine the optimal number of dismantling facilities in the system for different capital costs. Assuming a capital cost of $1 million in Figure 12, which was used in this study as indicated by industry feedback (Caffarey, 2014), there is a threshold in the number of facilities in the system and the most cost effective option is using two dismantling facilities.

Figure 12: Sensitivity Analysis of the Relation between the Capital Cost of Infrastructure and Number of Dismantling Facilities for In-state Recycling Using Truck Transportation.



Source: Lawrence Berkeley National Laboratory

When capital costs are significantly higher ($5 million), minimizing the number of dismantling facilities is the most cost-effective option as facility capital costs are the driver of total costs. The opposite stands for a very low capital cost where it can be neglected in comparison to the transportation costs.

CHAPTER 4:
PEV Battery Recycling Scenarios and Life-cycle Assessment

4.1 Background and Objectives

California currently lacks the infrastructure to manage LIBs at their end-of-life, and the supporting supply chain growth must comply with GHG emission restrictions (CARB 2011). The state also presents unique environmental challenges, as the impact of water use and criteria air pollutant emissions can vary significantly across the region. To fully understand the implications of scaling up PEV recycling in California, decision makers must be equipped with models that provide likely infrastructure build-out scenarios for battery collection, dismantling, and recycling, accounting for complete life-cycle environmental implications.

To accomplish this, researchers assessed the available recycling technologies and supporting infrastructure on the basis of environmental and economic criteria. Using state-specific data, researchers employed geospatial modeling to create scenarios for projected LIB waste streams and determine optimal dismantling and recycling facility locations for both in-state and multi-state systems. LCA was used to assess hydrometallurgy and pyrometallurgy recycling systems, resulting in new factors for life-cycle GHG emissions, primary and secondary energy demand, water use, and criteria air pollutant emissions. Hydrometallurgy is a more specialized, chemistry-specific process capable of recovering lithium and aluminum in addition to higher-value metals. Pyrometallurgy is a flexible process, capable of accepting a wide variety of LIB chemistries in a single facility, as well as nickel metal hydride (NiMH) batteries, that focuses on recovering only high-value materials including nickel, cobalt, and copper; unrecovered materials are incorporated into slag that can be sold as a cement supplement (Ellis and Mirza, 2011; EPA 2013).

4.2 Methods

4.2.1 Battery Production Life-Cycle Assessment

Performance characteristics of the Nissan Leaf battery (24 kWh capacity) are used as a general industry proxy in determining the full theoretical battery design for three LIB chemistries (LMO, LFP, NMC) (Nissan USA, 2014). Argonne National Laboratory's Battery Performance and Cost tool (BatPaC), which generates LIB material needs based on real world data, was used to model anode and cathode materials requirements (ANL, 2014b). The mass distribution for the remaining battery components are taken from standard values in Argonne's Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET2) tool, which estimates environmental outputs and resource requirements for electric vehicles (ANL, 2013a). The total masses for the three different electrode chemistries analyzed in this study are found to be 191 (LMO), 183 (LFP), and 167 (NMC) kg.

For LIB production, researchers expanded on the related LCA literature by including new environmental criteria results for battery production in primary and secondary energy sources,

water consumption, and water withdrawals for LMO, LFP, and NMC chemistries. Appendix B shows the sources used in the LIB production LCA.

Electricity mixes for production wae based on the GREET2 defaults, with aluminum smelting based on the average California mix (Gursel and Custodio, 2014). Transportation emission/consumption factors are taken from Carnegie Mellon's EIO-LCA model (CMU, 2014). Transportation distances for all materials other than cathodes are assumed to be 50 miles of road and 50 miles of rail. LMO cathode transportation is included in the GREET2 tool (ANL, 2013a). For LFP and NMC cathodes, where production was assumed to occur in South America, transportation distances are assumed to be 8,000 miles water freight, 50 miles road, and 50 miles rail.

4.2.2 Battery Recycling Life-cycle Assessment

This study characterizes the material flows and emissions for LIB recycling, with a focus on hydrometallurgical and pyrometallurgical recycling. Hydrometallurgy is a chemical leaching intensive process used to separate and refine materials with the capability of capturing both valuable metals and lithium. This process is currently under development for commercial use (Dunn et al., 2012). Pyrometallurgy uses a kiln firing process followed by leaching to recover slag and valuable metals. As discussed previously, existing literature has analyzed hydrometallurgy, but this study expands on those results by including separate energy sources, water use, and criteria air pollutants for LMO batteries using life-cycle emission factors from GREET2 and Scown, including recycling materials production, process demands, and recovered material benefits (ANL, 2013a; Scown, 2010).

Pyrometallurgy offers an economical method for material recovery in reducing solid waste flows from PEV LIB use, provided enough high-value materials can be recovered. Industry practitioners of pyrometallurgy maintain that this process has the potential for economical material recovery for a large array of electrode chemistries without significant alterations to the method (Caffarey, 2014). This characteristic is crucial for LIB recycling processes that must adapt to evolving technologies. The single-stack method offers economic advantages over hydrometallurgy in avoiding high operational costs and complexities (Cheret & Santen, 2007). However, challenges exist for pyrometallurgy with chemistries such as LMO, where the active materials are relatively cheap and recycling for reuse is not currently economical (Gaines, 2014).

The pyrometallurgy inputs and emissions were calculated based on Umicore's patented one-stack technique, where alloy outputs are refined using leaching. Typically, industrial pyroprocessing is completed using two smelting stacks, or furnaces, where pyrolyzing occurs in the first stack and smelting in the second stack. This requires high capital and operational costs. The Umicore technique avoids this by combining plastic pyrolyzing, smelting, and reduction into one stack. This is achieved by adding charges of slag, limestone, and sand with the batteries. Coke is the predominant fuel used in heating the smelting stack. The pyrolysis of plastic adds heat to the process while reducing fuel needs (Cheret & Santen, 2007; ANL, 2012).

Previous work has analyzed pyrometallurgy, but used general industry averages in applying values to LIB recycling (ANL, 2012). In this study, life-cycle emission and consumption factors

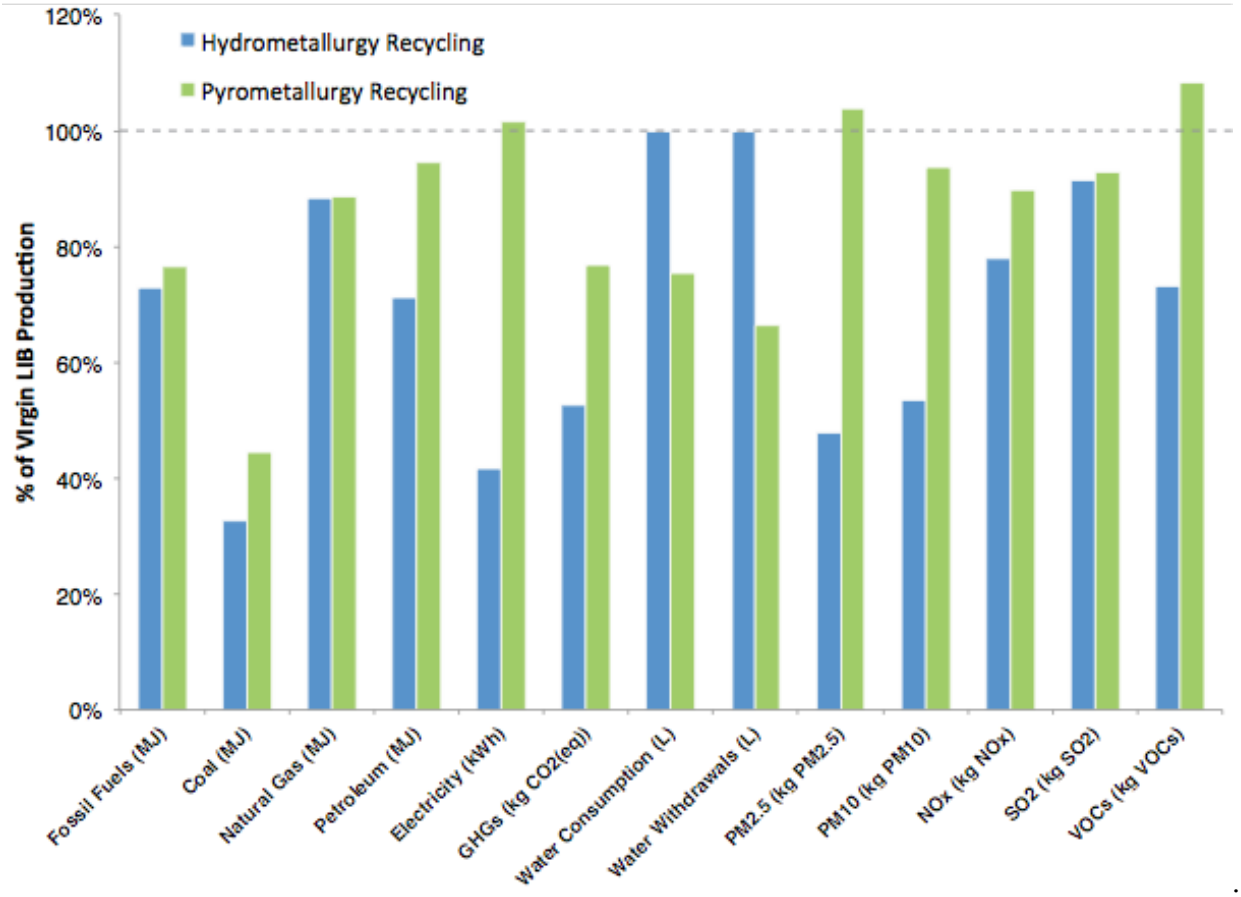
are calculated based on the material inputs, recycling processes, slag outputs for cement use, and materials recovered. Life-cycle pyrometallurgy emission factors are quantified for primary and secondary energy consumption, GHG emissions, water use, and criteria air pollutants. Appendix C details the inputs, outputs, and sources used in determining the life-cycle environmental impacts of pyrometallurgical battery recycling.

Total pyrometallurgy results are based on the assumption that 50 percent of Cu, Ni, and Fe are recovered and are used to offset virgin production of these materials. The NMC battery includes cobalt recovery at 25 percent. All slag produced in the recycling process is assumed to be processed and used as a cement substitute. The results are calculated per unit mass of battery for the Umicore samples, and then applied to the individual battery results. Pyrometallurgy electricity mixes are based on the California average for use in the GIS model in Chapter 3 (Gursel and Custodio 2014). Transportation for coke and limestone is based on the assumption of 50 miles road and 50 miles rail transport. Transportation of batteries to the recycling facility is based on GIS model results.

4.3 Results and Discussion

Figure 13 shows the LCA production and recycling results for the LMO battery. The hydrometallurgy results reflect the recycling process emissions and consumption factors from customizing GREET2 to separate primary and secondary energy sources. Based on the potential material recovery, pyrometallurgy can offer advantages in water use due to recovered steel and copper. Water use in recycling processes was not captured in the modeling. Hydrometallurgy recovers copper and aluminum, but GREET2 does not account for hydrometallurgy specific values for recycling these materials (ANL, 2013; Dunn et al., 2012). Hydrometallurgy recycling values were assumed to be similar to the industrial processes available in GREET2, and account for recovered steel and aluminum in LIB recycling. Hydrometallurgy achieves greater energy savings, especially in electricity consumption whereas pyrometallurgy has a high electricity demand due to recovered slag processing for use as a supplement for cement. Air pollutant and GHG emissions are also higher in pyrometallurgy due to coke production and combustion. On-site SO_2 emissions from pyrometallurgy are controlled using a limestone sulfur scrubbing system.

