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Sensitivity of battery electric vehicle economics to drive patterns, vehicle range, and charge strategies

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ABSTRACT

Battery electric vehicles (BEVs) offer the potential to reduce both oil imports and greenhouse gas emissions, but high upfront costs discourage many potential purchasers. Making an economic comparison with conventional alternatives is complicated in part by strong sensitivity to drive patterns, vehicle range, and charge strategies that affect vehicle utilization and battery wear. Identifying justifiable battery replacement schedules and sufficiently accounting for the limited range of a BEV add further complexity to the issue. The National Renewable Energy Laboratory developed the Battery Ownership Model to address these and related questions. The Battery Ownership Model is applied here to examine the sensitivity of BEV economics to drive patterns, vehicle range, and charge strategies when a high-fidelity battery degradation model, financially justified battery replacement schedules, and two different means of accounting for a BEV's unachievable vehicle miles traveled (VMT) are employed. We find that the value of unachievable VMT with a BEV has a strong impact on the cost-optimal range, charge strategy, and battery replacement schedule; that the overall cost competitiveness of a BEV is highly sensitive to vehicle-specific drive patterns; and that common cross-sectional drive patterns do not provide consistent representation of the relative cost of a BEV.

1. Introduction

Although there are many reasons why an individual car buyer chooses one vehicle over another, economics is an important factor for many consumers. For some end-users, such as fleet managers, total lifetime economics is one of the top factors affecting purchase decisions. In addition, understanding the economics of technologies that can support meeting broad societal objectives, such as the reduction of oil imports and greenhouse gases, can aid policy-makers in decision-making. Thus, there is a strong motivation to examine and compare the economics of today's and tomorrow's vehicle technologies.

Plug-in electric vehicles, which include both plug-in hybrid electric vehicles and battery electric vehicles (BEVs), offer the potential to reduce both oil imports and greenhouse gases, but assessing their economics is complicated by several factors. For one, plug-in electric vehicle batteries—typically a major component of total vehicle ownership costs—are subject to complex operational duty cycles specific to vehicle platform and driving habits, thus making battery life difficult to forecast. Further complicating battery life calculations are a battery's sensitivity to local climate and charge strategy, the proposals of some to reap revenue from vehicle-to-grid and vehicle-to-building services, and the potential for second-use revenue generation following the end of its automotive service life.

For plug-in hybrid electric vehicles with a limited all-electric operational mode, electricity and gasoline costs become highly sensitive to the distribution of daily vehicle miles traveled (DVMT) experienced over the life of the vehicle as well, herein referred to as a drive pattern. For example, some drivers may be able to complete the majority of their driving needs with a modest all-electric range, thus using very little gasoline, while other drivers may do just the opposite. A BEV, on the other hand, may require a driver to adapt his or her drive patterns to the limited range of the vehicle, or alternatively turn to fast charge or battery swapping options to complete long trips. Such techniques drastically complicate economic computations by introducing significant infrastructure requirements and inserting additional parties into the equation.

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Abbreviations: BEV, battery electric vehicle; BOM, Battery Ownership Model; CS1, Charge Strategy 1 (right-away charge from home); CS2, Charge Strategy 2 (just-in-time charge from home); CS3, Charge Strategy 3 (just-in-time charge from home, right-away charge from work); CV, conventional vehicle; DVMT, daily vehicle miles traveled; EIA, Energy Information Administration; PDF, probability density function; SOC, state of charge; TCO, total cost of ownership; TCS, Traffic Choices Study; V2G, vehicle to grid; V2B, vehicle to building; VMT, vehicle miles traveled.

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has developed a vehicle total cost of ownership (TCO) calculator known as the Battery Ownership Model (BOM) to address these and other challenges associated with the lifecycle economics of electric vehicles. In this paper, we apply the BOM to examine the sensitivity of BEV economics to drive patterns, range, and charge strategies when a high-fidelity battery degradation model, financially justified battery replacement schedules, and two different means of accounting for the unachievable vehicle miles traveled (VMT) of a BEV are employed.

2. Approach

The BOM is an advanced TCO calculator that takes into account various scenarios of vehicle and component costs, battery and fuel price forecasts, drive patterns, battery wear, charging infrastructure costs, purchase incentives, financing, ownership, and other criteria. The vehicle economics considered include vehicle and related infrastructure purchases, financing, fuel (gasoline and electricity) costs, non-fuel operating and maintenance costs, battery replacement, salvage value, and any costs passed on by a third party such as a service provider to account for the installation, use, and availability of infrastructure. Battery degradation, charging strategies, and drive patterns play an important role in each of these elements and are addressed as described below. An approximate graphical representation of the key elements and flow of data within the BOM is illustrated in Fig. 1.

A more detailed description of these elements can be found in O'Keefe et al. [1]. The vehicle performance and sizing model included is the National Renewable Energy Laboratory's Future Automotive Systems Technology Simulator (FASTSim) developed under funding provided by the Vehicle Technologies Program in the U.S. Department of Energy. Note that the battery second use and vehicle-to-grid elements are recent additions not described therein; discussion and use of these modules will be presented in future papers. In addition, the battery use and wear element has recently received considerable updates, as discussed below.

