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U.S. end-of-life electric vehicle batteries: Dynamic inventory modeling and spatial analysis for regional solutions

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ABSTRACT

While electric vehicles (EVs) have been promoted for green consumption, improper or inadequate management of end-of-life (EOL) EV batteries, as the current practice, compromises the benefits of EV adoption. This study aims to contribute to both theoretical research of material flow analysis and timely management of EOL EV batteries at various geographic scales (i.e., national, state, and county).

Theoretically, this study tests two battery lifespan scenarios (i.e., constantly at 3–8 years and dynamically increasing over time), three discard probability functions (i.e., uniform, truncated normal, and Weibull), and three EV sale projections (i.e., low, moderate, and high). Results show that the short-term EOL volume (by 2025) can be particularly sensitive to the lifespan parameter. The long-term estimates involve most uncertainties related to the EV market penetration. Various discard probability functions generally derive similar results.

In practical terms, the results suggest that necessary infrastructure for proper EOL EV battery management is needed sooner than the public may have perceived. This study urges for regional planning that incorporates both temporal and spatial considerations. To illustrate an example of regional solutions, this study adopts empirical data in California to simulate and spatially match EOL EV battery clusters and the renewable energy facilities that can potentially reuse EV batteries as energy storage. Meanwhile, the spatial mis-match between the supply and demand, as can be the case in other regions, calls for region-wide coordination in terms of both infrastructure development and transportation planning.

1. Introduction

The U.S. has witnessed an increasing popularity of electric vehicles (EVs). The one-million-EV goal, pledged by President Barack Obama in 2011, represents an ambitious milestone toward reducing oil dependence and greenhouse gas emissions, increasing energy security, improving fuel economy, and benefiting the environment (Shen et al., 2015). Through 2016, 4.8 million electric vehicles (EVs) had been sold in the U.S. Future EV markets are expected to maintain this rapid growth in the decades to come (Babaee et al., 2014; Ramage et al., 2010). Annual EV sales are projected to increase substantially and reach 2.3 million by 2040 (US EIA, 2017a).

As new EV models continue to be developed and adopted, there is an increasing need for proper management of phased-out EVs (Winslow et al., 2018). Notably, EV batteries show a shorter lifespan than EVs and thus retire faster (Ramoni and Zhang, 2013). Proper management of EV batteries presents a major challenge due to their significant mass (approximately 300 lbs–1000 lbs each unit), potential risks during freight transportation, toxic material and substances, and inadequate collection and treatment facilities. Unlike conventional automobile batteries, they cannot be conveniently removed or replaced by drivers. Battery types also vary by vehicle model and year. Therefore, specialized workers and facilities/infrastructure need to be planned in preparation for the growing volume of end-of-life (EOL) EV batteries.

At present, there are two main approaches for EOL EV batteries: recycling and reuse. Recycling focuses on recovering the substantial mass of materials (e.g., disassembly with material extraction and recovery) (Wang et al., 2014b). Prior research on EVB recycling has focused on efficient metallurgical and mechanical methods for recycling (Yun et al., 2018; Wang and Wu, 2017). Reuse focuses on “battery second use” (B2U), including remanufacturing (e.g., reuse in vehicles) and repurposing (e.g., for energy storage). While both approaches can help avoid the hazards of landfill disposal and reduce the lifecycle impacts of EV batteries, B2U generates additional benefits of prolonging

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battery lifespans and reducing demand for new batteries (Ahmadi et al., 2015; Richa et al., 2015). Integrating EOL EV batteries into energy storage systems can also improve the efficiency of electric grids substantially (Neubauer et al., 2015b; Standridge and Hasan, 2015). Batteries from Plug-In EVs (PEVs) are particularly suitable for B2U given their large nameplate capacity.

The U.S. markets for reusing and recycling post-vehicle EV batteries are still under development, despite the rapid growth in EV sales. Discarded lithium-ion batteries (LIBs) are subject to the U.S. Environmental Protection Agency's (EPA) Universal Waste Rule. A negligible percentage of LIBs (only 3%–5%) have been recycled or recovered (Friends of the Earth Europe, 2013; Georgi-Maschler et al., 2012), comparing to 97% to 99% of lead battery is recycled (Battery Council International, 2017; Zou et al., 2013). LIBs are generally considered as nonhazardous to the environment due to the absence of toxic elements, such as lead, mercury, or cadmium. However, landfilling LIBs still poses environmental and human health risks due to the leakage of organic electrolytes, the presence of metals (e.g., copper, nickel, and lithium), and the large quantity of carbonaceous materials (e.g., graphite and carbon black). LIB policies have drawn increasing attention (Richa et al., 2017). Although most states in the U.S. have banned lead-acid batteries from landfill disposal (NERC, 2017), only three states (California, New York, and Minnesota) have policies to manage EV batteries (both NiMH and LIBs). There is no federal regulation mandating battery recycling. Consequentially, only a small proportion of used batteries have been recycled domestically and retired batteries (e.g., those from Honda and Toyota) are often sent abroad for recycling. Supporting facilities, such as collection/dismantling centers, repurpose/remanufacturing sites, and recycling infrastructure, are still lagging in the U.S. (Wang et al., 2014a).

Long distance hauling for the significant volume of EOL EV batteries has been criticized by researchers for its economic inefficiencies and environmental risks (Hendrickson et al., 2015a,b). Since the U.S. Department of Transportation (U.S. DOT) classifies LIBs as hazardous materials, transportation cost accounts for 30–50% of total battery remanufacturing and repurposing cost (Standridge and Hasan, 2015). On the other hand, the secondary market of reused or recycled batteries necessitates some economies of scale (Wang et al., 2014b). Therefore, regional solutions are more preferable than national or local solutions that avoiding long-distance hauling and containing adequate EOL battery supply (Neubauer et al., 2015a). Besides, B2U businesses could also benefit the region's economy by promoting job opportunities and renewable energy development. The economic feasibility and preferable options vary by local conditions including transportation system, labor costs, and capital investment. Uncertainties reside in regional heterogeneities, as well as local policies.

However, one key challenge of developing regional EOL EV battery management systems and policies, is the lack of data references, such as the quantity or volume of retired batteries, battery type, technology availability, and demand for recycled products. Various models have been developed to project the growth of EVs, yet only a few studies have focused on EV batteries. Existing studies (CEC, 2015; Richa et al., 2014; Standridge and Corneal, 2014) also concluded an increasing number of annual retired EV batteries in the coming decades. But the results vary significantly because each study applied different methodologies and modeling parameters as well as data inputs. In addition, existing studies have focused on the national level only; regional analysis is very limited.

There have been limited studies to connect EOL EV battery management with urban and regional planning. Hoyer et al. (2015) applied mathematical optimization approaches to conduct technology and capacity planning for the recycling of lithium-ion electric vehicle batteries. Idjis and Da Costa (2017) show that recycling is rarely profitable when accounting for the significant amount of transportation cost; whereas the reuse option can be profitable contingent upon the location of certain facilities. Tang et al. (2018) show that it is important to set a reasonable minimum recycling rate as a benchmark for a reward-penalty mechanism, and further, environmental awareness has significant impacts on the social benefits of EV battery recycling. Nevertheless, investigations of planning implications at the regional level, especially in the context of spatial matching for EV battery recycling/reuse, has been lacking.