Figure 13: Resource Use and Environmental Emissions of Battery Production and Recycling (Using Hydrometallurgy and Pyrometallurgy)



Source: Lawrence Berkeley National Laboratory

Researchers benchmarked their LCA results against the existing literature in Table 3. The significant variation of results in these studies is due to differences in battery design, assessment scopes, and supply-chain processes (i.e., transportation and battery assembly). Recent studies have focused on nanotechnologies in anode production, which offer higher energy densities for battery operation but require greater inputs for production (EPA, 2013; Li et al., 2014). This study shows similar results to Dunn et al., whose authors also developed the GREET2 model (Dunn et al., 2012; ANL, 2012). This study utilized a fully optimized battery design that minimized economic costs in production, driving the lower energy consumption in Table 3 (ANL, 2014b).

The recycling results of three studies are shown in Table 3. The greater recovered energy in the EPA study is due to the direct physical recycling process that was included, where electrode materials can be recovered and reused without any further processing. NMC energy recovery in this study was greater than the other two chemistries because cobalt was recovered in the pyrometallurgy recycling process (Cheret & Santen, 2007).

Table 3: Comparison of Energy Results with Existing Literature

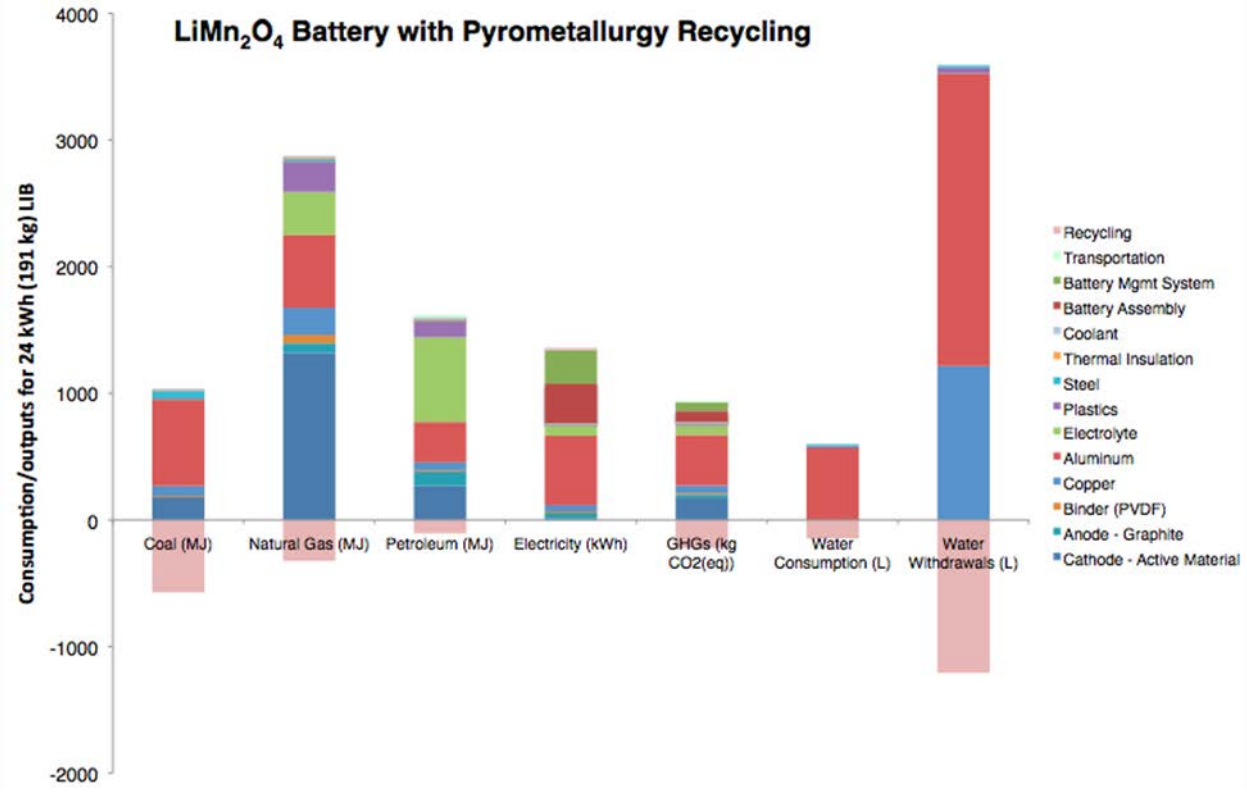
	Embodied Energy (MJ/kg)					
	LMO Battery		LFP Battery		NMC Battery	
Study	**Virgin LIB Production**	**Recycling**	**Virgin LIB Production**	**Recycling**	**Virgin LIB Production**	**Recycling**
Dunn et al. (2012)[a]	74	-5	-	-	-	-
Notter et al. (2010)	104	-	-	-	-	-
EPA (2013)[b]	220	-31.9	541	-70.5	435	-64.7
Majeau-Bettez et al. (2011)	-	-	165.9	-	169.5	-
Li et al. (2014)	-	-	-	-	290.2	-
Dunn et al. (2015)	74	-	80	-	110	-
This Study[c]	54.1	-6.5	64.4	-6.5	70.4	-12.2

[a]Hydrometallurgy recycling values, [b]Average of hydrometallurgy, pyrometallurgy and direct physical recycling values, [c]Pyrometallurgy recycling values.

Source: Lawrence Berkeley National Laboratory

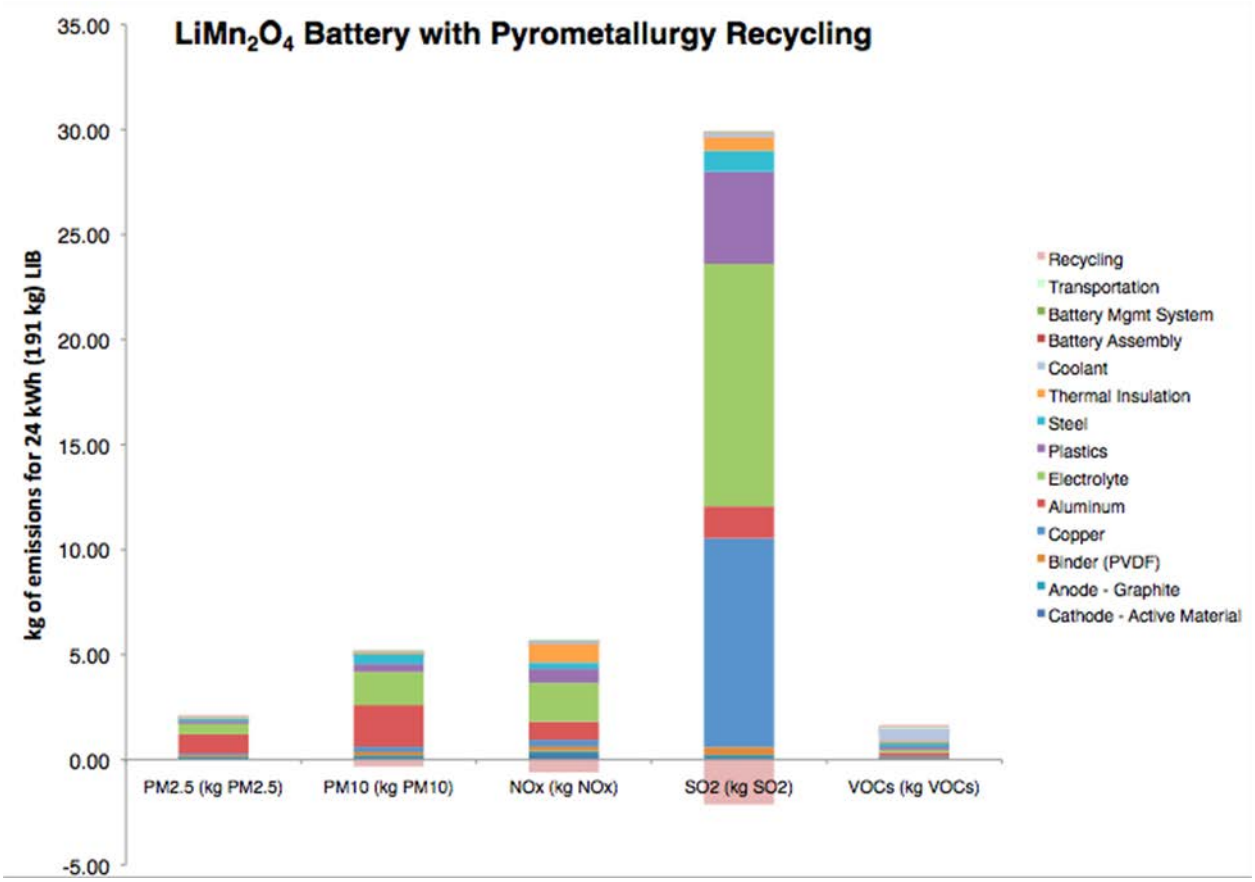
For more detailed results for what is displayed in Table 3, Figure 14, Figure 15, Figure 16, and Figure 17 show the detailed pyrometallurgy LCA results for all three battery chemistries.

Figure 14: Results of Energy Consumption and Water Use Metrics for a Pyrometallurgically Recycled LMO Battery.



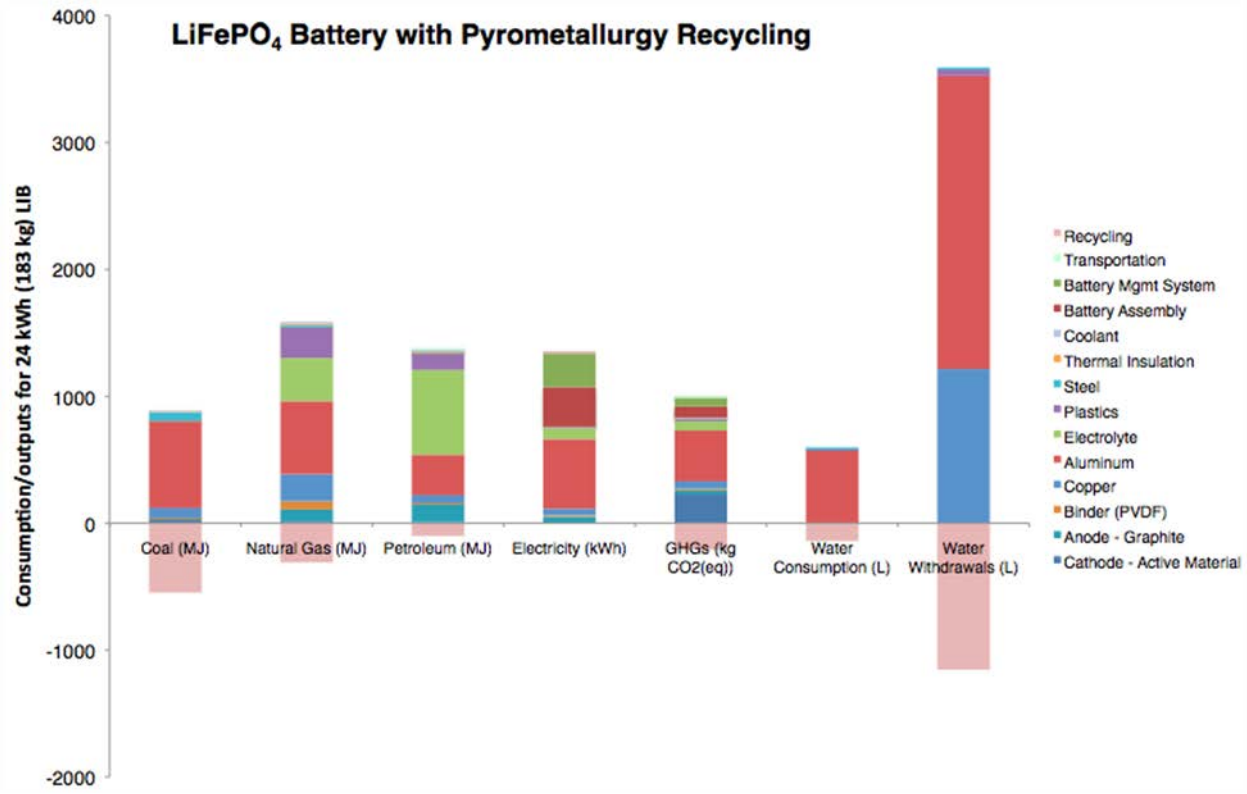
Source: Lawrence Berkeley National Laboratory