2.1. Cost metrics

The primary output of the BOM is the ratio of the total discounted costs of an advanced vehicle—in this discussion a BEV—to that of a conventional vehicle (CV), as defined in Eq. (1). The variable c is the cost to the vehicle owner/operator during the given period, i. The discount factor for the given period is d, and the total number of periods is N.

$$\text{BEV-to-CV cost ratio} = \frac{\left(\sum_{i=1}^{N} c_i \cdot d_i\right)_{BEV}}{\left(\sum_{i=1}^{N} c_i \cdot d_i\right)_{CV}} \tag{1}$$

When using this approach, it is important that the inputs and assumptions applied to the calculation of the BEV and CV costs are identical, such that the calculated cost ratio is indicative of the relative cost of replacing a specific individual CV subject to a particular drive pattern with a BEV operated under identical conditions and requirements. However, in the absence of range extension infrastructures such as fast chargers, battery swapping facilities, or electric roadways, the maximum daily range of a BEV is limited by battery size, vehicle efficiency, and charging strategy. This limits the total achievable VMT of a BEV under a given drive pattern, and thus it is necessary to accurately identify which day's travels can be completed by the BEV. Considering this point enables the accurate computation of battery wear and the cost of BEV operation. Further consideration for the cost of the BEV's unachievable VMT enables a fair comparison of BEV and CV ownership costs.

To achieve these ends, the electric range of the vehicle for the first year is calculated via a detailed vehicle simulation, and then reduced annually as the battery is calculated to degrade. When the combination of range and charge strategy is incapable of achieving the driving requirements of a given day, it is assumed that the BEV is left at home and one of two alternative means of transportation is employed: either (1) a low-cost approach in which a CV already owned by the household is used, or (2) a high-cost approach where a CV is rented via a car-share program.

Costs for the low-cost alternative means of transportation include the cost of fuel and per-mile tire and maintenance costs. This captures all of the additional costs incurred by the extra use of the CV and is therefore representative of the extra expense that would be incurred by the household. Attributing them to the BEV's total cost leaves the total cost of the additionally owned CV unaffected while ensuring that all of the household transportation costs are accurately accounted for. Note that the effect of the extra mileage accrued to the CV on its lifetime and residual value is not accounted for, however. This, alongside questions over the availability of the CV when needed in place of the BEV, implies that this accounting method is only valid when the frequency of use of the CV is relatively low. A more detailed analysis considering the complete driving requirements and fleet availability of a household could address these issues, but is beyond the scope of this study.

Costs for the high-cost alternative means of transportation are taken from a typical Zipcar rate structure, consisting of a $60 per month annual membership fee, an $8.75 per hour rental rate capped at $82 per day, and a mileage fee of $0.45 per mile for each mile in excess of 180 miles per day [2]. To acknowledge the common requirement of returning a car-share vehicle to the same location from which it was acquired, we assume 8 h of dwell time at the destination along with the required drive time of the day when computing the total duration of the car-share vehicle rental.

2.2. General variables

In all economic analyses we examine a 15-year period of ownership from 2012 to 2027, covering the entire assumed life of the vehicle. A driver discount rate of 8% is assumed, as are national average temperatures and tax rates for battery purchases, vehicle purchases, and vehicle registration. Although a $7500 BEV federal tax credit is accounted for, available state tax credits are ignored.

2.3. Battery degradation and replacement

A high-fidelity degradation model [3] for nickel–cobalt–aluminum lithium ion batteries capable of considering complex duty cycles and accurately capturing the impact of depth of discharge, temperature, and state of charge (SOC) has been incorporated into the BOM. Note that the effects of voltage are captured by accounting for the SOC history of the battery. Each of these factors has been shown to strongly affect battery performance over time, often in a nonlinear fashion, yet are commonly ignored or coarsely estimated in previous TCO studies. The effect of charge and discharge rate, which has not been directly incorporated into our employed degradation model, is assumed to have a minimal affect over the range of operational conditions explored herein.

In the BOM, our degradation model calculates capacity loss and resistance growth at the end of each service year based on the selected drive pattern, charge strategy, and environmental conditions, which are used in turn to compute the annual miles achievable by the BEV each year. The maximum charge SOC and timing of charge operations are selectively set as discussed later. Minimum SOC is adjusted each year such that no less than 80% of BOL power can be delivered at the end of charge depleting