The study models and analyzes EOL EV battery volume at multiple geographic scales (i.e., national, state, and county). At the national level, the goal is mostly to refine inventory estimates that incorporate market dynamics and technology advancement. We develop various sensitivity analyses and aim to provide insights into EOL EV battery estimates that are sensitive to the temporal factor. At the regional level, spatial considerations, besides the temporal factor, are included in the analysis. The goal of our regional analysis is set to advocate for the critical value of region-specific data references for policy making and of the system-planning approach to link EOL EV batteries with their B2U potential within a region. A case study is implemented at the county level in the state of California, which leads the nation in terms of both EV adoption and renewable energy development and thus can potentially benefit from an integrated approach of regional B2U EV battery management.

2. Inventory analysis methods and data inputs

This section discusses the generic modeling method of EOL EV battery estimates and reviews existing studies, with a focus on key modeling parameters, including system boundaries (in terms of both the life cycle stage and geographic location of battery uses), battery inflows, lifespans, and discard probabilities. It also includes details about data inputs for our model implementation in both the U.S. and the state of California, our case study region. Acknowledging the uncertainties in data inputs, we have also developed various sensitivity analysis, to be elaborated in Section 3. Further, spatial analysis that links the inventory analysis with potential reuses will be discussed in Section 4.

2.1. Product flow analysis

Product Flow Analysis (PFA) is an important model among the suite of tools for Material Flow Analysis (MFA), which quantifies the stocks and flows of materials given a specified system boundary through their life cycles (Brunner and Rechberger, 2004). Besides PFA (as the case of EVs and batteries in this study), MFA also examines materials (e.g., steel and plastics) (Simic and Dimitrijevic, 2012) and substances (e.g., Li_2CO_3) (Ziemann et al., 2018). While MFA models are generally designed to capture the entire lifecycle of materials, PFA often focuses on commodities at the consumption stage, especially from use to disposal (Wernick and Irwin, 2005).

Fig. 1 illustrates the analytical framework to capture product flows from first use to enter EOL management. Besides the volume of product

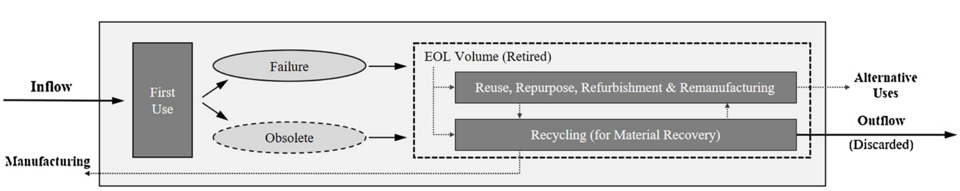

Fig. 1. Product Flow Analysis: Analytical Framework.

inflows and stock, variations in lifespan and discard rates would also affect the cumulative volume of EV batteries that reach their EOL within a certain period of time. Once reached EOL, EV batteries can be reused via repurposing, refurbishing, and remanufacturing. They can also be recycled to extract reusable components or precious metals which are of value on the commodity markets. Battery reuse and recycling may form an iterative process, as reused batteries can be sent to recycling upon retirement, while components recovered from recycling can be used during the battery reuse process. With proper federal and state policies in place (i.e., landfill ban), all retired batteries would be recycled. However, taking social factors into consideration, 100% recycling may not be economically efficient; the reuse option can be more economically viable than recycling (e.g., Kinnaman et al., 2014). The benefits of repurposing/remanufacturing batteries are contingent upon battery prices (both old and new), transportation costs, and economies of scales of recycling. All these factors can vary by region, and obviously, affected by government policies and recycling market development.

There is also a spatial dimension in PFA. The definition of a system or regional boundary will affect the EOL volume, especially if the products are purchased, retired, and managed in various regions. The numerical study here has assumed that all EV batteries purchased in the U.S. are discarded domestically where proper EOL management is needed. The refined regional model considers local boundaries (i.e., counties), and estimates the EOL EV batteries at where they are first purchased, which provide data reference to address regulation and economic concerns at the local and regional level.

Eq. (1) below calculates the EOL volume of products at time t, where $L(t, t^*)$ represents the probability of the product purchased at time t^* ($t^* < t$) entering the EOL management at time t (Müller, 2006). The probability of product retirement in a given year is related to both the product lifespan and product age (after sale/purchase) in that year. Existing studies, such as CEC (2015); Richa et al. (2014), also suggested the importance of differentiating battery types in the inventory analysis. For instance, the early hybrid EVs use small capacity batteries dominated by nickel metal hydride (NiMH) materials, yet the newer EVs deploy LIBs. Differences in technologies, material components, and reuse methods all affect the modeling parameters.

$$EOL\ Volume\ (t) = \int_0^t NewSales(t^*) \times L(t^*)dt^* \tag{1}$$

Most of the existing studies in North America focus on the nationwide battery waste stream and assume a fixed battery lifespan across their study period (CEC, 2015; Richa et al., 2014; Standridge and Corneal, 2014). Among the few studies at a refined geographic scale, Hendrickson et al. (2015a,b) estimated EOL EV batteries for California counties based on their PEV sale penetration. For a comparison, Table 1 summarizes the data inputs, assumptions of battery lifespans, adopted function of discard probabilities, as well as the projected volume of existing studies. Clearly there are significant variations in EOL EV battery estimates given various assumptions and parameters adopted in the calculations.

2.2. EV battery inflows

There are two main sources for EV battery inflows: (1) new EV battery sales, and (2) replacement batteries. Given the large volume of new EV sales and rapid changes in EV battery design, replacement batteries are a relatively small proportion compared to the total EV battery inventory. Thus, we only focused on new sales for this study. Further, we assumed that EV battery sales could be determined by EV sales for both the historical and projected volume.

The historical EV sales in the U.S. have been compiled by the Alternative Fuel Data Center (AFDC) from U.S. Department of Energy. While most of EVs on the market used to be hybrid EV (HEV), plug-in hybrid EV (PHEV) and battery EV (BEV) sales rapidly increased from

Table 1
Summary of Existing EOL EV Battery Studies.

Author(s)	Geographic Area	Study Period	Vehicle/ Battery Types	Battery Inflows	Lifespan Assumption	Discard Probability Function	EOL Volume
CEC (2015)	North America Countries	2000- 2030	NiMH and Lithium batteries	2.4 million units in 2030	8-10 years	Uniform distribution	1.3 million units a year (U.S.) by 2030
Richa et al. (2014)	United States	2015- 2040	Lithium-ion battery	700 thousand – 1.8 million units in 2035[1]	Low: 4-12 years; Middle: 6-14 years; High: 8-16 years	Trunk normal distribution	800 thousand – 2.8 million units in 2040 (U.S.)
Standridge and Corneal (2014)	United States	2010- 2050	BEV and PHEV	2.2-15.6 million units in 2040[2]	3-10 years	Uniform distribution	1.4-6.7 million units annually by 2035 (U.S.)
Hendrickson et al., 2015a,b	California Counties	2015- 2050	PEVs (BEV and PHEV)	Market penetration of 60-80% in 2050 based on S-adoption curve	60%, 70%, or 90% of EV batteries retire over 10 years	Uniform distribution	30,000-90,000 metric tonnes a year in 2050 (California State)

Note:
[1] From the U.S. EIA Annual Energy Outlook 2012.
[2] High bound estimate is from the Electric Vehicles Initiative (EVI, 2011); low bound is from the U.S. EIA; the medium estimate is the average of high and low bound estimates.