Figure 15: Results of Air Pollutant Emissions for a Pyrometallurgically Recycled LMO Battery



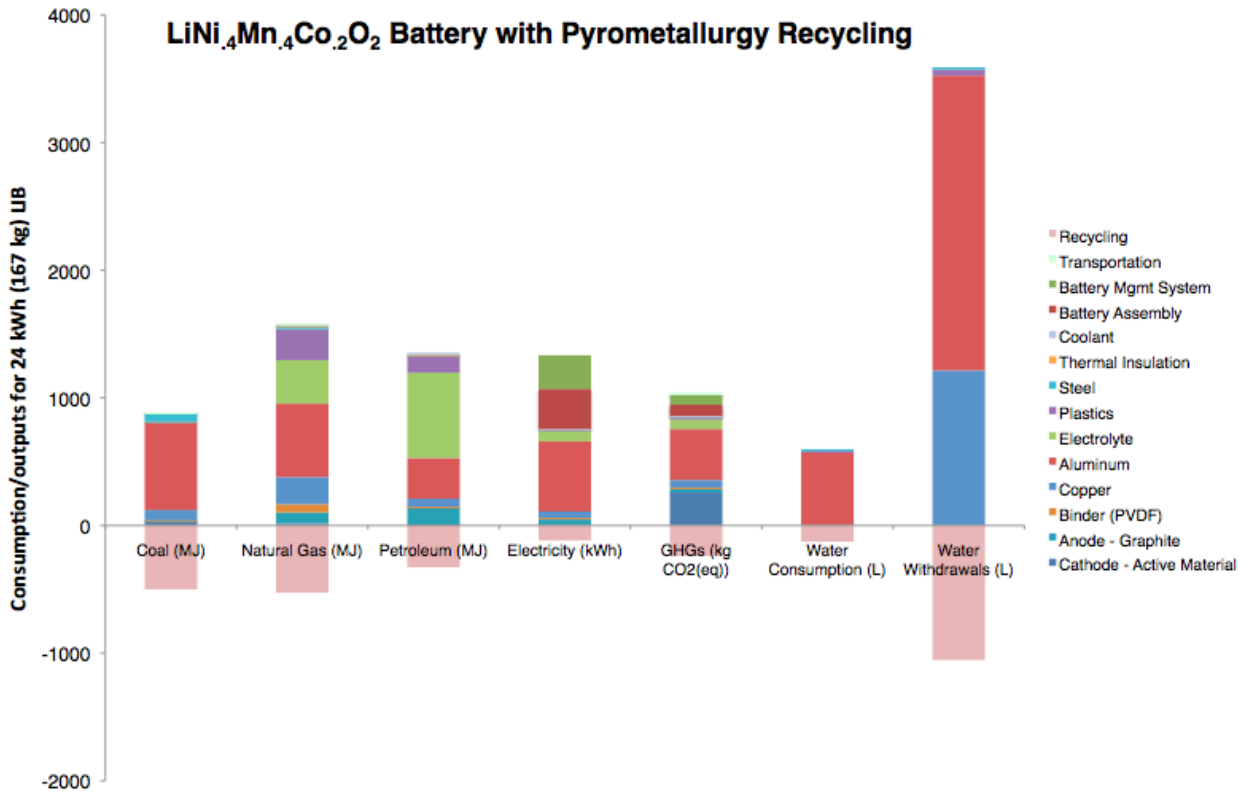
Source: Lawerence Berkeley National Laboratory

Figure 16: Results of Energy Consumption and Water Use Metrics for Pyrometallurgically Recycled LFP Battery



Source: Lawerence Berkeley National Laboratory

Figure 17: Results of Energy Consumption and Water Use Metrics for Pyrometallurgically Recycled NMC Battery



Source: Lawrence Berkeley National Laboratory

CHAPTER 5:
Assessment of PEV Battery Second Life Potential

5.1 Background and Objectives

Recycling is typically considered as the default end-of-life management for PEV batteries, but it may be worthwhile to use these retired batteries in stationary second-life applications. For second-life battery use to be viable, the benefits accrued from the second life must be greater than the impacts needed to enable it. These benefits and impacts include economic, energetic and environmental considerations.

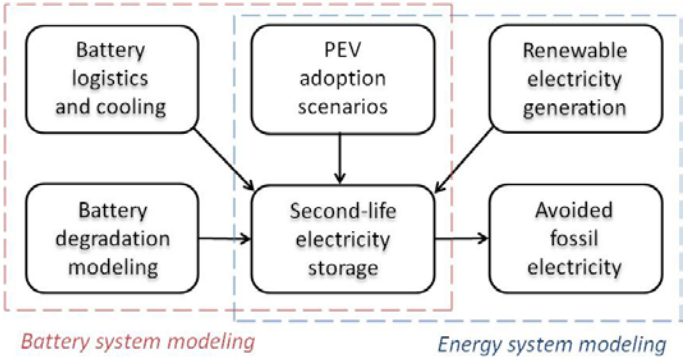
PEVs (and their retired batteries) will co-develop in the future with an evolving energy supply system, including increasing amounts of renewable electricity sources. The intermittency of these sources (e.g. solar and wind) demand an energy storage medium for maximum performance. In this study, the researchers explored the extent to which second-life use of retired PEV batteries can provide this electricity storage role. Researchers asked several research questions during this analysis. First, what are the factors that most significantly affect the net-energy viability of second-life usage of retired batteries PEVs? Second, will second-life use of retired PEV batteries play a significant energy storage role in California through 2050? Finally, in a life-cycle perspective, what are the quantifiable potential climate benefits from using second-life batteries to support intermittent renewable electricity sources?

5.2 Methods

5.2.1 Modeling Framework

Researchers developed and applied a parametric life cycle model to describe the interrelated energy and material flows of the PEV battery system. The model is driven by scenarios of future adoption of PEVs in California, and the resulting stream of retired PEV batteries. Researchers focused on the potential for second-life usage of the retired batteries, while assuming other life-cycle phases (battery manufacture, first life, and recycling) remain unchanged. The system boundaries of this study include all direct impacts of second-life use such as battery transport, cooling and charging. The boundaries also encompass parts of the broader energy system, including the displacement of fossil energy production by enabling diurnal energy shifting based on intermittent renewable electricity production. The analytical framework is shown schematically in Figure 18. Researchers assumed that future electricity output from renewable sources will exceed demand during peak generation times and electricity storage allows the use of this electricity later in the diurnal cycle during peak demand times.

Figure 18: Analytical Framework Integrating Battery System Modeling with Broader Energy System Modeling



Electricity storage in second-life PEV batteries enables dispatchable output of intermittent renewable electricity, thus avoiding fossil electricity generation. Scenario modeling of PEV adoption and battery degradation defines the scale of the operation.

Source: Lawrence Berkeley National Laboratory

Based on modeled material and energy flows through the year 2050, researchers calculated and compared several metrics of second-life system performance. These include the cumulative electricity delivered, the cumulative energy balance, the cumulative GHG balance, and the energy stored on invested (ESOI). The cumulative electricity delivered is simply the summation of the electrical energy discharged from the second-life batteries through 2050, in units of TWh. The cumulative energy balance is a summation of major energy flows throughout the system through 2050, and is defined by Equation 4.

Equation 4: Energy Balance of Battery Second Life

$$Energy\ Balance = E_{delivered} - E_{charging} - E_{cooling} - E_{transport}$$

where $E_{delivered}$ is the electrical energy delivered by the batteries during their second life, $E_{charging}$ is the electrical energy used to charge the batteries during their second life, $E_{cooling}$ is the electrical energy used for cooling of batteries during their second life, and $E_{transport}$ is the energy used to transport batteries to and from their second-life applications. Energy is accounted for in units of TWh of electrical energy, or its equivalent. Energy used for battery transport is assumed to be diesel fuel for trucks, thus the TWh of diesel used was divided by a factor of 3, corresponding to an assumed conversion efficiency of 33 percent from diesel fuel to equivalent electricity.

The cumulative GHG balance is a summation of actual and avoided GHG emissions to the atmosphere through 2050, and is defined by Equation 5.

Equation 5: GHG Balance of Battery Second Life

$$GHG\ Balance = GHG_{charging} + GHG_{cooling} + GHG_{transport} - GHG_{avoided}$$

where $GHG_{charging}$ is the GHG emissions from producing electricity to charge the batteries during their second life, $GHG_{cooling}$ is the GHG emissions from producing electricity to cool the batteries during their second life, $GHG_{transport}$ is the GHG emissions from transporting the batteries to and

from their second-life applications, and $GHG_{avoided}$ in the GHG emissions avoided by not generating fossil-based electricity during peak demand times. GHG emissions were accounted for in units of million metric tons of CO_2 equivalent (Mt CO_{2e}).

Energy stored on energy invested (ESOI) was introduced by Barnhart & Benson (2013) to compare the energy stored and delivered by a device during its service life to the energy needed to manufacture the device. Barnhart & Benson defined ESOI with Equation 6.

Equation 6: ESOI as Defined by Barnhart & Benson (2013)

$$ESOI_{B\&B} = \frac{C_0 \times \lambda \times \eta \times D}{C_0 \times \varepsilon}$$

where C_0 is the initial storage capacity of the battery, λ is the number of cycles in the battery's service life, η is the round-trip charge-discharge efficiency, D is the depth of discharge, and ε is the cradle-to-gate embodied primary energy per unit of electrical storage capacity. This definition is of limited use for battery second-life analysis, as the numerator ("energy stored") may aggregate the energy stored and delivered during both first and second lives, it does not explicitly consider battery degradation during the service life, and the denominator includes only the energy used at the beginning of the life cycle for material sourcing and battery manufacturing. Here, a metric is required that distinguishes between energy stored during first and second lives, as well as between energy inputs during manufacturing, operation, reconfiguration, and end-of-life stages. The ESOI metric was adapted by considering only the energy stored during the second life in the numerator, and the direct transport and cooling energy inputs needed to enable this second life in the denominator. $ESOI'$ is defined in Equation 7.