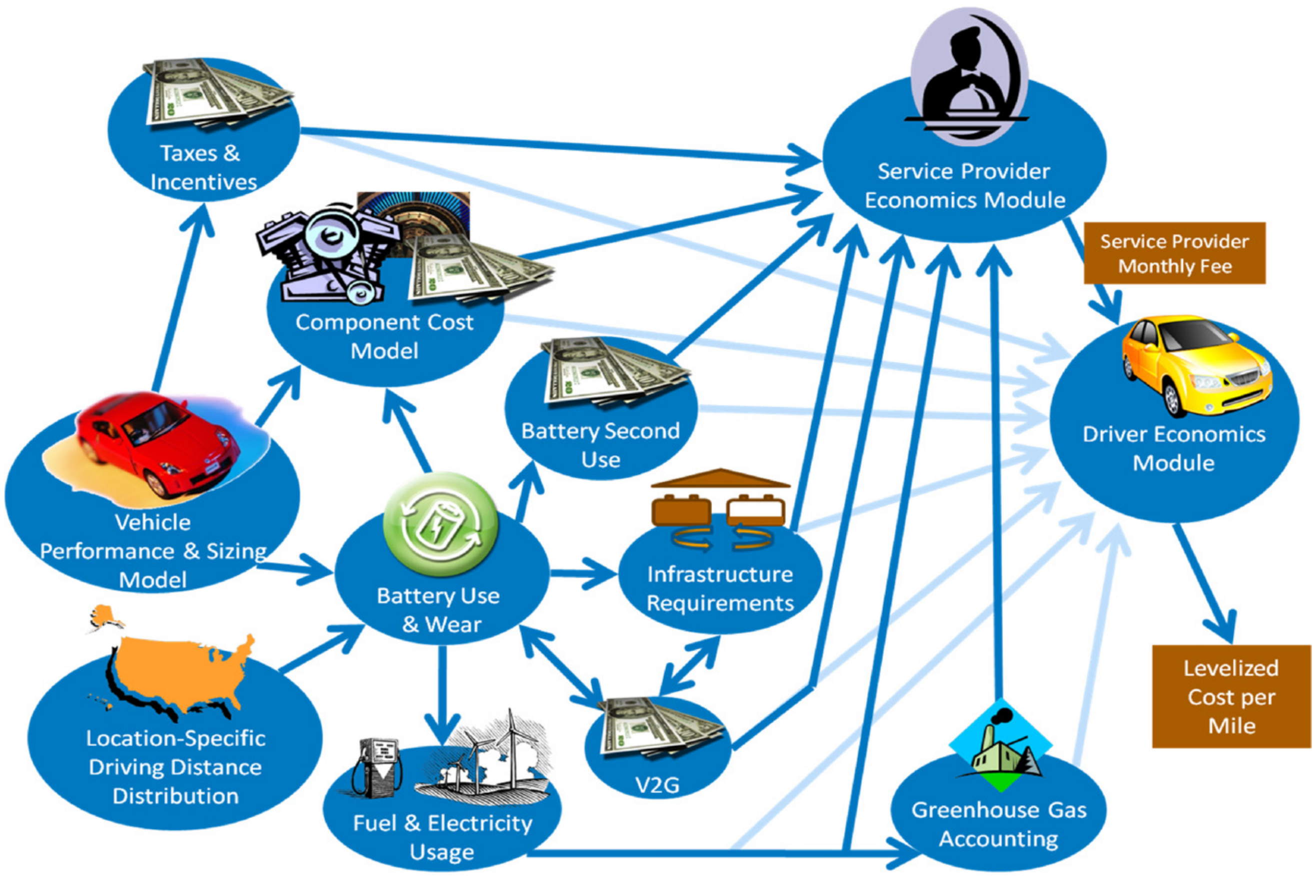

Fig. 1. Key elements and data flow within the Battery Ownership Model.

operation. Thus, minimum SOC generally increases over time as resistance grows. In this manner, we translate the effect of power fade to a reduction in available energy, and thereby vehicle range.

We leverage this capability to employ bounded, cost-optimal battery replacement schedules. The BOM first calculates the degradation and resultant available energy of the battery for each year up to a prescribed technical limit. In this study, that limit is defined by reaching a 15-year calendar limit or the loss of 50% of initial battery capacity. The 15-year calendar limit is selected to be coincident with the life of the vehicle, while the 50% of initial battery capacity limit is intended to represent the point at which the battery begins to degrade at a vastly accelerated rate and may no longer be safe for automotive use. Alternative values could be employed, preferably justified by life test data; however, such data is not available at present. The TCO is then computed for each possible automotive service tenure up to this limit, and the point at which TCO is minimized is employed for determining battery replacements. Note that a labor fee of $500 is included for each battery replacement in the TCO calculations, assuming a single technician working approximately 5 h at $100 per hour [4]. This framework therefore represents a cost-justified approach to determining battery life, rather than the arbitrary independent election of time, mileage, or capacity limits which may be inappropriate for accurate economic analyses.

2.4. Gasoline and electricity prices

National average gasoline price forecasts, as reported in the Energy Information Administration's (EIA's) 2011 high oil price scenario [5], are employed to calculate recurring energy costs. This scenario is selected as it best agrees with EIA's reported actual 2011 gasoline costs [6]. Electricity price projections from the EIA's 2011 baseline scenario are used to calculate energy costs, as its 2011 values agreed well with actual prices [6]. Both the gasoline and electricity prices employed in this study are shown in Fig. 2.

2.5. Electric range

The economics of BEVs and CVs are innately different—BEVs generally exhibit a high upfront cost but low operating costs, and CVs vice versa. Thus, increasing the total mileage achieved with a BEV is a path towards improving the BEV-to-CV cost ratio. We expect that the range of the BEV will strongly impact this cost ratio on the basis that a larger range will enable more trips, but incur higher upfront costs while also impact battery life. To assess this

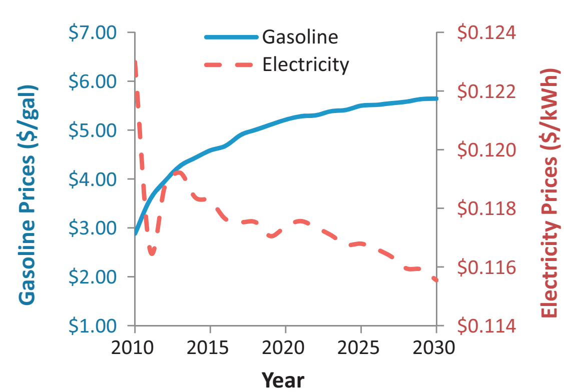

Fig. 2. Employed retail gasoline and electricity prices (2012 dollars).

Table 1
Employed charge strategies.

Abbreviation	Description
CS1	Right-away charge at home
CS2	Just-in-time charge at home
CS3[a]	Just-in-time charge at home, right-away charge at work

[a] Note that the cost of the charger and electricity at work are not accounted for in economic computations.

dependency, we simulate three BEVs with ranges of 50, 75, and 100 miles.

2.6. Charge strategy

Charge strategies can also affect economics via recurring costs, upfront costs, and achieved mileage. Adjusting the timing of charge events can extend battery life and reduce battery replacement costs. For a prescribed range, raising the maximum allowed SOC of the battery will decrease battery size and thereby initial cost, but will shorten battery life by increasing both exposure to higher voltages and the depth of discharge of each cycle. Increasing the frequency of charging (e.g., charging both at home and at work) can effectively increase the allowable daily mileage of a BEV, thus increasing total achieved mileage, but will affect battery life by increasing the number of cycles and generally reducing the depth of discharge.