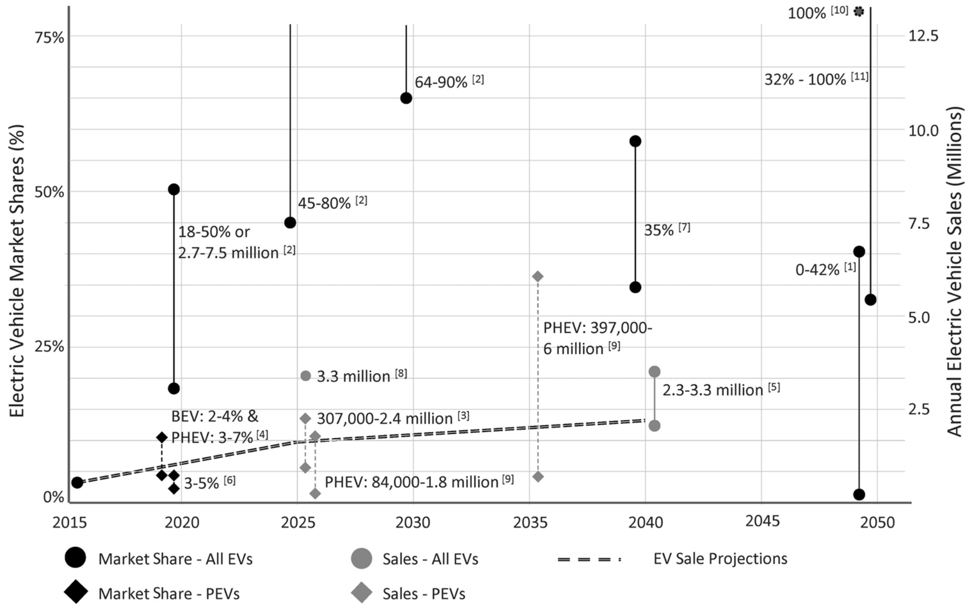

Fig. 2. Reviews on Projected EV Market Penetration (2015–2050).
Note: [1] Babaee et al., 2014; [2] Becker et al., 2009; [3] Block et al., 2015; [4] Lache et al., 2009; [5] U.S. EIA, 2017a; [6] Fulton, 2015; [7] BNEF, 2016, 2017; [8] Lutsey, 2015; [9]McManus and Senter, 2009 [10] Wu and Aliprantis, 2013; [11] Yeh et al., 2008.

18,000 in 2011 to 158,600 in 2016 (AFDC, 2016; InsideEVs, 2018). Historically, the changes in annual EV sales were positively correlated with that in motor gasoline prices. Since 2014, despite the drop in oil price, the annual EV sales remained at a high level (500,000 EVs/year) (AFDC, 2016; US EIA, 2017a).

The projections of EV sales vary significantly across existing studies, in terms of either the number of EVs sold or EV market share among all Light Duty Vehicles (LDVs) (Fig. 2). The US EIA (2017a) estimated that EVs would account for 12–18% of total market share for LDV sales in 2040 and that it would reach 2.25 million units in 2040, including 710 thousand HEVs, 570 thousand PHEVs, and 970 thousand BEVs (US EIA, 2017a). Based on scenario analyses of energy prices and macro-economic conditions, the estimates by the U.S. EIA suggested a fairly conservative EV market compared to other studies. A few other researchers are more optimistic about the future EV market. For example, Becker et al. (2009) suggested that the EV market share would reach 18%–50% in 2020 and 64%–90% in 2030. Studies generally agree that EVs will account for 3–11% of LDV sales or 0.8–3.3 million units before 2025 (Block et al., 2015; Fulton, 2015; Lache et al., 2009; McManus and Senter, 2009). In the long-run, Bloomberg New Energy Finance (BNEF (2017) suggested that 35%–60% of new cars sold in the U.S. in 2040 would be EVs. By 2050, studies have projected EV market share would reach 24%–100% (Babaee et al., 2014; Wu and Aliprantis, 2013; Yeh et al., 2008).

Our study has adopted a relatively conservative estimate of projected sales provide by U.S. EIA for two main reasons. First, EIA data are published consistently under the same set of scenarios/parameters/methodology with annual updates, which facilitate our multi-year analysis. Second, the baseline of EIA estimates fits the moderate ranges that reviewed from existing studies as shown in Fig. 2. To address the uncertainties about new EV (and batteries) volume as well as other parameters, sensitive analysis was developed and will be elaborated in Section 3.

It is important to note that most of the batteries in EVs purchased by now would have retired before 2025 because current batteries are designed to last less than 10 years. In contrast, the EOL EV batteries from 2026 to 2040 involve projected EV purchases after 2016. Thus, EOL EV battery volumes were analyzed separately in two time periods, i.e., 2000–2025 (short-term) and 2026–2040 (long-term). That is, EV historical sales and projected sales are used as data inputs for short-term and long-term EOL EV volume estimates, respectively. Then annual sales from 2017 to 2040 are projected based on linear interpolation.

Further, various EV types are examined. The annual sales of each EV type are estimated by multiplying its market share by the total LDV sales, as summarized in Table 2. On the basis of existing literature, by 2025, this study assumes that the HEV, PHEV, and BEV would account for 3.25%, 2.75%, and 4.50% of LDV sales in the U.S., respectively. By 2040, their market shares will increase to 4.00%, 3.25%, and 5.50%, respectively. Under a conservative scenario of EV market share (10.50% of vehicle sales in 2025 and 12.75% of that in 2040), this study

Table 2
Data Inputs for Annual EV Sales in the U.S.

	2016 (Existing)[1]		2025 (Short-term)[2]		2040 (Long-term)[2]	
	Annual Sales	Market Share	Annual Sales	Market Share	Annual Sales	Market Share
Light Duty Vehicles	17.5 million		16.5 million		17.7 million	
HEVs	349,300	2.83%	542,800	3.25%	706,500	4.00%
PEVs	145,500	0.83%	1,210,800	7.25%	1,545,500	8.75%
PHEVs	73,100	0.42%	459,300	2.75%	574,000	3.25%
BEVs	72,400	0.41%	751,500	4.50%	971,500	5.50%

Note:
[1] Historical data for 2016 (and before) are from AFDC (2016) and InsideEVs (2018).
[2] Sales for 2025 and 2040 are estimated by the Authors based on the U.S. EIA Annual Energy Outlook (2017a).

Table 3
Data Inputs for Annual EV Sales in California.

	2016 (Existing)[1]		2025 (Short-term)[2]		2040 (Long-term)[2]	
	Annual Sales	Market Share	Annual Sales	Market Share	Annual Sales	Market Share
Light Duty Vehicles	2.09 million		1.92 million		2.03 million	
HEVs	98,700	8.26%	n.a.	n.a.	n.a.	n.a.
PEVs	73,500	3.52%	230,500	12.00%	407,800	25.00%
PHEVs	33,200	1.59%	163,300	8.50%	203,100	10.00%
BEVs	40,300	1.93%	67,200	3.50%	204,700	15.00%

Notes:
[1] Historical data for 2016 (and before) are derived from California Auto Outlook (e.g., CNCDA, 2017).
[2] Sales for 2025 and 2040 are estimated based on California Zero Emission Vehicles (ZEV) Plan (ARB, 2017).

estimated that America's annual EV sales would reach 1.75 million by 2025 and further increase to 2.25 million by 2040.

The State of California is the home of 52% of new PEVs sales in the U.S. on an annual basis (ARB, 2017; Hendrickson et al., 2015a,b). According to the California Auto Outlook prepared by the California New Car Dealers Association (CNCDA), 33,200 PHEVs and 40,300 BEVs were sold in California in 2016, which together accounted for 3.5% of the total 2.09 million new LDV sales (CNCDA, 2017). The California Zero Emission Vehicles (ZEVs) Plan targets to achieve a market share of 15.4% among new car sales for ZEVs by 2024, and eventually reach 100% of market share in California by 2050 (ARB, 2017).

