

A Second Life for Electric Vehicle Batteries: Answering Questions on Battery Degradation and Value

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ABSTRACT

Battery second use-putting used plug-in electric vehicle (PEV) batteries into secondary service following their automotive tenure-has been proposed as a means to decrease the cost of PEVs while providing low cost energy storage to other fields (e.g., electric utility markets). To understand the value of used automotive batteries, however, we must first answer several key questions related to battery degradation, including: How long will PEV batteries last in automotive service? How healthy will PEV batteries be when they leave automotive service? How long will retired PEV batteries last in second-use service? How well can we best predict the second-use lifetime of a used automotive battery? Under the support of the U.S. Department of Energy's Vehicle Technologies Office, the National Renewable Energy Laboratory has developed a methodology and the requisite tools to answer these questions, including the Battery Lifetime Simulation Tool (BLAST). Herein we introduce these methods and tools and demonstrate their application. Under our assumed second use duty cycle of daily peak shaving, we have found that repurposed automotive batteries can last ten years or more in second use service when managed properly. In this role, capacity fade from automotive use has a much larger impact on second use value than resistance growth. Where capacity loss is driven by calendar effects more than cycling effects, average battery temperature during automotive service, which is often driven by climate, is found to be the single factor with the largest effect on remaining value. Installing hardware and software capabilities onboard the vehicle that can both estimate remaining battery capacity from in-situ measurements, as well as track average battery temperature over time, will thereby facilitate the second use of automotive batteries.

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INTRODUCTION

Increased market share of plug-in electric vehicles (PEVs) is one major strategy to reduce the nation's dependence on foreign oil and emissions of greenhouse gases by improving the overall fuel efficiency and cleanliness of vehicles in the United States. Accelerated market penetration of PEVs is presently restricted by the high cost of batteries, however. It has been estimated that an approximate 50% reduction in 2010 battery costs is necessary to equalize the economics of owning PEVs and conventionally fueled vehicles [1, 2].

Deployment of grid-connected energy storage systems, which could increase the reliability, efficiency, and cleanliness of the grid, is similarly inhibited by the cost of batteries. Over the past few years, mandates and incentives for energy storage have increased dramatically to overcome this barrier. For example, in 2010 the California legislature passed Assembly Bill 2514, which resulted in the California Public Utilities Commission releasing a procurement target for 1.3 gigawatts (GW) of energy storage in the state by 2020 [3]. Approximately 15% of this allotment has been planned for customer-sited, behind-the-meter storage [4], further encouraged by California's self-generation incentive program, which offers up to \$1.62 per watt installed [5].

Research, development, and manufacturing ramp-up efforts are underway to reduce battery costs by lowering material costs, enhancing process efficiencies, and increasing production volumes. However, it is also advisable to pursue increasing the total value of services provided by a battery over its lifetime. As PEV batteries may have substantial performance capability left at the end of their automotive service life, additional value could be extracted by committing them to other energy storage applications post automotive use, such as grid-connected services, including area regulation, backup power, or demand charge management. By extracting additional services and revenue from the battery in this post-vehicle application, the total lifetime value of the battery is increased, and the cost of the battery can be shared between the primary and secondary users. We refer to such strategies herein as Battery Second Use (B2U).

Many factors will determine the viability and economics of B2U strategies, from the costs of repurposing processes to the evolution of competing battery technologies. One of the most important factors in this equation is battery degradation in both the first (automotive) and second service lives. Herein we present the methodologies and tools developed by the National Renewable Energy Laboratory (NREL) under funding from the U.S. Department of Energy's Vehicle Technologies Office to provide the necessary understanding of

battery degradation. We also present their application to a specific lithium ion chemistry (consisting of a nickel-cobalt-aluminum cathode and graphite anode) and example PEVs to explore likely outcomes.

ANALYSIS

First we introduce our method for calculating battery degradation as a function of operating conditions. Next we discuss the motivation for and timing of battery replacement when in automotive service, leveraging our past studies that combined the battery degradation model with an automotive techno-economic analysis tool. Subsequently, we couple the battery degradation tool with an advanced long-term vehicle simulator to calculate expected battery wear during automotive service for different drive patterns, vehicle platforms, and climates. We then calculate the remaining life of these batteries when put to use under an anticipated second use duty cycle and discuss how this translates to remaining battery value. Finally, we explore practical methods for identifying second use value at the point of automotive retirement and its implications on the design of PEVs today.

Modeling Battery Degradation

Quantification of the relative amount of remaining performance of a battery at any point in time requires an understanding of battery degradation. Prediction of battery degradation to arbitrary operating conditions is currently a working area of research in the battery community. Many models that do so are empirically based, interpolating between or extrapolating from different sets of measured battery capacity and resistance data sets [6, 7, 8]. These suffer from extensively large data needs and are often inadequate for extrapolating beyond the duration of the life test data upon which they are based. Alternatively, physics-based, first-principles models have been proposed, but can be exceedingly complex and limited in scope to a narrow range of operating conditions [9, 10, 11].