We vary the maximum SOC limit of the battery from 90% to 100% in 5% increments. Note that battery size is increased as maximum SOC is decreased to maintain the prescribed range of 50, 75, or 100 miles. This effectively assumes the vehicle manufacturer is planning for and controlling maximum SOC rather than the end user controlling it and will pit extensions of battery longevity against the increased upfront cost of a larger battery.

Three different charge timings are employed as well, as summarized in Table 1. First is right-away charge at home, where charging is initiated immediately when a vehicle returns home. Second is just-in-time charge at home, where charge is initiated such that the battery reaches its maximum SOC concurrently with the time of departure. To make these bounding cases for right-away and just-in-time charge methodologies, we assume that no time is spent at a destination; thus, the rest time at either the maximum SOC (right-away) or the day's minimum SOC (just-in-time) is calculated by subtracting the required drive and charge time from a 24-h period.

Third is the combination of just-in-time charge at home and right-away charge at work. In this final scenario we identify work days as those where the daily distance is between one and two times the mode distance of the drive pattern. On these days we assume that half of the mode distance is traveled in the morning, followed by an 8-h stay at work, then the remainder of the day's driving distance is completed prior to returning home. Charging is initiated immediately upon arriving at work, whereas at-home charging is delayed to achieve the maximum SOC concurrently with leaving for the first trip on the subsequent day.

When this third charge strategy is implemented, the cost of the at-work charger and electricity for the at-work charging is not accounted for. This is done to provide a best-case scenario on the assumption that the infrastructure and electricity are provided by the government or employer as a benefit for driving a plug-in electric vehicle. We acknowledge that this may only be applicable to select early adopters and may not apply in the long term on a larger scale. Accurately accounting for these costs requires consideration of a third party responsible for the necessary infrastructure and electricity of the at-work charge point, its commercial electricity prices, hardware costs, approach to financing, return on equity, etc.,

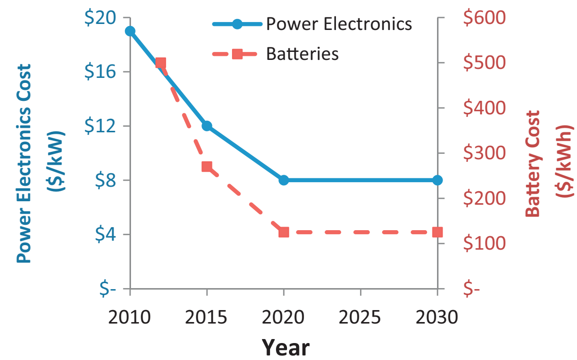

Fig. 3. Battery pack and power electronics manufactured cost schedule.

which will be addressed in a future publication. It is not expected that including these costs will substantially affect our results, however.

For all charging strategies we assume an average charge power of 5 kW, which determines the required charge time. This approximates an 85% efficient charger attached to a 32 amp, 240 V connection when an allowance for a reduced power taper charge is consider near the end of charge. Note that the charger efficiency is accounted for when computing the amount of electricity consumed from the grid. Drive time is computed by dividing the DVMT by an assumed average speed of 42 miles per hour. This speed is chosen to be representative of 55% city driving and 45% highway driving per [7], which aligns with our calculation of vehicle efficiency.

2.7. Vehicle performance and cost

We assume a vehicle platform sized similarly to that of a Chevrolet Cruze. A glider mass of 1139 kg, coefficient of drag of 0.29, and total frontal area of 2.27 m^2 are employed in the simulation. Battery, motor, and power electronics specifications are calculated to achieve a 0–60 mph acceleration time of 9 s and a vehicle range specific to the case at hand. Vehicle electricity consumption is calculated via simulation of both the highway and urban driving dynamometer schedule weighted and combined to effectively recreate the U.S. Environmental Protection Agency window sticker rating [8]. A constant auxiliary load of 300 W is included during drive cycle simulation, representative of only minimal system loads exclusive of cabin heating or air conditioning [9]. Tire and maintenance costs are set at $0.0533 per mile for both CVs and BEVs, per the AAA's 2010 estimate of typical mid-size car costs [10].

Battery and drivetrain manufacturing costs are computed based upon these results, the selected 2012 start year, and the component cost schedule shown in Fig. 3, the latter adapted from the U.S. Department of Energy's future component cost targets [11,12]. This yields a cost of $500 per kWh for batteries and $16.2 per kW for power electronics at the initial point of purchase, to which a manufacturing-to-retail markup factor of 1.5 is applied [13–15]. Note that the future battery costs are important for computing the cost of battery replacements and battery salvage value when applicable.

The cost or value of battery recycling is ignored due to the high level of uncertainty involved. The errors associated with this assumption are expected to be small due to the expected low relative cost of recycling and the impact of the time value of money. Similarly, salvage value due to potential battery secondary use is also ignored. However, the remaining automotive value of a battery is calculated by prorating its remaining life against the cost of new batteries at the 15-year driver time horizon and discounting that value by 25% when applicable.

Table 2
Vehicle specifications.