Our study has roughly adopted the market share of EVs as set in the ZEV Plan for the short-term analysis and is much more conservative for the long-term (Table 3). Next, we projected the state LDV sales as a proportion of the U.S. Multiplying the vehicle sales volume in California by the assumed rates of EV market share, this study projected that the annual EV sales in California would increase to 230,500 in 2025 and continue to reach 407,800 in 2040, which is relatively low compared to other studies (Hendrickson et al., 2015a,b). Still, the significant volume demonstrates the urgency of managing EOL batteries.

At the county level, this study estimated annual EOL EV batteries based on EV sales in individual counties that are calculated as previously discussed. State-wide EV sales were allocated to each individual county based on the county-to-state ratios, which were derived from the database of the California Clean Vehicle Rebate Project (CVRP, 2010–2016). CVRP (2017) documents individual EVs (e.g., location and year of purchase) that have received government-funded EV ownership incentives. The annual EVs reported under CVRP represented around 70% of annual EV sales in the state (ARB, 2017). Therefore, we assumed that the records could reasonably represent the temporal and spatial distribution of California EVs, as illustrated in Fig. 3. For example, the State of California provided rebates to 43,418 PHEV/BEV owners in 2016, while Los Angeles County reported 11,640 rebates. Hence, 26.8% (11,640 out of 43,418) is considered the county-to-state ratio for Los Angeles County in 2016. The county-to-state ratios were computed for all 58 California counties from 2010 to 2016. Acknowledging that those ratios may fluctuate for the first few years before stabilizing, this study applied the three-year moving average.

2.3. EV battery lifespan

As discussed in Section 2.1, EV battery lifespan is a critical parameter in PFA models for EOL EV battery volume estimates. In general, the EV battery lifespan are affected by: (1) battery capacity and degradation rate, which vary by EV types (i.e., HEVs, PHEVs, and BEVs); (2) technology and materials used in EV batteries, which are anticipated to be upgraded continuously and extend battery lifespans; and (3) consumer usage pattern (e.g., charging frequency and method, driving behaviors, and road conditions). These factors all contribute to the wide range of lifespan parameters that have been adopted in the literature.

At present, manufacturers aim to produce batteries that could last as long as 15 years, while the functional period specified in the manufacturer warranty spans 8–10 years (ARB, 2010). Recent customer surveys revealed that battery lifespans can be as short as 4–6 years in early EV models (Plug-In America, 2012). Existing studies have often resorted to such references and assumed fixed lifespans for EOL EV battery estimates (CEC, 2015).

Notably, battery lifespans have been increasing over time due to anticipated technology advancement. The National Academy of Sciences (NAS) suggests 3–8 years for EV batteries sold by 2010, 7–12 years for those sold between 2010 and 2020, and 9–15 years for those to be on the market between 2020 and 2030 (Ramage et al., 2010). New technologies, such as battery performance management (BPM), optimization approaches, and innovative structure and materials, are all expected to prolong EV battery (Al-karakchi et al., 2015; Cao, 2016; Cano et al., 2018; Catenacci et al., 2013)

This study aims to assess the sensitivity of EOL estimates in terms of lifespan parameters by comparing the scenarios of constant lifespan (i.e., 3–8 years) to dynamic lifespan (as suggested by the NAS from pre-2010 to 2030). As there are many factors that may affect battery lifespan in addition to battery types such as technology advancement and consumer usage pattern, in this study, we did not distinguish battery types when obtaining the battery lifespan, rather we focus on the average performance of different EV batteries at an aggregate level given those uncertainties and data constraints.

For the range value of lifespans, the average was calculated, as shown in Table 4. Then we referred to the best-fitting trend-line through data points in 2010, 2020, and 2030, and created estimates of battery lifespan at 5-year intervals. This method allowed us to focus on general trends of EOL EV battery volumes and avoid outliers introduced by drastic technology advancement during one particular year.

2.4. Discard probability

Another parameter in PFA is the product discard rate, i.e., $L(t, t^*)$ in Eq. (1). Prior studies in EOL EV battery inventory analysis typically applied a uniform distribution or a truncated normal distribution. They are relatively simpler distributions and serve as good starting point for analysis before more complex probability distribution functions are adopted.

As an alternative, Weibull distribution was also adopted in this study given its extensive applications in investigating battery failure and the e-waste stream (Kumar and Sarkar, 2012; Terazono et al., 2006). Given its ability to model a variety of product life behaviors, Weibull distribution is considered to be more realistic. It has also been applied to the analysis of e-waste (e.g., reliability analysis, product life analysis, and failure forecast), but is yet to be adopted in modeling EV battery discard probability.

In this study, we adopted a two-parameter Weibull distribution: the *scale* and *shape*. The scale parameters stand for the relative magnitude of lifespans, which is commonly equal to the average EV lifespan (Barré et al., 2013). Whereas the shape parameters describe the contrariness of

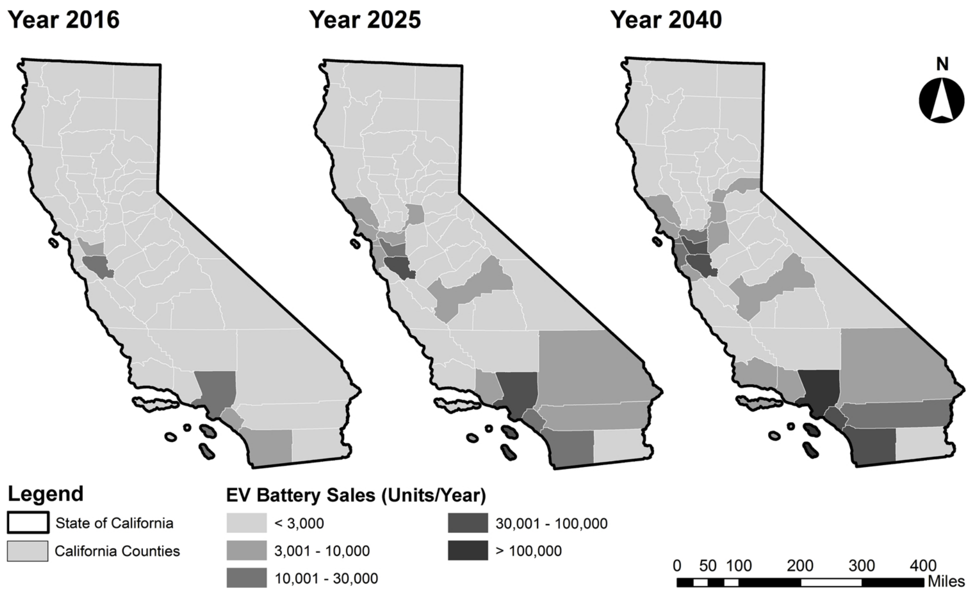

Fig. 3. Annual EV Sales at the California Counties (2016, 2025, 2040).
Map by Author. County-level data estimated using the method described in Section 2.2.

Table 4
Lifespan Assumptions Adopted in This Study.