Equation 7: Second-life Energy Stored on Energy Invested

$$ESOI' = \frac{E_{delivered}}{E_{cooling} + E_{transport}}$$

where $E_{delivered}$, $E_{cooling}$ and $E_{transport}$ are as defined in Equation 4. Further seeking to refine the metric, researchers defined $ESOI''$, which also includes round-trip efficiency losses in the denominator (Equation 8).

Equation 8: ESOI Including Round-Trip Efficiency Losses

$$ESOI'' = \frac{E_{delivered}}{E_{transport} + E_{cooling} + E_{loss}}$$

where $E_{delivered}$, $E_{cooling}$ and $E_{transport}$ are as in Equation 4, and E_{loss} is defined in Equation 9.

Equation 9: Second-life Round-Trip Energy Loss

$$E_{loss} = E_{delivered}\left(\frac{1}{\eta} - 1\right)$$

where η is the round-trip charge-discharge efficiency. The $ESOI''$ metric (Equation 8) considers the round-trip efficiency loss as invested operational energy input, rather than as simple reduction of delivered energy as in Barnhart & Benson's definition (Equation 6).

The system model consists of four elements: battery supply, battery degradation, battery second-life use, and battery logistics. Battery supply is described in detail in Chapter 2; the other elements are described in the following sections.

5.2.2 Battery Degradation

It is broadly understood that battery performance degrades with usage and time, but comprehensive and quantitative description of such degradation remains elusive. More is known about early stages of battery degradation, such as the growth of solid electrolyte interface (Millner, 2010). Less is known about later stages of degradation such as lithium plating, growth of dendrites, and structural failure (Barré et al. 2013). This makes the robust modeling of life-cycle battery performance more challenging, as the literature lacks detailed quantitative description of the latter stages of battery life.

It is generally recognized that a battery will experience an initial capacity loss that decreases in rate, after which an inflection point is reached and the battery suffers terminal degradation that increases in rate (Spotnitz 2003). In this analysis, researchers developed a simple model to generically describe this pattern of life-cycle PEV battery degradation based on 3 parameters: Phase 1 initial degradation rate, Phase inflection point, and Phase 2 terminal degradation rate. The energy storage capacity of the battery is tracked over time, expressed as a percent of the capacity when the battery was new. Phase 1 of the degradation profile is described mathematically by Equation 10.

Equation 10: Phase 1 Battery Degradation Profile

$$C_1 = 100 - (303 \times D^x)$$

where C_1 is the energy storage capacity of the battery during Phase 1 (expressed as percent of original capacity), D is the ideal cumulative energy discharged from the battery (disregarding capacity loss), and X is an exponential factor with a base-case value of 0.55. This equation is based on Wang et al. (2011), who considered the ideal cumulative energy discharge (D) by as the number of cycles multiplied by the depth of discharge multiplied by the full cell capacity (i.e. not including the effects of capacity degradation). The cumulative energy discharge accounting for battery degradation was recalculated, and the analysis was conducted based on cumulative energy delivered by the battery, expressed in multiples of original storage capacity. The capacity loss function corresponds to graphite-$LiFePO_4$ cells with a charge/discharge rate of 2C and a temperature of 60 °C (Equation 11 from Wang et al. 2011). Other Li-ion battery chemistries and usage conditions will result in other degradation patterns, though due to the scarcity of robust literature data, these uncertainties were assumed to be accommodated within the parameter variations. The Phase 1 degradation rate is varied by changing the value of the exponential factor X from its base-case value of 0.55, to a faster degradation value of 0.60 and a slower degradation value of 0.50.

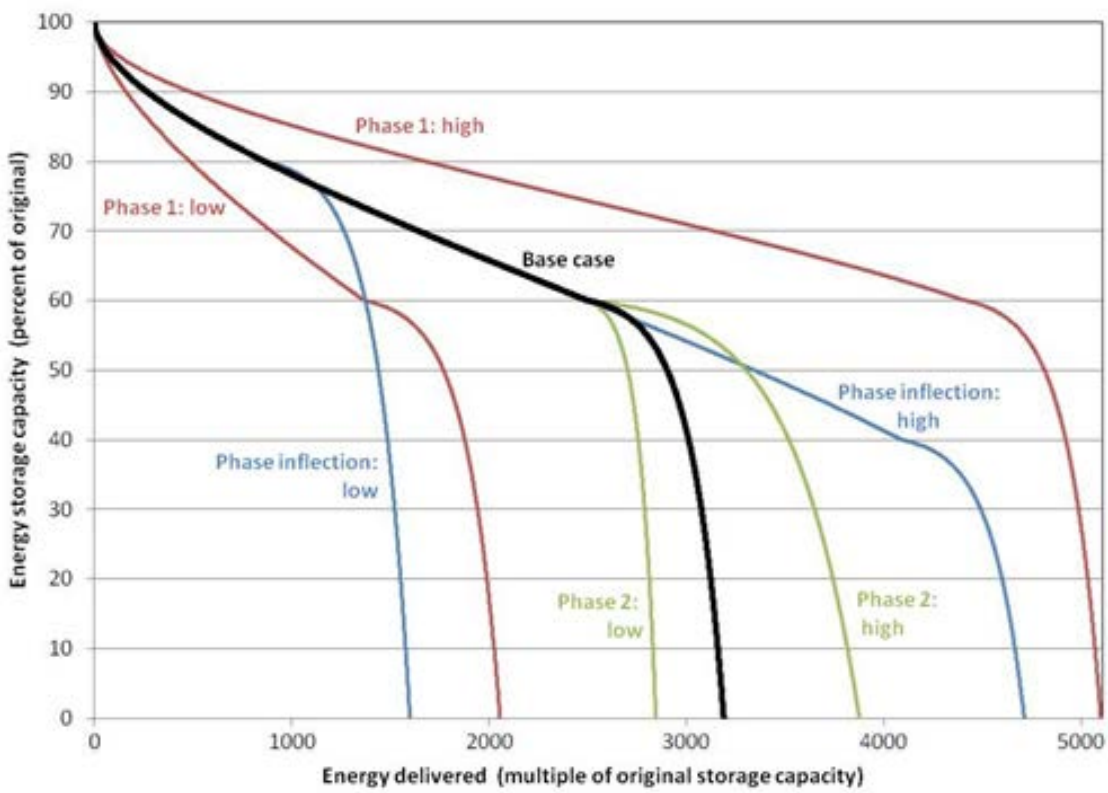
The inflection point was modelled between initial Phase 1 and terminal Phase 2 degradation, specified as a percentage of original energy storage capacity. In the absence of more compelling data, a base-case inflection point at 60 percent of original capacity was assumed, with values of 80 percent and 40 percent corresponding to faster and slower degradation. The terminal Phase 2 degradation was modelled based on exponential decay defined by Equation 11.

Equation 11: Phase 2 Battery Degradation

$$C_2 = P - 1.006^{(E \times Y)}$$

where C_2 is the energy storage capacity of the battery during Phase 2 degradation (expressed as percent of original capacity), P is the location of the inflection point between Phases 1 and 2 (in percent of original capacity), and E is the cumulative energy delivered by the battery during Phase 2 (in multiples of original full storage capacity), and Y is a multiplier. The Phase 2 degradation rate was varied by changing the value of the multiplier Y from its base case value of 1 to a faster degradation value of 2.0 and slower degradation value of 0.50. The base-case degradation curve, as well as curves representing variations of each parameter, is shown in Figure 19.

Figure 19: Modeled Range of Battery Degradation Profiles

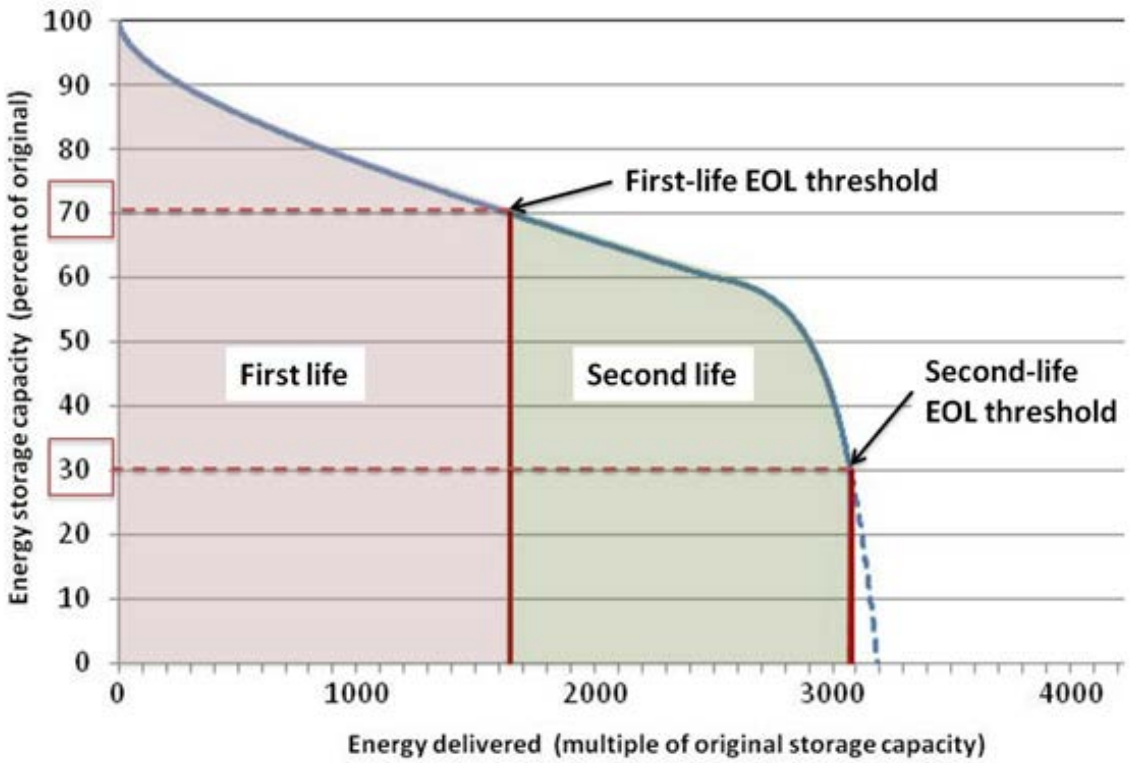


Each profile is composed of an initial Phase 1 degradation, followed by an inflection point and terminal Phase 2 degradation.

Source: Lawrence Berkeley National Laboratory

Within each defined battery degradation profile, researchers consider various arrangements for first and second lives. The base-case condition assumes the first life (as a PEV battery) continues until the energy storage capacity decreases to a threshold value of 70 percent of its original value when the car was new. The battery (or its disassembled cells) is assumed to be placed into a stationary second-life application, which continues until the storage capacity declines to a final threshold, assumed to be 30 percent in the base case. This is illustrated in Figure 20 for the base-case conditions, where 53 percent of total life-cycle electricity is delivered during the first-life and 47 percent is delivered during the second-life. Figure 21 shows corresponding results for alternative values of battery degradation parameters. To determine the significance of different threshold locations, the first-life threshold was varied between 60 percent and 80 percent, and the second-life threshold was varied between 20 percent and 40 percent.