Vehicle	Electric range (mi)	Maximum SOC	Engine or motor power (kW)	Battery energy (kWh)	Vehicle efficiency (kWh/mi)	2012 vehicle retail price
CV	0	n/a	100	0	32 mi/gal	$17,687
		100%	79.7	16.6	0.332	$29,098
BEV50	50	95%	80.3	17.5	0.333	$29,791
		90%	80.8	18.6	0.334	$30,606
		100%	85.3	25.7	0.343	$36,050
BEV75	75	95%	86.3	27.2	0.345	$37,193
		90%	87.2	28.8	0.347	$38,469
		100%	91.1	35.4	0.355	$43,487
BEV100	100	95%	93.0	37.6	0.358	$45,174
		90%	94.4	40.0	0.361	$47,014

For calculation of the BEV-to-CV cost ratio, we also simulate a CV under identical technical and economic assumptions, the key difference being the use of an internal combustion powered drivetrain. A study of currently and recently available CVs, hybrid electric vehicles, plug-in hybrid electric vehicles and BEVs suggests that the cost of conventional drivetrains are reasonably well estimated by combining a flat fee of $531 with a fee that scales with engine power at the rate of $14.5 per kW, where the difference in cost and retail price is captured by our manufacturing-to-retail markup factor of 1.5 [18]. This same data can be used to calculate a glider price of $14,715.50 (not subject to the 1.5 markup factor) for the midsize vehicle class we consider, which we apply to both our CV and BEVs. The resultant CV demonstrates 32 miles per gallon with a calculated retail price of $17,687, similar to that of a 2012 Chevrolet Cruze. The CV and BEV vehicle specifications are summarized in Table 2.

2.8. Employed driving data

The BOM requires that a drive pattern in the form of a DVMT probability distribution function (PDF) be input for calculating total miles traveled, total all-electric miles traveled, battery wear, etc. Herein we employ real world driving data collected from the Puget Sound Regional Council's 2007 Traffic Choices Study (TCS) to generate the necessary DVMT PDFs [16].

The TCS was an investigation of the response of travel behavior to variable toll charges in the Seattle metropolitan area. The study placed global positioning systems in 445 vehicles from 275 volunteer households that recorded driving data over an 18-month average per household period. The experiment started with a baseline period in which no artificial tolls were applied to affect behavior. We process the data for use in this study by (1) only considering data collected during the approximately 3-month baseline period, (2) eliminating vehicles for which no driving took place during the baseline period, (3) eliminating vehicles for which significant errors in data recording were identified, and (4) reducing detailed trip data to DVMT based upon the length of each trip and the date on which it was started. The resultant data are then converted into 398 longitudinal (one vehicle, multiple days) discrete DVMT PDFs for use by the BOM. For comparison purposes, the DVMT of each of the 398 vehicles are combined to create a cross-sectional DVMT PDF representative of the fleet of TCS vehicles. A cross-sectional DVMT PDF is created from the 2001 National Highway Travel Survey data as well [17].

In addition, we calculate the median, mean, and standard deviation of DVMT for each individual vehicle. The data are then compiled into the three PDFs shown in Fig. 4. For these calculations, days where the vehicle is not driven are excluded. These plots reveal that DVMT median, mean, and standard deviation values are typically around 23, 30, and 17 miles, respectively. For comparison, the TCS cross-sectional DVMT PDF yields DVMT median, mean, and standard deviation values of 25, 34, and 49 miles, respectively. Note that although the median and mean values for the cross-section compares well to the longitudinal data, the standard deviation of the cross-section is not representative of what is commonly seen from the individual longitudinal DVMT PDFs.

Projected annual mileage was also calculated for each vehicle (Fig. 5). Annual mileage for the TCS cross-sectional PDF is 9910 miles per year, which agrees well with the longitudinal data. Note that this is slightly less than the national average annual VMT

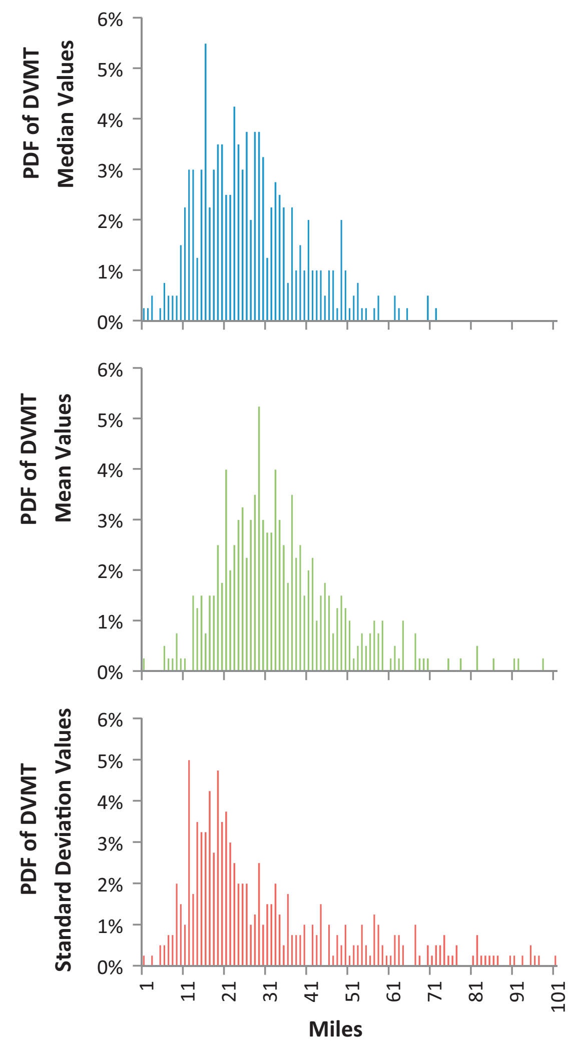

Fig. 4. PDF of median, mean, and standard deviation of DVMT for the processed TCS study data.