Technology Year	Low bound Lifespan	High bound Lifespan	Average Lifespan	Application Period (Purchase Year)
Constant Lifespan				
2010	3	8	5.5	2000-2040
Dynamic Lifespan				
2010	3	8	5.5	2000-2014
2015	5	10	7.5	2015-2019
2020	7	12	9.5	2020-2024
2025	8	14	11	2025-2029
2030	9	15	12	2030-2034
2035	9	16	12.5	2035-2040

a product retired pattern, and they rarely change over time (Wang et al., 2013). We adopted the scale parameter of 3.5 for our model, by referring to the parameters in existing studies (e.g., 1.7–3.3 for household e-waste in Oguchi (2006) and 3.5 for Ni-Cd batteries in Matsuno et al. (2012)). As more empirical data becomes available, more complex three-parameter Weibull distribution shall be developed to better capture battery discard probabilities (e.g., components from recycling of EOL EV batteries can also be used in manufacturing of new EV batteries).

Given the limited practice and information about EV battery reuses and recycling, we focused on the first use of EV batteries and assumed that all discarded EV batteries need EOL management in the discard year. Then we assumed that the probability of a battery entering EOL lies in one of the following three distributions:

Distribution 1: Discard rates follow a uniform distribution within the high/low bound period.

Distribution 2: Discard rates follow a 95% truncated normal distribution function within the high/low bound period.

Distribution 3: Discard rates follow a Weibull distribution with a uniform shape parameter setting at the value of 3.5 and scale parameters equal to average lifespans of each application period.

Note that the three probability distributions above did not directly capture the impact of battery recycling rate or reuse rate, which would be an interesting area of future studies by extending the form of discard probabilities or considering more than one type of battery inflow streams, should more data become available.

3. Estimation of EOL EV batteries in the U.S

By employing the PFA method and data parameters in Section 2, here we present the results of EOL EV battery estimates at the U.S. national-level. As explained in Section 2.2, short-term (2000–2025) and long-term (2026–2040) EOL EV battery volume were estimated separately. Careful efforts were taken in sensitivity analyses, which explore the impact of uncertainties about future EV sales, different battery lifespans, and discard probabilities. In addition, we developed the estimates of EOL EV batteries by EV type, which, as discussed earlier, has direct implications for material management strategies.

3.1. Short-term estimates

During the short-term (before 2025), the uncertainties of estimating EOL EV batteries largely relate to battery discard rates. When assuming a constant lifespan of EV batteries explained in Table 3 (i.e., a lifespan of 3–8 years with an average of 5.5 years), the annual EOL batteries from existing EVs peaked around 500,000 units in 2018, reduced to 400,000 units in 2020, and almost all existing EV batteries are expected to retire by 2025. The estimates from three distribution functions (i.e., uniform, truncated normal, and Weibull) largely conform to each other over time (Fig. 4). It confirms the findings from previous studies (e.g., Chen and Graedel, 2012) that the discard distribution function may not play a role as important as the lifespan parameters in MFA.

When adopting dynamic lifespan estimates (i.e., the average battery lifespan increases due to technology advancements), the annual EOL batteries from existing EVs peaked earlier and at a lower rate (around 400,000 units in 2017) compared to the constant lifespan scenario. The number further decreased at a slower rate to 300,000 units in 2020 and to 100,000 units in 2025. That is, prolonging the battery lifespan would reduce the quantity of EOL EV batteries in the near future. Still, over 300,000 units retire annually by 2025. It is imperative to explore proper management for the large volume of EV per year batteries to be retired soon.

When various EV types are examined, Fig. 5 shows HEVs contribute to the largest share of retired batteries and those from PEVs are estimated to increase rapidly from 6.8% in 2015 to 27% in 2025 under the scenario that combines dynamic lifespans a Weibull distribution function. The results suggest that proper infrastructure planning is needed in the future, given batteries from PEVs have larger capacity and

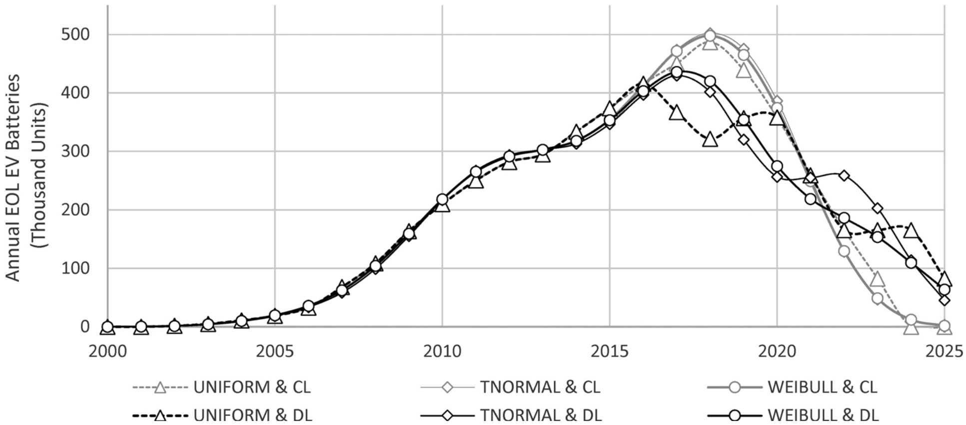

Fig. 4. EOL EV Batteries from Existing EVs by Different Distribution Function and Lifespan Scenarios (2000–2025).
Note: [1] UNIFORM: Uniform distribution function for discard probabilities; [2] TNORMAL: Truncated normal distribution function for discard probabilities; [3] WEIBULL: Weibull distribution function for discard probabilities; [4] CL: Constant lifespan scenarios; [5] DL: Dynamic lifespan scenarios.

require specialized facilities for proper processing so to be recycled or reused.

3.2. Long-term estimates

In the long term, Fig. 6 shows our estimates through 2040 when a Weibull distribution function and dynamic lifespan assumptions are adopted. The units of EOL EV batteries are estimated to continuously increase from 400,000 in 2016 to 650,000 in 2025, and further reach 1.65 million in 2040. Given the uncertainties of future EV markets, this study deployed a sensitivity analysis testing the units of retired EV batteries under high and low market penetration scenarios, which present 150% and 50% of EV sales of the moderate market penetration (i.e., baseline scenario), respectively.

The sensitivity analysis suggests, in the case of low EV market penetration, at least 300,000 to 400,000 units of EOL EV batteries in the U.S. will require proper management every year in the short term (2018–2025). In the case of high market penetration, the units of EOL EV batteries would increase rapidly from 2020-2025. The annual EOL EV batteries may increase to 900,000 units in 2025 and reach 2.45 million units in 2040.

3.3. Comparison with existing studies

In comparison to the inventory modeling results from existing studies (as summarized in Table 1), our estimates generally show higher volume in the short term (by 2018) and lower volume in the long term (Fig. 7). In addition, the peak time of EOL EV battery generation is relatively early compared to other studies. It suggests that the EOL EV battery management is needed sooner than later. The difference also suggests that adopting constant EV battery lifespan parameters in PFA may underestimate the immediate need of EOL EV battery management nationwide. Specifically, rapid technology advancements may result in variations of materials or products under study, and varying discard probability rates over time. It is important to incorporate technology changes in MFA and PFA studies by considering dynamic discard rates.

4. Estimation of EOL EV batteries at the county level in California

This section presents our analysis of EOL EV batteries in California and by county, with a focus on exploring regional opportunities to link retired EV batteries with their B2U potentials. By developing region-specific data references, we demonstrate the importance of refined PFA in facilitating the development of regional solutions to EOL EV batteries (i.e. mandatory programs, recycling businesses, and infrastructure planning). For the purpose of battery B2U as energy storage systems, the EOL volume estimates are limited to the PEVs only.