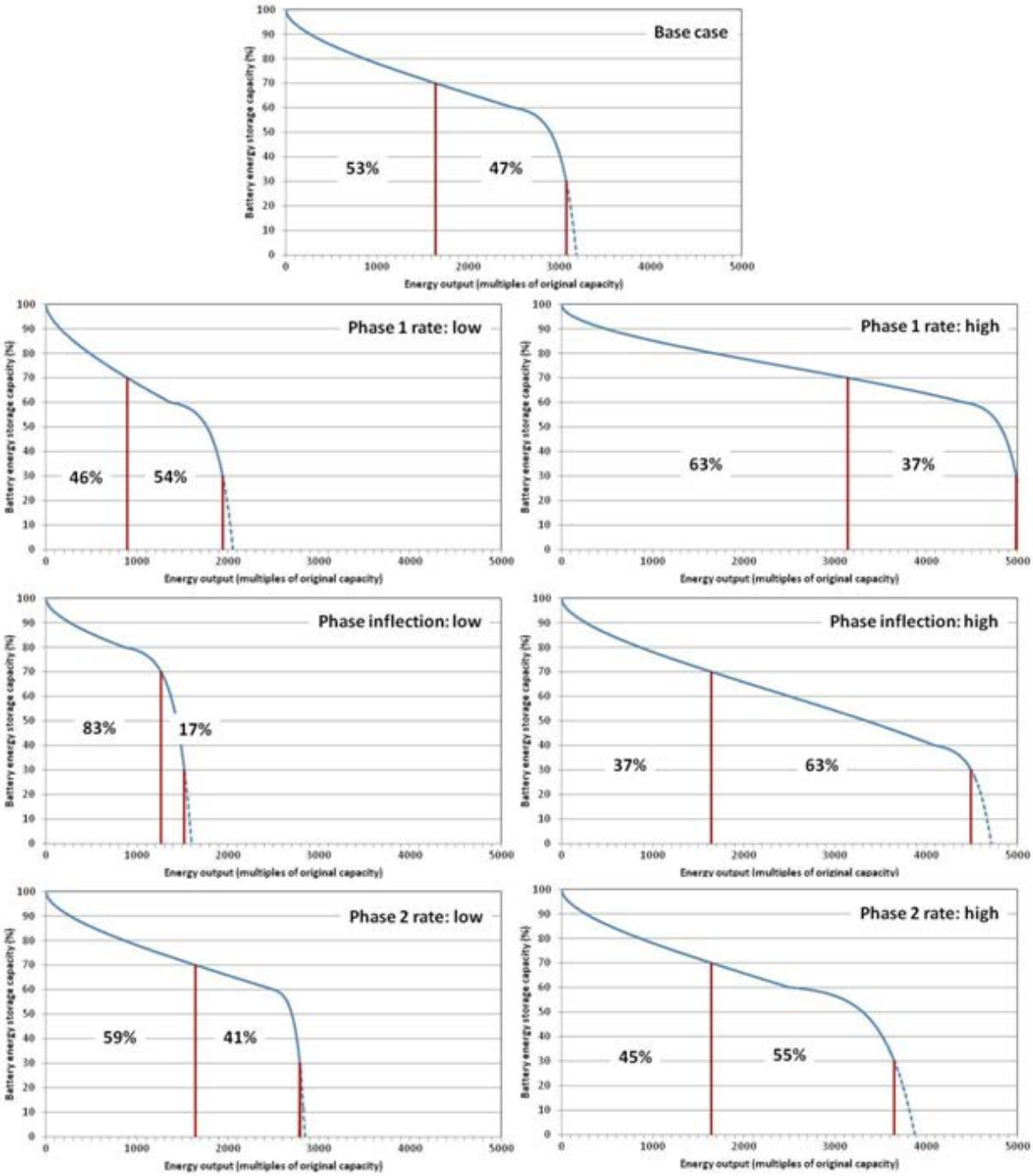
Figure 20: Relation between First-life and Second-life of Batteries



The relation was determined by the degradation profile and by first- and second-life end-of-life thresholds. The base-case is shown in the image above.

Source: Lawrence Berkeley National Laboratory

Figure 21: Battery Degradation Profiles under Base-case Conditions (Top); Low and High Values of Phase 1 Degradation Rate, Phase Inflection Point, and Phase 2 Degradation Rate



The percent numbers in the image above indicate the percentage of total life-cycle electricity output that is delivered during the first-life and second-life.

Source: Lawrence Berkeley National Laboratory

5.2.3 Battery Second Life Use

Researchers considered the use of second-life PEV batteries to enable diurnal energy shifting, allowing expanded use of intermittent renewable energy sources such as wind and solar. This daily storage and discharge of renewable electricity is assumed to substitute electricity generation from natural gas-fired power plants. In a sensitivity analysis, researchers considered the substitution of electricity from coal-fired power plants. Although coal-fired electricity is unlikely in California, the second-life batteries may, in principle, be used in other locations where coal-fired power is more common. The base-case analysis assumes second-life batteries are used in decentralized photovoltaic (PV) facilities, while decentralized wind and centralized renewable generation were considered in a sensitivity analysis. GHG intensities of electricity generation are based on median values from recent authoritative LCA studies. For PV electricity, average values for crystalline silicon PV (Hsu et al., 2014) and thin-film PV (Kim et al., 2014) were used. For wind electricity, data from Dolan & Heath (2012) was used. Emissions from natural gas-fired electricity are based on O'Donoughue et al. (2012), while those from coal-fired electricity are based on Whitaker et al. (2012). These values are detailed in Table 4.

Table 4: Life-cycle GHG Emissions from Four Electricity Sources

Electricity source	Life-cycle GHG emission (gCO_{2e}/kWh)	Reference
Wind	15	Dolan & Heath (2012)
Photovoltaic	27	Hsu et al. (2014), Kim et al. (2014)
Natural gas	510	O'Donoughue et al. (2012)
Coal	980	Whitaker et al. (2012)

Source: Lawrence Berkeley National Laboratory

Researchers considered the direct energy use and GHG emissions from activities needed to enable second-life applications, including battery cooling. Cooling of batteries during use is important to avoid excessive degradation due to overheating. Researchers estimated the waste heat to be removed based on the round trip efficiency of the batteries, and the cooling energy inputs based on the coefficient of performance (COP) of the cooling system, described by Equation 12.

Equation 12: Cooling Energy Requirements

$$E_{cooling} = E_{delivered} \times \frac{1-\eta}{COP} \quad (8)$$

where $E_{cooling}$ is the electrical energy needed for battery cooling, $E_{delivered}$ is the electricity delivered by the batteries, η is the round-trip charge/discharge efficiency of the batteries (in percent), and COP is the coefficient of performance of the cooling system. The base-case analysis assumes a round-trip efficiency of 80 percent for the second-life batteries, and a COP of 4. In a sensitivity

analysis, researchers considered a round-trip efficiency range of 70 percent to 90 percent, and a COP range of 2 to 6.

5.2.4 Battery Logistics

Battery logistics analysis is described in detail in Chapter 3, and summarized here. Researchers conducted geographic information system (GIS) modeling to estimate the energy use and GHG emissions associated with the supply chain of the PEV batteries during their second life stage. Geospatial optimization methods were used to model the effects of the supply chain logistics, integrating energy and environmental metrics (Corbett et al., 2010). A location-allocation analysis was used to determine the optimal facility locations, with the objective function to minimize the total weighted distance (ton-km) that the batteries must travel from their initial collection points to their second life application locations and finally to their recycling point. For modeling the supply chain logistics, the weighted distance is the appropriate function to minimize, as the environmental impacts are linearly related to the total distance traveled.

Researchers modeled three alternative logistics scenarios for battery second-life use: decentralized solar, decentralized wind, and centralized wind/solar. The centralized scenario assumes that all batteries are used in a single large facility in Kern County, where the average solar and wind intensities are both greatest. The decentralized solar and wind scenarios assume that the amounts of second-life batteries are distributed to different counties in proportion to each county's resource intensity for solar and wind, respectively. The total resource intensity of each county is calculated using the direct normal irradiance, taking into consideration the minimum intensity requirements for electricity production (IPCC, 2011). These three scenarios cover the range of potential battery distribution alternatives that are expected to occur through 2050.

To model the supply chain, researchers created a network dataset in an ArcGIS software environment to calculate the transportation distances. Batteries are assumed to be transported by trucks. Data on California's highway network and the borders of the counties were sourced from the US Department of Commerce and the US Census Bureau (US Census Bureau, 2013). Solar and wind intensity data were sourced from the National Renewable Energy Laboratory (NREL, 2014a). Geographically explicit car dealership locations were acquired from the Data Lists website (Data Lists, 2014).

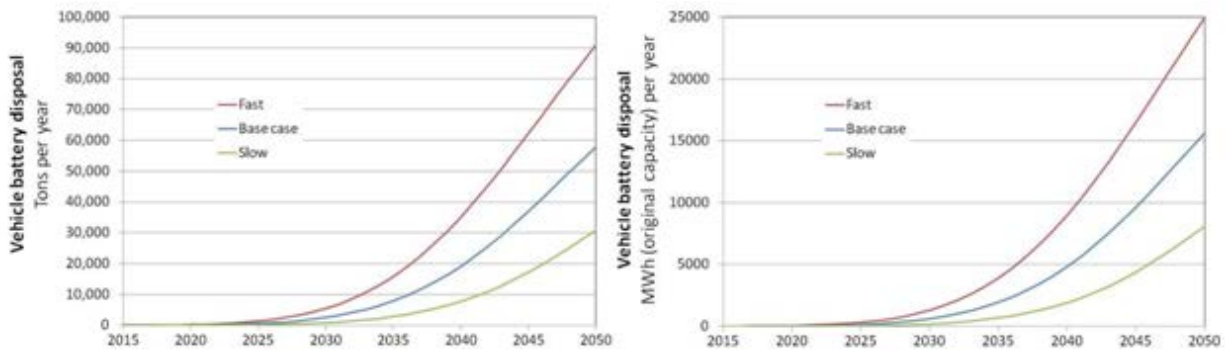
The collection points of the vehicle batteries are assumed to be car dealerships, as these locations are currently used for battery testing and take-back (Smith, 2014). The mass of batteries that would be disposed at each collection point is calculated based on the spatial location of each dealership and the amount of batteries disposed per county in 2050 (Scown et al., 2013). The transportation between consumers and collection points is typically not accounted for in the literature, and is excluded from this model (Yeh & Chow, 1996). From the initial collection points the batteries are transported to dismantling facilities for processing, where 10 percent of the battery mass is assumed to be diverted to traditional recycling (Spiers, 2014). The batteries are then transported to the location of their second-life applications, and at the end of their second life they are sent to a centralized battery recycling facility. For the facility optimization process, all California county centroids were considered as candidate locations

(Vidovic et al., 2011). GIS modeling identified the optimal facility locations for each logistics scenarios, and transportation energy use and GHG emissions were calculated. GIS modeling results for the 3 different logistics scenarios for second-life battery use in California (decentralized solar, decentralized wind, and centralized renewable) are shown in Chapter 3.