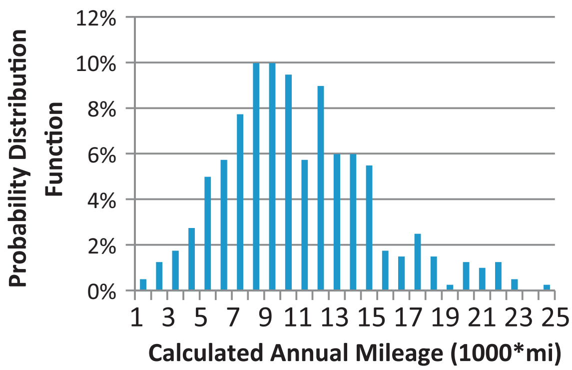

Fig. 5. PDF of calculated annual mileage for the processed TCS study data.

of 11,078 reported in [17] and of 12,375 reported in [19], but such variation is to be expected in a relatively small, geographically focused sampling of vehicles.

These drive patterns are expected to strongly affect the BEV-to-CV cost ratio, as distributions with shorter typical DVMTs will be able to complete a larger fraction of their total mileage with a range-restricted BEV. However, extremely short DVMTs associated with fewer annual miles will have a negative effect on the cost ratio. To study the complex sensitivity of cost to these factors, we simulate the DVMT PDF drive patterns of each of the 398 individual TCS vehicles for every combination of the aforementioned range and charge strategy variables.

The primary shortcomings of the TCS data as we use it are that (1) each drive pattern does not fully capture seasonal variations, (2) it does not account for changes in driving behavior as the vehicle ages, and (3) sampling biases imply the data may not fairly represent the distribution of income levels, household size, proximity to public transit, etc., beyond or even within the Seattle area. These factors prevent our analysis from making blanket statements regarding the overall cost effectiveness of BEVs at the national level; however, they do not prevent a valuable demonstration and exploration of the sensitivity of BEV economics to drive patterns, vehicle range, and charge strategies.

3. Results and discussion

To study the interplay of three vehicle ranges, three maximum SOCs, three charge timing schedules, and two alternative means of accounting for unachievable VMT with 398 drive patterns, we simulate 21,438 unique cases. Presentation and interpretation of this many data points can be challenging. For a specific set of assumptions, it is useful to inspect a single cumulative distribution function of all 398 drive patterns. However, discussion of 54 cumulative distribution functions covering all combinations of range, charge strategies, and unachievable VMT accounting methods is not straightforward either. We therefore employ a 75th percentile BEV-to-CV cost ratio metric, for which 25% of all vehicle drive patterns exhibit a lower BEV-to-CV cost ratio. This metric reveals that one of the strongest sensitivities in our analysis is the cost of unachievable VMT; therefore, we divide our subsequent presentation and discussion of results accordingly.

3.1. Low cost of unachievable VMT

The cost of unachievable VMT is low where we assume that a second, conventionally powered, range-unlimited vehicle also owned by the household is available for days in which the total traveled distance exceeds the range of the BEV. The CV only incurs the fuel, tire, and maintenance costs. This directly affects our TCO calculations by reducing the cost of the non-BEV VMT, but also indirectly affects TCO via battery lifetime. In essence, our cost-optimal decision to replace the battery is driven by the comparison of the value of increased BEV VMT (resulting from the higher capacity of the new battery) with the cost of covering those miles via the alternative mode of transportation. Because the cost of the alternative mode of transportation is exceptionally low in this scenario, it is highly unlikely that the savings created by increased electric range will justify the cost of a new battery. Thus, we find that it is generally most cost effective to not replace the original battery—indeed, every case simulated with the low cost of unachievable VMT had a battery life equal to our maximum calendar limit of 15 years. Note that no cases were limited by the imposed 50% capacity limit.

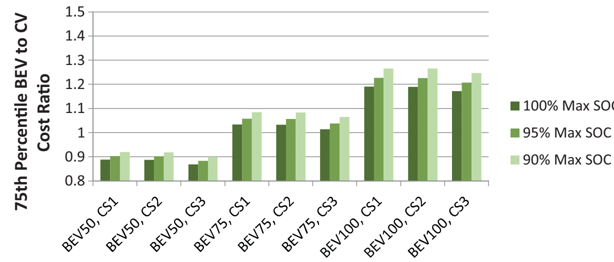

Fig. 6. 75th percentile BEV-to-CV cost ratios for low cost of unachievable VMT.

The combination of these effects and the high cost of batteries (relative to a conventional powertrain) leads us to the conclusion that election of the highest maximum SOC and shortest range considered herein will maximize cost-effectiveness, as seen in Fig. 6. The positive impact of reduced upfront battery cost significantly outweighs the negative impact of reduced electric range and accelerated battery degradation resultant from these parameters. This leads to a BEV-to-CV cost ratio below 1.0 for many cases, implying that ownership of a BEV is more cost effective than ownership of a CV.

The low cost of unachievable VMT assumption, where we assume a CV to be available at the per-mile cost of fuel, tires, and maintenance, is a major factor in enabling these results. The validity of this assumption is most applicable to multi-vehicle households when the frequency of use of the CV is low, thus minimizing the chance that the CV—which may be principally utilized by another member of the household—is unavailable or unsuitable. An analysis of the frequency of CV use during the first year of operation is presented in Fig. 7, performed for all three vehicle ranges, the CS2 charge strategy, and 100% max SOC. It shows that while very few drive patterns can be completely served by a BEV of any of the ranges explored herein, the BEV75 and BEV100 require the use of the CV less than 41 days out of the year for a large fraction of drive patterns. However, it also shows that the BEV50 requires use the CV on no less than 60 days per year for more than 80% of the top quartile drive patterns. Further investigation reveals that this increases to more than 100 days per year for approximately half of

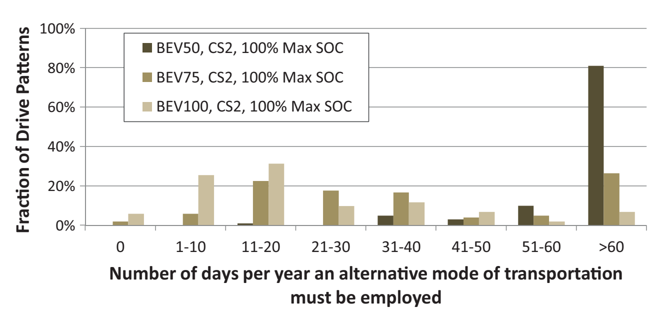

Fig. 7. Frequency at which an alternate means of transportation must be procured for the top quartile of most cost-effective drive patterns.