4.1. EOL EV battery volumes in California

Given the ambitious ZEV plan in California, it is anticipated to see a rapid growth in retired batteries from PEVs. The dynamic lifespan model revealed a linear growth in EOL EV batteries in the coming decades and the volume would reach 100,000 units annually in 2025 and exceed 250,000 units annually in 2040. Cumulatively, the EOL EV batteries were estimated to be 560,000 units between 2010 and 2025, and over 2.7 million units between 2025 and 2040. The dynamic lifespan model resulted in considerably less volume than that from the constant lifespan scenario (i.e., 560,000 vs. 881,000 units in the short-term and 2.7 million units vs. 4.2 million units during long-term).

Assuming each battery weights 250 Kg (see Table A2), annual EOL EV battery volume in California is estimated to reach over 27,500 tons

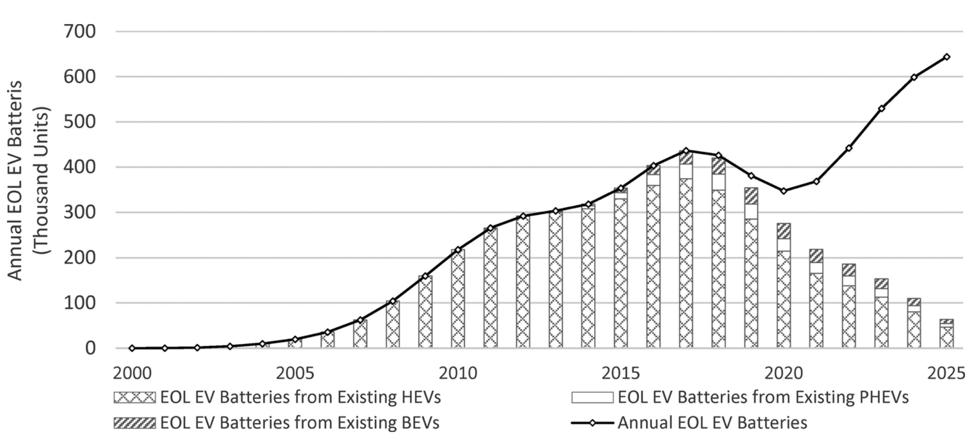

Fig. 5. Annual EOL EV Batteries by Vehicle Types (2000–2025).

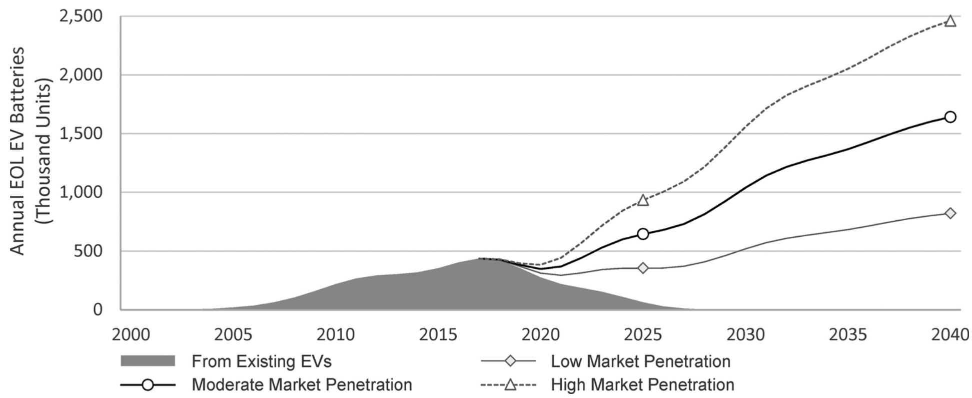

Fig. 6. Annual EOL EV Batteries in the U.S. (2000–2040).

by 2025. It demonstrates the critical need of battery recycling and reuse facilities, which are yet to be developed. Currently, the few EV battery recycling/reuse facilities in North America operate at an annual capacity of around 1000 to 5000 tons each (American Manganese Inc., 2018; Kampker et al., 2017; Li-Cycle Corp., 2018). When the technology of recycling, repurposing, and remanufacturing improves, the market could reach economies of scale at the regional level. Still, multiple facilities may need to be planned so that the EV batteries retired from California can be recycled or reused regionally and the impacts of long-haul transportation can be avoided.

At the county level, the cumulative volumes of EOL EV batteries during 2010–2025 are mapped in Fig. 8. San Francisco Bay Area (i.e., Alameda County and Santa Clara County) and Los Angeles County present the highest volumes over time. Notably, the EOL volume in peripheral regions around the San Francisco Bay area (i.e., Sonoma, Marin, and Sacramento) and Fresno County at Central Valley seem to be more sensitive to battery lifespan changes because those are the regions with emerging EV adopters and therefore newer models. This also suggests that the temporal factor can be critical in examining the geographic distribution of EOL batteries, which are related to not only the EV penetration rate but also the battery age/type.

4.2. Spatial matching of EOL EV battery volume and potential reuses

Given the existing strength of renewable energy development in California, this study identified repurposing EOL EV batteries for energy storage as an immediately applicable and preferable solution for both environmental benefits and economic gains. To date, California has 9.8 GW solar and 5.8 GW wind power facilities installed (US EIA, 2017b). Existing studies suggest that the battery energy storage system could maximize electricity generation from renewable sources and reduce life-cycle energy costs (ARB, 2017; Hendrickson et al., 2015a,b). However, recycling businesses and B2U infrastructure are still insufficient due to concerns about necessary economies of scales (Hendrickson et al., 2015a,b; Wang et al., 2014b).

To ease the comparison of demand (i.e., energy storage systems to used at renewable energy power plants) and supply (i.e., EOL EV battery volume), our analysis converted the capacities of the power plants (in the units of MW), as recorded in the U.S. EIA Energy Mapping System database (US EIA, 2017b), to equivalent battery units. The equivalent units could directly refer to the EV sales and provide insights on the facility/labor requirement during the collection and processing stages. The conversion was based on the assumptions that: (a) each EOL EV battery has 20 KWh usable capacity and 250 Kg in weight; and (b) 30 MW h of energy storage capacity is needed for each 100 MW capacity at renewable energy plants. Such assumptions were supported by empirical data (Appendix Tables A1 and A2) and existing studies (CSIRO, 2016; Hendrickson et al., 2015a,b).

Due to various technical and feasibility issues (e.g., non-standardization of EV cells and safety and reliability issues, and consumer usage patterns), not all retired EV packs would be suitable for stationary energy storage (Richa et al., 2017). Our conservative estimates of the total volume of EOL EV batteries (560,000 units, 11,200,000 KWh, or 1.54 million tons)) would significantly exceed the demand (235,000 battery equivalent units or 4,700,000 KWh) in California in the short term. Reusing 50% of retired EV batteries in the State could meet the demand for all utility-scale renewable energy plants (Appendix Table A2). It suggests a promising future for implementing regional solutions for B2U EV battery management. Meanwhile, other B2U solutions need to be explored, although steady growth in renewable energy development in California could potentially fill some of the remaining gaps. Meanwhile the transportation of these EOL batteries clearly presents logistics

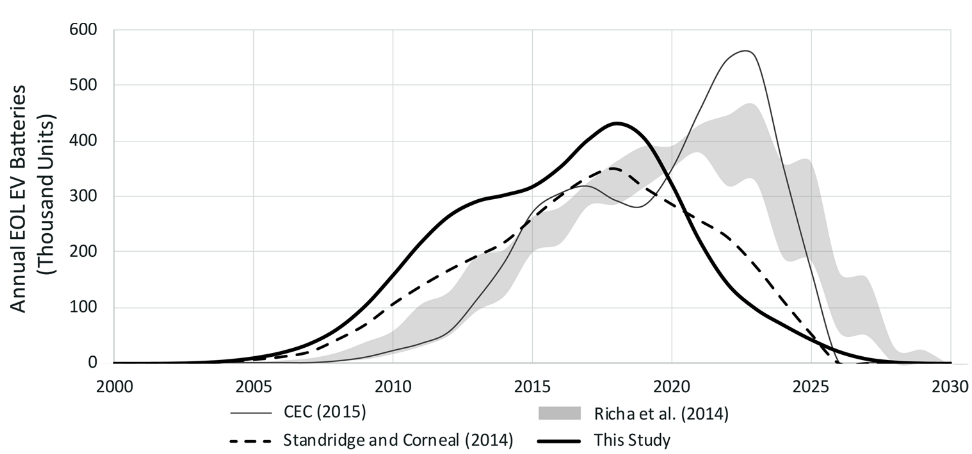

Fig. 7. EOL EV Battery Estimates: A Comparison of Existing Studies.