5.3 Results and Discussion

Modeled results for PEV battery disposal, based on scenario projections of PEV adoption in California through 2050, are shown in Figure 22. Under base-case conditions, about 60,000 metric tons of batteries per year are anticipated for 2050, ranging from 30,000 to 90,000 tons/year in the slow and fast adoption scenarios. This battery supply represents about 15,000 MWh of original (when the batteries were new) energy storage capacity, ranging from 8,000 to 25,000 MWh.

Figure 22: Projected Supply of Disposed Vehicle Batteries in California



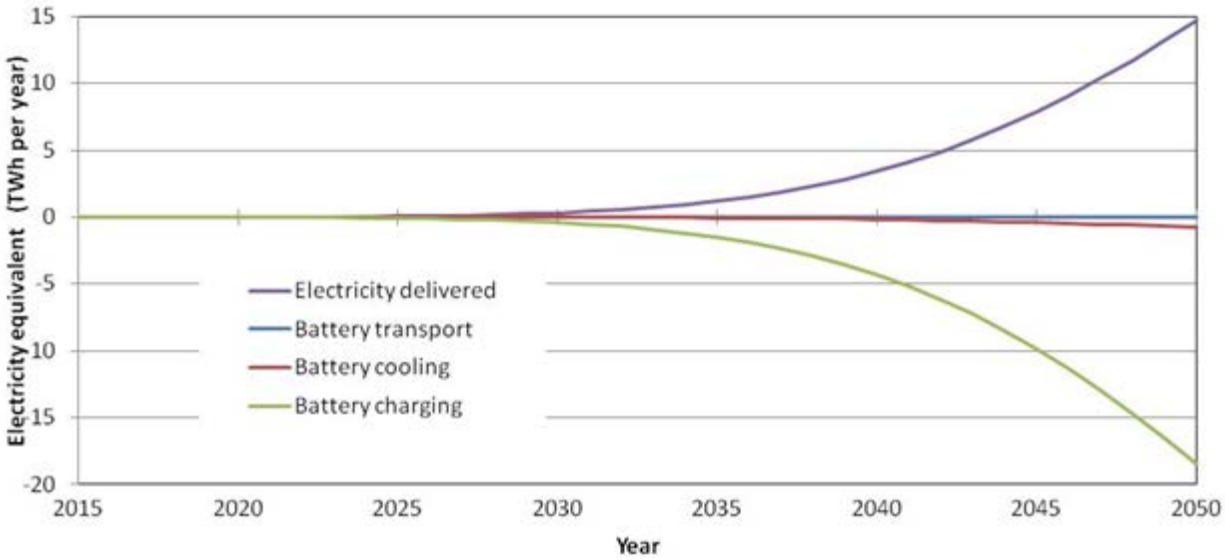
Left figure shows tons of batteries disposed per year; right figure shows MWh of original storage capacity of batteries disposed each year.

Source: Lawrence Berkeley National Laboratory

The energy and emissions intensities of transporting batteries to and from their locations of second-life use are detailed in Chapter 3, based on results from the GIS analysis of supply-chain logistics. This includes collection of the batteries from dealerships, distribution of batteries to the second-life site, and final transport from the second-life site to a recycling facility. The centralized renewable scenario requires the least energy use and emits the least GHG, per ton of battery used in second-life applications. The decentralized solar scenario is most intensive, while the decentralized wind scenario is medium intensity.

The energy balance under base-case conditions is shown in Figure 23, and detailed in Table 5. In 2050, about 15 TWh of electricity are projected to be delivered by second-life PEV batteries. This will require about 18 TWh of renewable intermittent electricity for charging, taking into account the assumed round-trip efficiency of 80 percent. Cooling of the second-life batteries in use requires about 1 TWh of electricity. Energy use for transport of batteries to and from their locations of second-life use is comparatively minor.

Figure 23: Energy Balance of Modeled Second-life Battery Use in California



Second-life batteries are projected to deliver about 15 TWh of electricity per year in 2050.

Source: Lawrence Berkeley National Laboratory

Table 5: Base-case Analysis of Second-life Battery Use

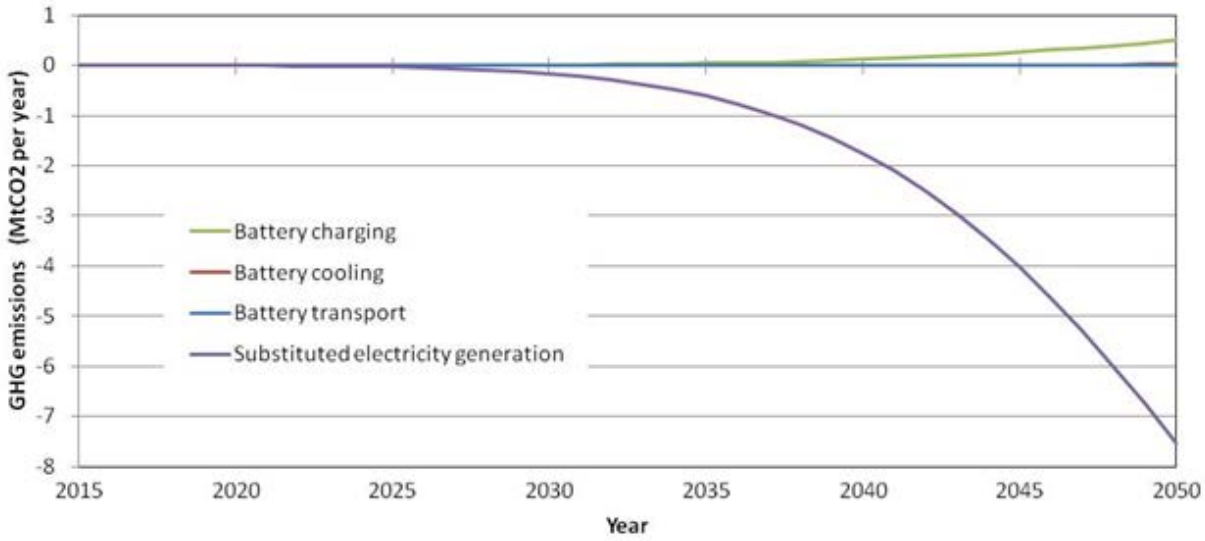
	Cumulative	2050
	TWh	**TWh per year**
Energy balance	-31.76	-4.43
Battery transport	-0.06	-0.01
Battery cooling	-5.28	-0.74
Battery charging	-132.10	-18.43
Electricity delivered	105.68	14.75
	Mt CO_{2e}	**Mt CO_{2e} per year**
GHG balance	-50.11	-6.99
Battery transport	0.05	0.01
Battery cooling	0.14	0.02
Battery charging	3.59	0.50
Substituted electricity generation	-53.90	-7.52

This table shows cumulative (2015-2050) and annual (2050 only) components of energy and GHG balances.

Source: Lawrence Berkeley National Laboratory

The GHG balance under base-case conditions is shown in Figure 24. In 2050, charging the second-life batteries will emit about 0.5 Mt CO_{2e} per year, due to life-cycle emissions from intermittent PV electricity generation. Discharging this electricity later during the diurnal cycle, to replace natural gas-fired electricity generation, will avoid about 7.5 Mt CO_{2e} per year. Battery transport and cooling are projected to cause relatively minor GHG emissions.

Figure 24: GHG Balance of Modeled Second-life Battery Use in California

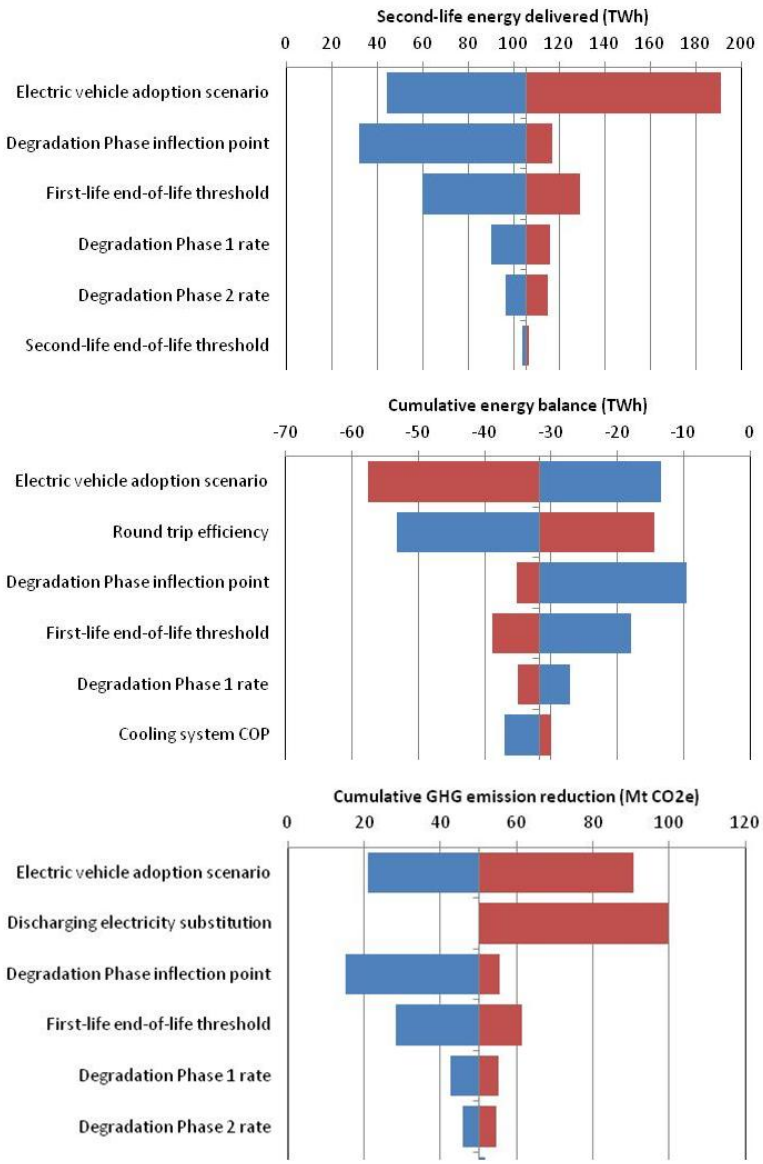


This figure is based on the assumption that batteries will be charged with solar PV electricity and battery discharging will replace natural gas-fired electricity generation. Net emissions reduction of about 7 $MtCO_{2e}$ per year is projected for 2050.

Source: Lawrence Berkeley National Laboratory

Figure 25 shows the sensitivity of three performance metrics to parameter variations. The central axis of each figure shows the base case value of the metric, and each bar shows the effect of each individual parameter shifting to its low value (left bars) and high value (right bars). The cumulative electricity delivered, cumulative energy balance, and cumulative GHG reduction metrics are all very sensitive to the PEV adoption scenario, which directly affects the amount of second-life batteries available. These metrics are also sensitive to the battery degradation inflection point, when the batteries change from initial Phase 1 degradation to terminal Phase 2 degradation. The cumulative GHG reduction is very sensitive to the source of substituted electricity. If coal-fired electricity is displaced by the renewable intermittent electricity supported by second-life batteries (instead of base-case natural gas-fired electricity), the cumulative GHG emission reduction is doubled.