NREL has developed a semi-empirical life model that attempts to bridge this gap, offering a combination of increased confidence in interpolations and projections while maintaining simplicity of implementation and a basis in actual laboratory data [12]. It separately accounts for both capacity and resistance effects induced by cycling-based and calendar-based mechanisms. Cycling-based mechanisms specifically address the effect of charging and discharging the battery, while calendar-based mechanism address degradation that occurs even in the absence of current flow. Nonlinear effects of time, temperature, depth of discharge (DOD), and state of charge (SOC) are included. The specific model employed herein is fit to an extensive set of degradation data for a lithium-ion cell with a nickel-cobalt-aluminum cathode and graphite anode. We apply this model within an assumed 15-year vehicle life, at which point approximately 67% of all vehicles have been removed from service [13].

Battery Replacement in Automotive Service

An understanding of the time and state of health (SOH) of a PEV battery when it is removed from automotive service is also critical to calculating remaining battery performance. This requires knowledge of PEV battery replacement decisions, which can be made on multiple bases. In cases where the battery warranty ensures some minimum available performance criteria, the replacement decision may be straightforward. Vehicle leasing that entails similar performance guarantees would also be straightforward. At the time of writing, the 2014 Chevrolet Volt propulsion battery is warrantied to stay above 70% capacity during its 8-year/100,000-mile term [14]. The 2014 Nissan LEAF battery is similarly warrantied over a 5-year/60,000-mile term [15]. Nissan also offers a battery warranty extension for \$100/month that can be extended for the total lifetime of the vehicle [16].

Where this is not the case and the vehicle is owned by its user, the majority of battery replacement decisions will be made by that user. The user's motivation for battery replacement may be (1) improved acceleration, (2) increased interior volume within the vehicle, (3) increased electric range of the vehicle, (4) decreased fuel costs, or (5) increased resale value. Our analyses suggest that vehicle acceleration is most likely limited by inverter and motor selection throughout the life of the vehicle, not the battery. Recovering additional interior volume following installation of a smaller battery would require considerable modification to a vehicle beyond battery replacement. Thus, motivations 1 and 2 are ruled out on the basis that these scenarios are expected to occur infrequently. Motivations 3, 4, and 5, on the other hand, are all viable, and all have quantifiable economic implications to the user (increased range leads to more miles driven on electricity rather than more expensive fossil fuels).

Thus, it is reasonable to assume that batteries will be replaced when either (1) a warranty (or similar) performance level is breached, or (2) there is an economic motivation for the user-owner to do so. Previous studies on battery degradation with NREL's Battery Ownership Model and the Battery Lifetime Analysis and Simulation Tool for Vehicles (BLAST-V)-advanced techno-economic simulators for PEVs employing the aforementioned battery degradation model-have found it likely that (1) PEV batteries will retain more than 70% of their original performance over the first 8 years of operation, and (2) replacing batteries within the anticipated 15-year lifetime of a vehicle will not be economically justified [17, 18, 19]. While there will be exceptions for select high-wear cases (particularly for high-mileage drivers in hot climates), they are likely to be a small percentage of the total B2U supply stock.

As such, the majority of B2U batteries should be expected to become available only at the end of a complete 15-year automotive service life, and the subsequent analyses herein shall be restricted to these cases.

Battery Degradation in Automotive Service

NREL's BLAST-V was applied to compute the SOH of PEV batteries following 15 years of automotive service. This highly detailed PEV simulator includes consideration of driver patterns and aggression,

climate, cabin thermal dynamics, infrastructure, and many other factors to compute the wear incurred by the battery and utility delivered to the driver. More detail on the functionality of this tool can be found in the BLAST-V documentation [20].

Recent BLAST-V studies have found that driver patterns and climate have the largest effect on battery degradation among many other factors, including driver aggression, vehicle and battery thermal management systems, available infrastructure, etc. [19, 21, 22]. Thus BLAST-V is employed herein to predict battery degradation metrics for cold (Minneapolis, Minnesota), moderate (Los Angeles, California), and hot (Phoenix, Arizona) climates across a set of 91 year-long PEV-friendly drive patterns. These drive patterns are a subset of data recorded from the Puget Sound Regional Council's Traffic Choices Study [23], processed per Neubauer and Wood [19], that yield a year-one vehicle miles traveled $\geq 8,000$ miles and a utility factor $\geq 80\%$ when driven with a battery electric vehicle (BEV) with a 75-mile-range (BEV75), as presented in Figure 1.