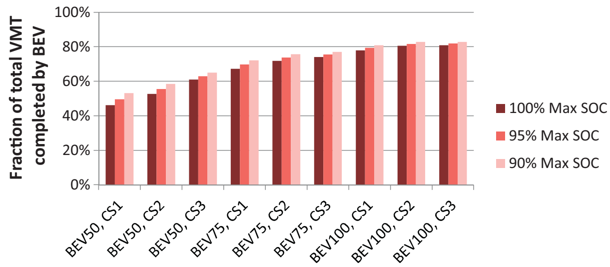

Fig. 8. Fraction of total VMT completed by BEV for the top quartile of cost-effective drive patterns under the high cost of unachievable VMT assumption.

the top quartile drive patterns. Although it is currently unclear at what point the frequency of CV use will notably impact the validity of our assumption, these numbers do encourage additional analyses that account for a household's collective driving requirements and fleet size each day of the year, particularly for BEVs with a 50-mile or shorter all electric range.

In Fig. 8 this behavior is translated to the percentage of total VMT over the 15 year analysis period that is completed by the BEV, averaged over all drive patterns within each scenario. Here, the limited utility of a BEV50 charged only once per day is clearly evident. On the other hand, we see that the BEV100 enables approximately 80% of a drive pattern's total VMT to be completed electrically on average.

Regarding the sensitivity of cost to drive patterns, we find that the ratio of the highest BEV-to-CV cost ratio (corresponding to the least cost-effective drive pattern for a given set of assumptions) to the lowest BEV-to-CV cost ratio (corresponding to the most cost-effective drive pattern for a given set of assumptions) can reach nearly 2:1 for the low cost of unachievable VMT cases, as seen in Fig. 9. However, it is somewhat sensitive to vehicle range and charge strategy, dipping to as low as 1.6:1 as range decreases. Calculation of the BEV-to-CV cost ratio using cross-sectional TCS and National Highway Travel Survey drive patterns underestimates the BEV to CV cost ratio for 52–56% and 60–64% of the results produced using vehicle specific longitudinal TCS drive patterns, respectively, when a low cost of unachievable VMT is assumed.

3.2. High cost of unachievable VMT

When the cost of unachievable VMT is increased to the level incurred by a typical car-sharing program, both the economic sensitivity to charge strategy and the cost-optimal battery retirement schedules change significantly. Recall that shorter 50-mile range vehicles yielded considerably more cost-effective solutions to the exclusion of the employed charge strategy under the low cost of unachievable VMT assumption. Use of the high cost of unachievable VMT assumption, however, shows that the 50-mile range vehicle offers both the lowest and highest cost option dependent upon which charge strategy is elected, as seen in Fig. 10. We also find that

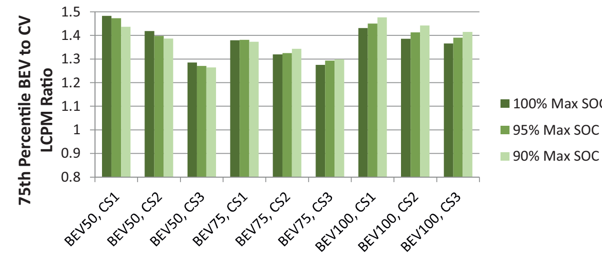

Fig. 10. 75th percentile BEV-to-CV cost ratios for high cost of unachievable VMT.

the 75-mile range vehicle is cost-optimal under all charge strategies with the exception of the BEV50 charged from home and work.

In contrast to the low cost of unachievable VMT cases where battery replacement was never economically incentivized, calculated cost-optimal battery lifetimes under the high cost of unachievable VMT assumption now vary considerably as seen in Fig. 11. Here the increased BEV range that comes with a fresh battery is more highly valued, as it results in less use of the pricey car share service. We observe that lower maximum SOC and switching from right-away to just-in-time charge timing both increase battery life, as expected. What was slightly unexpected was the increase in battery life from charging both at home and at work; not only does this strategy increase the utility of the vehicle, it also may extend the battery life by reducing the depth of discharge of individual cycles for this particular battery chemistry. This latter effect is also seen in the trend to longer battery life with increased range.

Despite these variations, we generally find that the highest concentration of battery lifetimes is at the 15 year calendar limit and that no cases were limited by the imposed 50% capacity limit. This trend is exaggerated when we restrict our investigation to the top quartile of cost effective drive patterns, illustrating that even when the cost of unachievable VMT is high and the cost of a new battery is low, it is difficult to financially justify a battery replacement.

Regarding the sensitivity of cost ratio to drive pattern, we find that the ratio of the highest BEV-to-CV cost ratio (corresponding to the least cost-effective drive pattern for a given set of assumptions) to the lowest BEV-to-CV cost ratio (corresponding to the most cost-effective drive pattern for a given set of assumptions) ranges from a low of 1.8:1 to higher than 3.5:1, as seen in Fig. 12. Note that the maximum is much larger than the typical value computed using the low cost of unachievable VMT, and that the range of values spans a much broader spectrum as well. Further, the trend with vehicle range is reversed – now the sensitivity of cost to drive pattern is highest when the electric range is at its lowest value. Calculation of the BEV-to-CV cost ratio using cross-sectional TCS and National Highway Travel Survey drive patterns are found to overestimate the BEV-to-CV cost ratio for 54–77% and 74–93% of the results produced using vehicle specific longitudinal TCS drive patterns, respectively, when a high cost of unachievable VMT is assumed.