Figure 25: Change in Three Metrics Due to Variation of Individual Parameters between "Low" and "High" Values



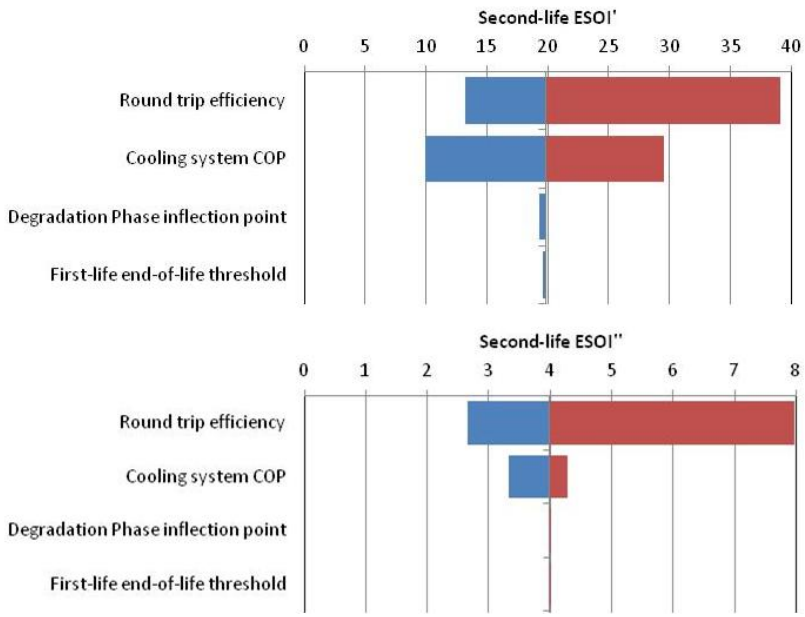
From top to bottom: cumulative second-life energy delivered; cumulative energy balance; cumulative GHG emission reduction. For each metric, the six most significant parameters are shown.

Source: Lawrence Berkeley National Laboratory

The ESOI performance of second-life systems is primarily affected by round-trip efficiency and cooling system COP. For base-case conditions, the *ESOI′* metric of second-life battery use is 19.8. The broader *ESOI′′* metric, including energy investment for battery transportation and cooling as well as round-trip losses, is 4.0. The sensitivity of these performance metrics to parameter variations is shown in Figure 26. The $ESOI_{B\&B}$ (see Equation 6) of new lithium-ion batteries was

estimated by Barnhart & Benson (2013) at about 10, comparing the first-life electricity output to the primary energy investments for raw material supply and battery manufacture.

Figure 26: Change in Second-life ESOI Metrics Due to Variation of Individual Parameters between "Low" and "High" Values



Top figure shows *ESOI'* including operational energy investments for battery transport and cooling. Bottom figure shows *ESOI''* also including round-trip charge-discharge losses as operational energy investment. For each metric, the four most significant parameters are shown.

Source: Lawrence Berkeley National Laboratory

This exploratory analysis suggests that second-life use of retired PEV batteries may play a modest, though not insignificant, role in California's future energy system. The electricity delivered under base-case modeling conditions, 15 TWh/year in 2050 (Figure 23 and Table 5), is roughly 5 percent of the current total electricity production in California of about 300 TWh/year. The total anticipated electricity production in California in 2050 is about 310 TWh/year (based on Scenario 2 of Greenblatt (2013). Electricity production from onshore wind, distributed PV, and centralized PV is anticipated to increase from current low values to about 100 TWh/year by 2050. The second-life battery use analyzed here is projected to support and enable part of this increased production, by storing electricity produced during peak generation periods and delivering it later during peak demand periods.

Under base-case modeling conditions, second-life battery use in California is projected to reduce GHG emissions by about 7 $MtCO_{2e}$/year in 2050 (Figure 24 and Table 5). This is roughly 1.5 percent of current total California emissions, and is about 4 percent of the anticipated total emission reduction of 160 $MtCO_{2e}$/year from 2010 to 2050 (based on Scenario 2 of Greenblatt (2013)). Emissions from electricity production are anticipated to decrease from about 100

$MtCO_{2e}$/year currently to about half that amount in 2050, and the 7 $MtCO_{2e}$/year avoided due to projected second-life battery use comprise about 15 percent of that reduction.

The magnitude of energy and climate benefits of second-life battery use is directly proportional to the number of retired vehicle batteries available, which depends strongly on the future adoption rate of PEVs in California. This PEV adoption rate, bounded by the slow and fast rates shown in Figure 22, thus becomes a key uncertainty surrounding future benefits of second-life battery use in California. The capacity threshold for retirement of batteries from a PEV is also identified as an important variable. In the analysis, the base-case threshold between first and second lives is 70 percent of original capacity, and moving this threshold to 60 percent or 80 percent is found to have a significant impact of second-life performance. PEV batteries are typically considered to be still useful in vehicles until they degrade to about 70 percent of their original capacity, though there has been little rational analysis to support this retirement threshold. Recent work suggests that PEV functionality remains high, even as the battery capacity drops below the commonly accepted threshold of 70 percent capacity. Saxena et al. (2015) found that a large fraction of the mobility needs of US drivers continue to be satisfied with PEV batteries with less that 70 percent remaining capacity. This suggests that future rationalization of the retirement threshold may lengthen first lives for batteries, and correspondingly shorten their second-life potential.

For any given amount of batteries produced, the degradation profile determines how much electricity can be stored and delivered by the batteries during their life spans. Acknowledging the complexity of physical and chemical factors determining battery degradation, researchers simply characterized the degradation based on three parameters: Phase 1 initial degradation rate, Phase inflection point between Phases 1 and 2, and Phase 2 terminal degradation rate. The inflection point location has the greatest influence on second-life battery performance. The base-case assumes that Phase 1 degradation continues until the battery reaches 60 percent of its original storage capacity, when terminal Phase 2 degradation begins. Delaying this inflection to 40 percent of original capacity significantly increases second-life opportunities, while early inflection at 80 percent of original capacity substantially decreases them. The rate of Phase 1 degradation has moderate impact on second-life, while the rate of Phase 2 degradation has very little impact. These results suggest that designing and building batteries such that terminal degradation is delayed or avoided, will enable much greater opportunities for second-life benefits.

The uncertainties of this analysis are substantial, due to the limited quantitative data available on performance of batteries during their full life-cycle. Much more is known about battery performance during their earlier stages of use and degradation, while comparatively little detail is available to inform robust modeling of later stages of battery use and degradation. Researchers accommodated this uncertainty by conducting a comprehensive sensitivity analysis of model parameters, to determine which system-wide factors are most critical for successful second-life battery use. Several parameters are particularly significant: PEV adoption rates, inflection point between initial and terminal degradation, threshold between first- and second-life applications, round-trip change/discharge efficiency, and the source of electricity generation that is offset by enabled renewable generation. Future work should focus on understanding and

optimizing these factors, to allow second-life PEV batteries to play a beneficial role in California's energy future.

GLOSSARY

Term	Definition
ANL	Argonne National Laboratory
APEEP	Air Pollution Emission Experiments and Policy Model
BAU	Business as Usual
CO_{2e}	Carbon Dioxide Equivalent
COP	Coefficient of Performance
DNI	Direct Normal Irradiance
EIO-LCA	Economic Input-output Life-cycle Assessment
Energy Balance	A summation of major system-wide energy flows
EPA	Environmental Protection Agency
ESOI	Energy Stored on (Energy) Invested
DOT	Department of Transportation
GHG	Greenhouse Gas
GHG Balance	A summation of system-wide actual and avoided GHG emissions to the atmosphere
GIS	Geographic Information Systems
GREET	Greenhouse Gas, Regulated Emissions, and Energy Use in Transportation Model
HOV	High-occupancy Vehicle
Hydrometallurgical Recycling	Lithium-ion battery recycling process that uses chemical leaching to extract materials
kWh	Kilowatt-hour
LCA	Life-cycle Assessment
LIB	Lithium-ion Battery
MSA	Metropolitan Statistical Area
Mt	Million metric tons
MWh	Megawatt-hour (=10^3 kWh)

Term	Definition
NETL	National Energy Technology Laboratory
NHTS	National Household Transportation Survey
NREL	National Renewable Energy Laboratory
PEV	Plug-in Electric Vehicle
PM	Particulate Matter
PV	Photovoltaic
Pyrometallurgical Recycling	Lithium-ion battery recycling process that uses smelting to recover precious metals and slag
Second Life	Use of retired PEV batteries for additional electricity storage applications
Sigmoid Curve	"S"-shaped curve used to approximate market adoption of new technologies
TWh	Terawatt-hour (=10^9 kWh)
VOC	Volatile Organic Compounds
VSL	Value of Statistical Life
ZEV	Zero Emission Vehicle

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APPENDIX A:
PEV Adoption Assumptions

Table 1: County-level Data

County name	FIPS	Census region name	CBSA code	MSA: 1:metro 2:micro	Central or outlying	Early adopter MSA?	Median income nat'l %ile	Population density nat'l %ile	Adoption group number
Alameda	6001	Pacific	41860	1	Central	1	86%	80%	1
Alpine	6003	Pacific	0	0	NO MSA	0	31%	0%	5
Amador	6005	Pacific	0	0	NO MSA	0	48%	12%	5
Butte	6007	Pacific	17020	1	Central	0	20%	23%	5
Calaveras	6009	Pacific	0	0	NO MSA	0	54%	9%	4
Colusa	6011	Pacific	0	0	NO MSA	0	34%	3%	5
Contra Costa	6013	Pacific	41860	1	Outlying	1	92%	71%	1
Del Norte	6015	Pacific	18860	2	Central	0	6%	5%	5
El Dorado	6017	Pacific	40900	1	Outlying	0	84%	19%	2
Fresno	6019	Pacific	23420	1	Central	0	34%	26%	5
Glenn	6021	Pacific	0	0	NO MSA	0	19%	4%	5
Humboldt	6023	Pacific	21700	2	Central	0	11%	7%	5
Imperial	6025	Pacific	20940	1	Central	0	13%	7%	5
Inyo	6027	Pacific	13860	2	Central	0	33%	0%	5
Kern	6029	Pacific	12540	1	Central	0	34%	18%	5
Kings	6031	Pacific	25260	1	Central	0	31%	20%	5
Lake	6033	Pacific	17340	2	Central	0	7%	10%	5
Lassen	6035	Pacific	45000	2	Central	0	50%	1%	4
Los Angeles	6037	Pacific	31100	1	Central	1	66%	86%	1
Madera	6039	Pacific	31460	1	Central	0	29%	14%	5
Marin	6041	Pacific	41860	1	Central	1	97%	47%	1