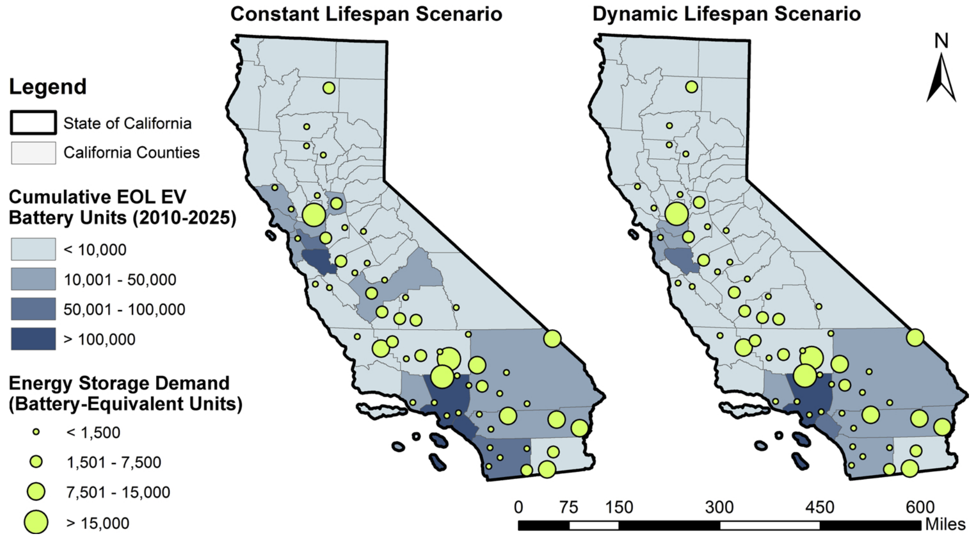

Fig. 8. Cumulative EOL EV Batteries by County and Their Potential Reuses in California before 2025.

challenges.

Spatially, the energy storage demand and cumulative volume of EOL EV batteries in California are overlaid in Fig. 8. This study assumed that the economies of scale in EOL EV batteries would matter more than the transportation distance from collection to treatment location in the short term. Therefore, neighboring plants are aggregated in terms of energy storage demand and location, i.e., power plants within 10 miles of each other were aggregated into one point. In this study, we consider 150-mile travel distance as the threshold for regional management. Fig. 8 presents an uneven distribution of demand and supply. While the EOL batteries are clustered in Los Angeles County and the San Francisco Bay area, potential reuses, i.e., at renewable energy power plants, are sprouted along the Central Valley, as well as southeastern California. Typically, a mismatch between energy storage demand and supply of reused batteries may be balanced by the transportation system. Nevertheless, longer travel distance leads to more transportation cost, which would account for a significant portion of repurposing/remanufacturing costs and makes it infeasible. In addition, transporting EV batteries over a long distance may result in more environmental risks. This suggests the needs of regional coordination for collection and disassembly facilities. The renewable energy plants in the northern Los Angeles County and in the northern San Francisco Bay Area would be close to the origins of retired EV batteries. Power plants located in the Central Valley, northeast of San Bernardino, or in southeastern California would have limited access to the EOL EV batteries as a useful supply. This suggests that it would be beneficial to have long-term infrastructure planning that better connects EOL EV batteries with potential users. Planning for the necessary infrastructure (e.g, location and capacity) for EOL EV batteries need to take into account such spatial mismatch, which is likely to be the case for other regions. In addition, region-wide transportation planning and alternative B2U approaches in closer proximity should be also considered. Better facility siting and transportation planning not only may address the mismatch, but also lead to other social benefits such as local economic development and job creation.

5. Discussion and conclusion

Globally, one in five EVs were sold in the U.S. (EVI, 2018). Other regions would look to the U.S. for proper management and planning for EOL EVs. The underdevelopment of EOL EV battery infrastructure is associated with a lack of awareness regarding the growing EOL volume as well as its ensuing impacts. The progressive EV promotion in the past urges for the need of proper managing EOL EV batteries in the near future. American automobile makers have been collaborating with battery producers, researchers, and other organizations to develop EOL battery programs. There seems to be inadequate attention to regional solutions, including the avoidance of environmental pollutions of long-distance hauling, the benefits for the region to promote B2U programs, and consequently, a lack of policy and planning support. Therefore, system-wide planning, especially at the regional level, is rather limited. Limited references of inventory estimates that incorporate EV market dynamics have been clearly a barrier.

This study of EOL EV batteries makes unique contributions to the theoretical field of MFA research and the practice of EOL EV management at various geographic scales. At the national level, this study tested two lifespan scenarios (i.e., constantly at 3–8 years, and dynamically increasing over time), three battery discard probability functions (i.e., uniform, truncated normal, and Weibull) and three scenarios of EV sale projections (i.e., low, moderate, and high). We found the short-term EOL volume (by 2025) can be particularly sensitive to the lifespan parameter. The long-term estimates involve most uncertainties related to the EV market penetration projections. The results from the three discard probability functions tested generally confirm to each other. Through our conservative estimates, the results suggest that proper EOL EV battery management and necessary infrastructure are needed sooner than the public may have perceived. Due to short lifespans of batteries from early EV models, the number of retired batteries has been increasing steadily every year since 2007. The annual EOL EV batteries is expected to reach 300–400 thousand units in the U.S. in the next few years. Thus, there is an important need to promote EV battery recycling participation rates of consumers, car dealers, and manufacturers, as well as improvements in recycling technology and infrastructure.

At the regional level, spatial and temporal heterogeneities directly affect the choice of EOL management strategies and necessary infrastructure. We found temporal considerations, in terms of both changes in EV market penetration patterns and EV model development, are critical in regional infrastructure planning for EOL EV batteries. In addition, we developed techniques that explicitly link EOL EV batteries with their potential B2U applications. In the case study in California, the study found that energy storage systems at renewable energy power plants can be a feasible solution to divert EOL EV batteries from landfills and long distance hauling. Reusing 50% of retired EV batteries before 2025, cumulatively 280,000 battery units, could sufficiently support all existing wind and solar utilities in the state. Further sensitivity analysis (Table A3) also resulted in consistent conclusions. It demonstrates the regional market for B2U applications, as well as the need to explore other EOL management strategies at the regional level.

The regional battery repurposing facilities could reach economies of scale, yet are currently missing. Spatial analysis clearly demonstrates the mismatch between EOL EV battery clusters and potential reuses at the regional level. Potential outsourcing of EOL EV battery management also involves intra-regional transportation. Therefore, region-wide coordination in terms of both infrastructure development and transportation planning should be considered. Importantly, effective policy-making for EOL EV battery management need to address regional heterogeneities resulting from multiple factors such as various density of stock, secondary market, and existing infrastructure.