Note that range of a BEV can vary greatly with operating conditions. Our definitions of nameplate range for PEVs are calculated via simulation and weighting of drive cycles per [24], which approximates the U.S. Environmental Protection Agency-rated range of a given vehicle. It is, however, common that our simulated PEVs achieve a greater than nameplate range as operating conditions allow.

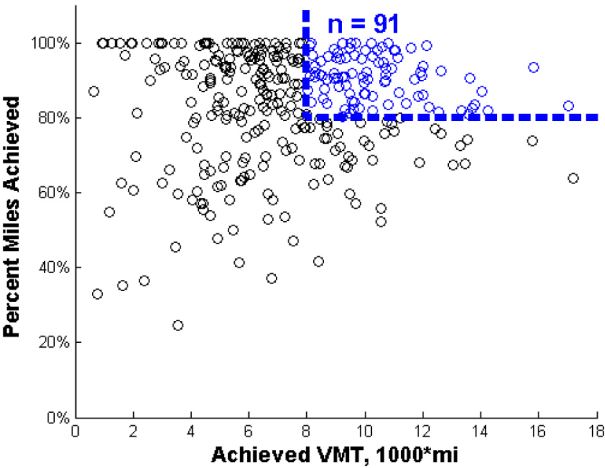


Figure 1. Utility factor vs. achieved vehicle miles traveled for selected drive patterns

For these drivers and climates, two different PEVs are simulated: (1) a midsize sedan BEV75, and (2) a midsize sedan plug-in hybrid electric vehicle (PHEV) with a 20-mile electric range (PHEV20). The BEV75 is equipped with a 22.1-kWh battery that operates between 100% and 0% SOC. The PHEV20 is equipped with a 7.74-kWh battery that operates in charge depleting mode between 100% and 20% SOC, then switches to charge sustaining mode. The PHEV battery is assumed to have 50% lower cell resistance than the BEV battery to reflect the higher relative power-to-energy ratio required of the PHEV20. Each vehicle employs a heat-pump cabin heater, a conventional cabin air conditioner, and an active battery cooling system. Further details of the battery and thermal systems models can be found in Neubauer and Wood [19].

Road load energy consumption is based upon simulation of NREL's Drive-Cycle Rapid Investigation, Visualization, and Evaluation (DRIVE) cycle, scaled for normal-aggression drivers and the average speed of the specific trip being simulated [19]. Auxiliary loads-battery thermal management and cabin heating and cooling-are computed based on thermal simulations of the vehicle-battery system per Neubauer and Wood [19].

We assume that only at-home Level 2 charging (6.6 kW alternating current) is available, and that the battery cooling system actively cools the battery when at the charger. All vehicles are simulated for 15 years, our assumed end of automotive service. The vehicle simulation specifications are given in Table 1.

Table 1. Vehicle Simulation Specifications

Drivetrain	BEV75	PHEV20
Vehicle type	Midsize sedan	Midsize sedan
Battery size	22.1 kwh	7.74 kwh
Typical electric range @ BOL	75 miles	20 miles
Maximum SOC @ BOL	100%	100%
Minimum SOC @ BOL	0%	20%
Auxiliary equipment	Heat-pump cabin heater Conventional cabin air conditioner	
Charging infrastructure	At-home Level 2 (6.6 alternating current, 93% efficiency) Battery cooling active at charger	

BOL = beginning of life

The resultant battery SOH data are presented in Figures 2, 3, 4, 5 for all drive patterns. Table 2 presents the median SOH values taken from all of the drive patterns.

These data show that for both the BEV75 and PHEV20, capacity loss is dominated by calendar effects (Q1), resulting in losses of 25% to 35% after 15 years of automotive life, depending on climate and driving pattern. The effect of climatic differences between Minneapolis and Los Angeles is significant, resulting in 4% more Q1 capacity loss in Los Angeles. The difference between Phoenix and Los Angeles is only 1%, however, presumably due to the presence of the active cooling system above 20°C. Median Q1 capacity losses are approximately 4% higher in the PHEV20 than the BEV75. While the cycling effect on capacity (Q2) is much greater (approximately 12%) in PHEVs than in BEVs due to the increased frequency of high DOD cycling, this has no immediate impact on battery performance or value, as the total capacity loss is determined by the greater of Q1 and Q2, not the sum.

Calendar effects on resistance (R1) are nearly identical for the BEVs and PHEVs. In all cases, the 25th to 75th percentile spread is extremely small. For the BEV, it is likely that the calendar effects on resistance are significantly larger than the cycling effect (R2); however, for the PHEV this trend is reversed: cycling effects (R2) are much more likely to dominate total resistance growth. The sum of R1 and R2 is much larger in the