County name	FIPS	Census region name	CBSA code	MSA: 1:metro 2:micro	Central or outlying	Early adopter MSA?	Median income nat'l %ile	Population density nat'l %ile	Adoption group number
Mariposa	6043	Pacific	0	0	NO MSA	0	25%	2%	5
Mendocino	6045	Pacific	46380	2	Central	0	18%	4%	5
Merced	6047	Pacific	32900	1	Central	0	22%	23%	5
Modoc	6049	Pacific	0	0	NO MSA	0	4%	0%	5
Mono	6051	Pacific	0	0	NO MSA	0	67%	1%	4
Monterey	6053	Pacific	41500	1	Central	1	69%	22%	1
Napa	6055	Pacific	34900	1	Central	0	82%	27%	2
Nevada	6057	Pacific	46020	2	Central	0	70%	19%	4
Orange	6059	Pacific	31100	1	Central	1	90%	91%	1
Placer	6061	Pacific	40900	1	Central	0	87%	32%	2
Plumas	6063	Pacific	0	0	NO MSA	0	21%	1%	5
Riverside	6065	Pacific	40140	1	Central	0	70%	37%	4
Sacramento	6067	Pacific	40900	1	Central	0	67%	72%	4
San Benito	6069	Pacific	41940	1	Outlying	0	76%	8%	3
San Bernardino	6071	Pacific	40140	1	Central	0	61%	19%	4
San Diego	6073	Pacific	41740	1	Central	1	78%	58%	1
San Francisco	6075	Pacific	41860	1	Central	1	90%	97%	1
San Joaquin	6077	Pacific	44700	1	Central	0	49%	48%	5
San Luis Obispo	6079	Pacific	42020	1	Central	0	68%	15%	4
San Mateo	6081	Pacific	41860	1	Central	1	97%	75%	1
Santa Barbara	6083	Pacific	42060	1	Central	1	72%	25%	1

County name	FIPS	Census region name	CBSA code	MSA: 1:metro 2:micro	Central or outlying	Early adopter MSA?	Median income nat'l %ile	Population density nat'l %ile	Adoption group number
Santa Clara	6085	Pacific	41940	1	Central	0	98%	71%	2
Santa Cruz	6087	Pacific	42100	1	Central	0	79%	52%	3
Shasta	6089	Pacific	39820	1	Central	0	20%	9%	5
Sierra	6091	Pacific	0	0	NO MSA	0	28%	0%	5
Siskiyou	6093	Pacific	0	0	NO MSA	0	7%	1%	5
Solano	6095	Pacific	46700	1	Central	0	82%	50%	2
Sonoma	6097	Pacific	42220	1	Central	0	76%	37%	3
Stanislaus	6099	Pacific	33700	1	Central	0	43%	39%	5
Sutter	6101	Pacific	49700	1	Central	0	39%	25%	5
Tehama	6103	Pacific	39780	2	Central	0	11%	3%	5
Trinity	6105	Pacific	0	0	NO MSA	0	6%	1%	5
Tulare	6107	Pacific	47300	1	Central	0	26%	17%	5
Tuolumne	6109	Pacific	38020	2	Central	0	33%	4%	5
Ventura	6111	Pacific	37100	1	Central	0	91%	45%	2
Yolo	6113	Pacific	40900	1	Outlying	0	70%	28%	3
Yuba	6115	Pacific	49700	1	Central	0	20%	21%	5

APPENDIX B:
Battery Production Data Sources

Table 1: Material Inputs for Lib Chemistries

	LMO		LFP		NMC	
	Mass (kg)	**Data Source**	**Mass (kg)**	**Data Source**	**Mass (kg)**	**Data Source**
Cathode - Active Marerial	68.8	ANL (2013a)	55.5	EPA (2013)	41.9	EPA (2013)
Anode - Graphite	23.8	ANL (2013a)	28.8	ANL (2013a)	26.6	ANL (2013a)
Binder (PVDF)	4.7	ANL (2013a)	4.7	ANL (2013a)	4.7	ANL (2013a)
Copper	20.6	ANL (2013a), Scown (2010)	20.6	ANL (2013a), Scown (2010)	20.6	ANL (2013a), Scown (2010)
Aluminum	36.1	ANL (2013a), Scown (2010)	36.1	ANL (2013a), Scown (2010)	36.1	ANL (2013a), Scown (2010)
Electrolyte: $LiPF_6$	3.4	ANL (2013a)	3.4	ANL (2013a)	3.4	ANL (2013a)
Electrolyte: Ethylene Carbonate	10.0	ANL (2013a)	10.0	ANL (2013a)	10.0	ANL (2013a)
Electrolyte: Dimethyl Carbonate	10.0	ANL (2013a)	10.0	ANL (2013a)	10.0	ANL (2013a)
Plastic: Polypropylene	3.2	ANL (2013a)	3.2	ANL (2013a)	3.2	ANL (2013a)
Plastic: Polyethylene	0.6	ANL (2013a), Scown (2010)	0.6	ANL (2013a), Scown (2010)	0.6	ANL (2013a), Scown (2010)
Plastic: Polyethylene Terephthalate	2.3	ANL (2013a)	2.3	ANL (2013a)	2.3	ANL (2013a)
Steel	2.6	ANL (2013a), Scown (2010)	2.6	ANL (2013a), Scown (2010)	2.6	ANL (2013a), Scown (2010)

	LMO		LFP		NMC	
	Mass (kg)	**Data Source**	**Mass (kg)**	**Data Source**	**Mass (kg)**	**Data Source**
Thermal Insulation	0.6	ANL (2013a)	0.6	ANL (2013a)	0.6	ANL (2013a)
Coolant: Glycol	1.9	ANL (2013a)	1.9	ANL (2013a)	1.9	ANL (2013a)
Electronic Parts (BMS)	2.3	ANL (2013a)	2.3	ANL (2013a)	2.3	ANL (2013a)
TOTAL	191.0		182.6		166.8	

APPENDIX C:
Battery Recycling Data Sources

Table 1: Pyrometallurgy Recycling Resource Inputs, Emission Factors, and Data Sources

	Inputs (kg)	Outputs (kg)	Fossil Fuels (MJ)	Coal (MJ)	Natural Gas (MJ)	Petroleum (MJ)	Electricity (kWh)	GHGs (kg CO_{2e})	Source/Notes
Coke	400								
Production			102.97	102.97			15.60	52.00	NREL (2014b), Coal energy density: EIA (2014)
Combustion								1472.00	Gursel & Custodio (2014)
Transportation (mi)	100		55.23			55.23		4.21	
Limestone ($Ca(OH)_2$) Scrubber	27.75		0.86	0.03	0.15	0.67	0.46	0.12	Limestone production: Gursel & Custodio (2014), Scrubbing process: Rosemount Analytical (2009), assume water is recycled, 3% coke sulfur content
Sand	110								
Production			48.00					3.31	CMU (2014), purchaser price: USGS (2003)
Transportation			15.19			15.19		1.16	

	Inputs (kg)	Outputs (kg)	Fossil Fuels (MJ)	Coal (MJ)	Natural Gas (MJ)	Petroleum (MJ)	Electricity (kWh)	GHGs (kg CO_{2e})	Source/Notes
Limestone	100								
Production			3.09	0.11	0.55	2.43	1.67	0.44	Gursel & Custodio (2014), assumed 60% CaO content.
Pyroprocessing								44.00	
Transportation (mi)	100		13.81			13.81		1.05	
Li-ion Batteries	1200								
Transportation (mi)	143		422.29			422.29		31.45	
Cu	84								
Ni	30								
Fe	420								
Al	60								
Co	168								
Li_2O	12								
Other	426								
Slag	200	679							
Processing for Cement Use			298.53				844.98	59.04	Gursel & Custodio (2014), assumed 20% slag in concrete mix.

	Inputs (kg)	Outputs (kg)	Fossil Fuels (MJ)	Coal (MJ)	Natural Gas (MJ)	Petroleum (MJ)	Electricity (kWh)	GHGs (kg CO_{2e})	Source/Notes
Portland Cement Offset			2225.93	1.14	6.33	30.08	326.70	735.37	Gursel & Custodio (2014)
Alloy (Offsets)	0	538							
Cu	0	78	1341.41	299.43	803.57	238.41	192.18	223.14	Virgin material production from ANL (2013a)
Ni	0	30	2640.60	12.16	1339.99	1288.45	107.43	258.60	
Fe	0	272	9716.16	7080.99	2048.62	586.55	534.77	1092.99	
Co	0	158	13859.48	63.84	7032.58	6763.06	3854.09	1358.09	
Alloy Leaching					68.10				ANL (2013b)
TOTAL (per kg battery)			**-6.83**	**-3.00**	**-1.69**	**-0.55**	**0.10**	**-1.15**	

Table 2: Pyrometallurgy Recycling Resource Inputs, Emission Factors, and Data Sources

	Water Consumption (L)	Water Withdrawals (L)	$PM_{2.5}$ (kg $PM_{2.5}$)	PM_{10} (kg PM_{10})	NO_x (kg NO_x)	SO_2 (kg SO_2)	VOCs (kg VOCs)	Source/Notes
Coke								
Production			0.57		0.31	1.60	1.28	NREL (2014b), Coal energy density: EIA (2014)
Combustion					6.20		2.14E-02	Gursel & Custodio (2014)
Transportation			1.78E-03	7.90E-03	0.04	3.30E-03	4.50E-03	
Limestone ($Ca(OH)_2$) Scrubber	0.01	7.27	2.02E-05	2.55E-05	8.16E-05	1.96E-04	4.45E-05	Limestone production: Gursel & Custodio (2014), Scrubbing process: Rosemount Analytical (2009), assume water is recycled, 3% coke sulfur content
Sand								
Production		606.34	0.01	0.06	0.01	8.87E-03	1.82E-03	CMU (2014), purchaser price: USGS (2003)
Transportation			4.90E-04	2.17E-03	0.01	9.08E-04	1.24E-03	
Limestone								
Production	0.04	26.20	7.29E-05	9.20E-05	2.94E-04	7.07E-04	1.60E-04	Gursel & Custodio (2014), assumed

	Water Consumption (L)	Water Withdrawals (L)	$PM_{2.5}$ (kg $PM_{2.5}$)	PM_{10} (kg PM_{10})	NO_x (kg NO_x)	SO_2 (kg SO_2)	VOCs (kg VOCs)	Source/Notes
								60% CaO content.
Pyroprocessing								
Transportation			4.45E-04	1.98E-03	9.78E-03	8.25E-04	1.13E-03	
Li-ion Batteries								
Transportation (mi)			0.01	0.06	0.24	0.02	0.03	
Cu								
Ni								
Fe								
Al								
Co								
Li_2O								
Other								
Slag								
Processing for Cement Use		639.77	0.37	1.66E-03	0.08	0.24		Gursel & Custodio (2014), assumed 20% slag in concrete mix.
Portland Cement Offset	81.77	5668.33	0.08	1.00	3.51	1.74	0.05	Gursel & Custodio (2014)
Alloy (Offsets)								

	Water Consumption (L)	**Water Withdrawals (L)**	**$PM_{2.5}$ (kg $PM_{2.5}$)**	**PM_{10} (kg PM_{10})**	**NO_x (kg NO_x)**	**SO_2 (kg SO_2)**	**VOCs (kg VOCs)**	**Source/Notes**
Cu	0.09	4602.59	0.09	0.27	0.35	11.26	2.57E-02	Virgin material production from ANL (2013a)
Ni	0.00	0.00	0.09	0.19	0.36	11.83	1.51E-02	
Fe	1674.20	1796.70	0.64	1.96	1.23	3.96	9.44E-01	
Co	0.00	0.00	0.37	0.85	1.87	2.53	7.92E-02	
Alloy Leaching								ANL (2013b)
TOTAL (per kg battery)	**-0.77**	**-6.32**	**3.96E-04**	**-1.73E-03**	**-3.15E-03**	**-1.12E-02**	**6.50E-04**	