Recall that when a low cost of unachievable VMT is assumed, our computations showed these two cross-sectional drive patterns

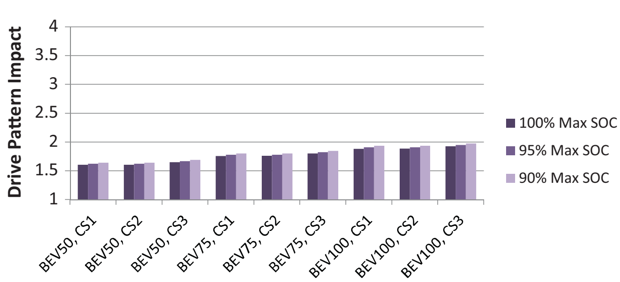

Fig. 9. Ratio of highest to lowest BEV-to-CV cost ratio for low cost of unachievable VMT.

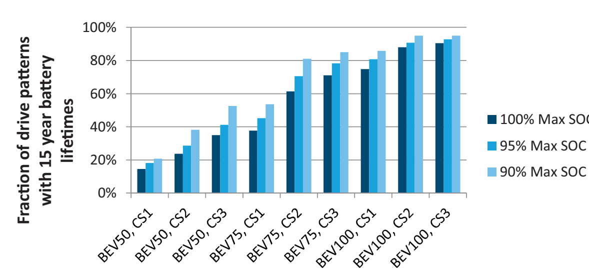

Fig. 11. Fraction of drive patterns yielding a 15 year battery lifetime for high cost of unachievable VMT.

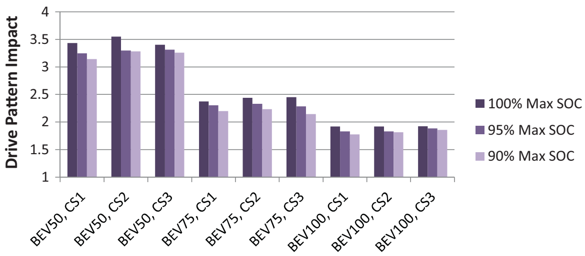

Fig. 12. Ratio of highest to lowest BEV-to-CV cost ratio for high cost of unachievable VMT.

underestimated the cost for most drive patterns. The culmination of these data suggests that economic analysis of cross-sectional drive patterns do not provide any consistent representation of the economics of the underlying individual vehicles.

4. Conclusions

In this study we apply the National Renewable Energy Laboratory's Battery Ownership Model (BOM) to the investigation of the sensitivity of BEV economics to charging strategy, vehicle range, and driving pattern. Charging strategies consider the maximum SOC, frequency of charging events, and timing of charging events as variables, while vehicle range sweeps from 50 to 100 miles. For drive patterns we employ 3 months of recorded data from each of 398 vehicles in the Puget Sound Regional Council's TCS. The use of this data, combined with the BOM's incorporation of a high-fidelity battery degradation model, cost-optimal battery replacement scheduling, and two alternative means of accounting for unachievable VMT enable this study to quantify effects of charging strategy, vehicle range, and driving pattern not previously disclosed in the literature.

Perhaps the most interesting finding of this study is the level of impact that the cost of unachievable VMT has on economics and cost-optimal operational strategy. When these miles can be completed at low cost, such as when a second, range-unlimited vehicle is available in the household, the inclusion of a 75-mile-range BEV in the household proved to be more cost-effective than an additional CV for nearly 25% of the drive patterns studied. The 50-mile-range BEV studied suggested higher cost savings for a larger proportion of drive patterns, but the frequency at which an alternative means of transportation must be employed may be high enough to make this vehicle less cost-effective than predicted herein. For all range vehicles, the economic sensitivity to charge strategy is marginalized by the low cost of unachievable VMT, which minimizes the penalty for battery degradation and eliminates financial incentives for battery replacement. Even with future battery manufacturing costs at $125 per kWh, battery replacement is never economically incentivized in our simulated scenarios under this low cost of unachievable VMT assumptions.

Increasing the cost of unachievable VMT to a level representative of popular car-share programs, on the other hand, results in larger incentive to travel more miles on electricity. This effect, balanced by the relatively high costs of batteries, creates an economic system favoring slightly longer range and charge strategies that foster longer battery life and increased electric VMT. However, under the assumptions employed herein, the higher cost of unachievable VMT also make it highly unlikely that BEV ownership would be financially advantageous when compared to a CV.

Also noteworthy, though perhaps not unexpected, is the sensitivity of total cost of ownership to drive patterns. Within the TCS dataset employed herein, we have observed that changing the drive pattern can increase the BEV to CV cost ratio by up to a factor of 3.6, and that this sensitivity is a function of vehicle range, charge strategy, and the cost of unachievable VMT. Combined with our finding that drive patterns are unique (no distinct groupings of vehicles with significantly similar median driving distances, standard deviations, or other relevant statistical parameters have been identified), and our demonstration that economic analysis of cross-sectional drive patterns do not provide a consistent representation of the economics of the underlying individual vehicles, we conclude that longitudinal vehicle- or driver-specific drive patterns must be treated independently for an accurate and meaningful economic analysis to be performed. For consumers, this implies that detailed knowledge of their individual or household driving patterns is required to make cost-optimal BEV purchase decisions. Similarly, automobile manufacturers can benefit from the longitudinal drive patterns of their customers to optimize vehicle offerings that maximize potential sales (noting that cost-effectiveness is only one of many factors consumers will use in making their purchase decision).

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