Material flow accounting plays a critical role in sustainable material management at all geographic scales. This study demonstrates an integrated regional approach to minimize negative impacts of EOL EV battery management. The efforts reported here clearly suggests the critical value of consistent data reporting and sharing for inter-region coordinated waste management practice. As many sustainable initiatives make their data available to the public, we urge the EV programs to collect waste flow data and consider the full lifecycle of EV battery management.

Our modeling framework presented here provides benchmarks of local and regional waste outflows, allows researchers to scale-up impacts, produces policy references, and facilitates the policy design. When additional data become available, the framework in this study can be further refined to capture transboundary effects, such as considering EVs purchased or retired in other states or across county boundaries. Such information is critical for empowering regional coordination.

Another possible area of future study is to refine the battery capacity analysis both at the regional and national level, should more data become available. As shown in our results and sensitivity analysis at the regional level (Table A3), the amount of battery capacity available is critical to the economies of scale for local and regional practices (e.g., transportation needs, infrastructure planning, and regional coordination). When the battery recycling market is further developed, more refined analysis can be conducted to compare multiple EOL EV battery management options at various capacity levels.

Besides region-specific studies, future studies may also consider management of specific battery technology. Existing studies have mainly focused on Li-ion technology. At a more refined scale, EOL volume estimates of each type of EV batteries can provide additional insights into closed-loop planning and management of materials within the region, considering that scale matters in the EOL management process.

All in all, the significant number of retired EV batteries calls for improvements in current management policies for EOL EV batteries. Although the majority of states in the U.S. have banned lead-acid batteries from landfill, LIB recycling has neither been promoted nor mandated. Reusing retired EV batteries could be economically feasible and environmental favorable at the regional level. However, proper planning and policy setting is still missing. Incentivizing EV adoption will lead to significant increases in EV battery outflow, which is largely ignored in the EV promotion plans at present. Long-term policy-making should prepare for the consequences of stimulating EV development. Public sectors should make concerted efforts to facilitate partnerships to encourage efficient reuse and recycling of retired EV batteries and guide the industries through the product life cycles of EV batteries.

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Appendix

Table A1 presents the summary statistics of the battery characteristics (i.e., capacity and weight) of each PEV model that was sold in California. The data about PEV model types and PEV model counts by made-year were compiled from the Clean Vehicle Rebate Project (CVRP) database, which includes information about 172,461 PEVs. Given that the CVRP database records more than 60% of EVs sold in California from 2010 to 2016, this study assumed that the distribution of PEVs by made-year as reported by the CVRP can represent that of all PEVs sold in California.

Based on the summary statistics from Table A1, we calculated sale-weighted average battery capacity and weight, as shown in Table A2. Average battery capacity of PHEV ranges 11–12 KWh and that of BEV is 36–37 KWh. The sale-weighted average battery capacity is about 25 KWh and the weight is around 250 Kg. Assuming 80% of initial capacity remains when batteries are retired, this study finds around 20 KWh battery capacity could be reused.

Table A1
PEVs reported by Clean Vehicle Rebate Project.

Vehicle Make	PHEV						BEV					
			No. of Vehicles Received Rebate						No. of Vehicles Received Rebate			
	Capacity (KWh)	Weight (Kg)	Before 2013	2014	2015	2016	Capacity (KWh)	Weight (Kg)	Before 2013	2014	2015	2016
Audi	9	125	0	0	0	857	n.a.	n.a.	n.a.	n.a	n.a	n.a
BMW	7.1 - 9	98-120	0	0	0	0	22 - 32	256-342	0	794	2,540	2,669
Cadillac	18	254	0	120	96	41	n.a	n.a.	n.a	n.a	n.a	n.a
Chevrolet	16 - 18	181	11,123	6,901	6,842	8,418	19	254	399	714	1,832	2,201
CODA	n.a.	n.a.	n.a.	n.a	n.a	n.a	30	395	48	0	0	0
Fiat	n.a.	n.a.	n.a.	n.a	n.a	n.a	24	291	1,253	4,807	5,534	4,897
Ford	7 - 8	124	2,442	4,830	5,319	4,661	23	270	805	851	901	413
Honda	7	100	156	146	64	4	20	270	253	165	19	1
Hyundai	10	110	0	0	23	428	n.a.	n.a.	n.a.	n.a	n.a	n.a
Kia	n.a.	n.a.	n.a.	n.a	n.a	n.a	27	277	0	179	550	618
Mercedes-Benz	13	114	0	0	19	37	28	204	0	309	1253	393
Mitsubishi	n.a.	n.a.	n.a.	n.a	n.a	n.a	16	150	140	46	21	18
Nissan	n.a.	n.a.	n.a.	n.a	n.a	n.a	24 - 30	272	12,172	8,753	5,702	4,668
Smart	n.a.	n.a.	n.a.	n.a	n.a	n.a	17.6	148	389	1,000	542	350
Tesla	n.a.	n.a.	n.a.	n.a	n.a	n.a	60 - 80	540	6,213	5,289	8,422	8,023
Th!nk	n.a.	n.a.	n.a.	n.a	n.a	n.a	28 - 30	260	50	0	0	1
Toyota	9	120	6,776	6,538	2,345	629	41.8	390	809	849	64	5
Volkswagen	n.a.	n.a.	n.a.	n.a	n.a	n.a	24	330	0	117	2,823	2,652
Volvo	10	115	0	0	0	128	n.a	n.a.	n.a	n.a	n.a	n.a
Wheego	n.a.	n.a.	n.a.	n.a	n.a	n.a	30	330	2	0	0	0

Table A2
Sales-weighted Average EV Battery Capacity in California.

	Before 2013	2014	2015	2016
Average Battery Capacity: PHEV (KWh)	12.88	11.44	12.00	12.76
Average Battery Capacity: BEV (KWh)	37.02	34.34	36.46	37.13
Average Battery Weight: PHEV (Kg)	153.43	144.46	150.59	155.30
Average Battery Weight: BEV (Kg)	348.11	332.25	348.34	355.44
PHEV Sold in California	36,495	29,939	27,740	40,800
BEV Sold in California	33,504	29,536	34,477	38,807
Sales-weighted Average Capacity (KWh)	24.43	22.81	25.56	24.64
Sales-weighted Average Weight (Kg)	246.61	237.72	260.17	252.86

Table A3
Sensitivity Analysis of Cumulative Reusable EOL EV Batteries Capacity in California.

Collection Rate	Reusable Rate of Remaining Capacity		
	100% (80% of initial capacity)	90% (72% of initial capacity)	80% (64% of initial capacity)
100%	11,200 MW h	10,080 MW h	8,960 MW h
75%	8,400 MW h	7,560 MW h	6,720 MW h
50%	5,600 MW h	5,040 MW h	4,480 MWh

The estimates of total reusable capacity of cumulative EOL EV batteries are shown in Table A3. The baseline value of 11,200 MW h, i.e., 100% collection rate and 100% reusable rate of remaining capacity, is resulted from discussions in Section 4.2. Then various reusable rates of battery remaining capacity (from 80% to 100%) and collection rates (from 50% to 100%) were evaluated. Assuming that the total demand for batteries as energy storage is around 4700 MW h at all renewable utilities in California (Section 4.1), this sensitivity analysis suggests that the total reusable capacity of EOL batteries would be able to meet the regional demand, even at a low collection rate or under poor battery conditions. In other words, alternative EOL management solutions at the regional level still need to explore.

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