A cost of ownership analysis of batteries in all-electric and plug-in hybrid vehicles

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Abstract The ever-faster transformation of road vehicles from traditional fuel engines to electric motors, is leading to increasingly widespread research on and development of electric vehicles and related infrastructures. In this context, this article addresses the cost aspect of batteries from the owner's perspective. Specifically, it proposes an analysis of the optimal usage cost of batteries in order to maximize the benefit-cost ratio and battery replacement intervals. In order to analyze battery degradation, various tests were utilized for both a full-battery electric vehicle (BEV) and a plug-in hybrid electric vehicle (PHEV). The results demonstrate greater wear of the PHEV battery when the vehicle is under charge-sustaining mode, that is, when using the combustion engine, while driving with frequent starts and stops. On the other hand, the degradation costs of the BEV battery are generally close to optimal in every scenario, in which the main parameter affecting battery wear is average daily mileage.

Keywords Battery usage · Cost of ownership · Electric vehicles · Energy

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1 Introduction

The recent, remarkable increase in the production and utilization of electric vehicles (EVs) is decreasing the use of petroleum products, and gradually accomplishing the challenge of decarbonizing road transport to reach the goal of reducing CO_2 emissions (Teixeira and Sodré 2018). For instance, the number of electric light-duty vehicles in the world, including full-battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), practically tripled in the last three years, so continuing an exponential trend during the last decade (https://www.iea.org/reports/global-ev-outlook-2022). However, the fluctuations in electric vehicle (EV) sales are constantly evolving, even in terms of the EV type (LMC Automotive Limited 2021), depending on the geographic area considered. For example, in 2021 about half of the sales were in China, where BEVs are largely the majority, while the electric car registrations and sales increased in the United States, but after two years of decline. In Europe, where the number of BEVs and that of PHEVs are generally closer to each other when compared with those in the U.S. and China, the increase continues very remarkably (https://www.iea.org/reports/global-ev-outlook-2022). Nevertheless, the transformation of the existing very large, global fleet of conventional internal combustion engine (ICE) vehicles will take several more years (Kalghatgi 2018).

This notable increase in the EV market is one of the reasons for the rapidly decreasing price per kilowatt-hour of battery packs (Nykvist and Nilsson 2015) and the significant increase in research and development for new batteries of various chemistries with ever-improving performance (Larcher and Tarascon 2015). Nonetheless, the cost of batteries still weighs heavily on the total cost of

electric cars, especially in the case of BEVs. In fact, car makers may take advantage of the lowered cost of battery cells to increase the total capacity of battery packs by adding a greater number of cells, in order to increase the maximum mileage or driving range of their BEVs before charging. This solution reduces the so-called range anxiety in EV drivers (Shi et al. 2019).

The analysis of the degradation in rechargeable (i.e., secondary) batteries generally considers the maximum number of equivalent cycles before reaching the state of health of a battery equal to 80%, that is, an irreversible loss of 20% of its nominal capacity (Lu et al. 2013). However, part of this capacity fading is also due to irreversible degradation over time, also known as calendar aging, which should be investigated in applications where rest time far exceeds that of active operation, such as in the case of EVs (Dubarry and Liaw 2007; Redondo-Iglesias et al. 2017). Therefore, the real cost of a car battery strictly depends on the time interval for a pack to reach its end of life and its consequent replacement with a fresh one.

This paper describes a cost analysis model that includes the degradation trend of battery life over time for PHEVs and BEVs, in which the size and actual use of their batteries differ. Furthermore, the stress and aging of these batteries also depend on mobility characteristics (i.e., urban, highway, etc.). For this reason, we applied the proposed cost model to various scenarios, according to the Vehicle Chassis Dynamometer Driving Schedules defined by United States Environmental Protection Agency (https://www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules), thus extending our previous work in Bocca and Baek (2020). The novelty of this paper is summarized as follows:

- Proposal of a battery cost analysis model
- Analysis of the battery usage of BEV and PHEV depending on mobility characteristics
- Analysis of the optimal usage cost of batteries in order to maximize the benefit-cost ratio
- Analysis of the battery degradation based on battery usage, warranty and capacity.

This paper is organized as follows: Sect. 2 reports the background and related work regarding the cost analysis of batteries in EVs, Sect. 3 describes the adopted life-cycle cost model in the case of BEVs and PHEVs, Sect. 4 reports the results of the battery life degradation and costs for two different EVs after simulating various tests and, finally, concluding remarks are set forth in Sect. 5.

2 Background

Most EVs can be classified into two large groups: battery electric vehicles and hybrid electric vehicles, the latter still retaining the traditional internal combustion engine as the main power source. Both of these groups can be further divided into subgroups. The first group can be subdivided into full-battery (BEV) and range-extended battery (BEVx or REEV) electric vehicles, and the second group can be subdivided into full-hybrid (FHEV or HEV) , plug-in hybrid (PHEV) and mild-hybrid (MHEV) electric vehicles, as shown in Fig. 1 (green-based and blue-based colors, respectively).

As reported in LMC Automotive Limited (2021), the global demand for BEVs, FHEVs and MHEVs is generally evenly split, while the demand for PHEVs is about half of that for BEVs or MHEVs. However, this distribution could easily change due to the impressive year-over-year growth in EV production and sales, making market share prediction more uncertain.

Indeed, a BEVx has a fuel auxiliary power unit (APU) to extend the maximum mileage. However, a BEVx is still considered a full-battery electric vehicle, as the use of the auxiliary unit is a fallback option to charge the battery when mostly depleted, and not a normal operating condition (https://ww2.arb.ca.gov/sites/default/files/2020-01/appendix_i_credit_alternative_2_ac.pdf). For this reason, the market share of this EV type is usually included with that of the BEVs. Although micro-hybrid electric vehicles are sometimes included among EVs, in this analysis we do not consider them, as they are basically traditional ICE vehicles with electric start-stop systems.
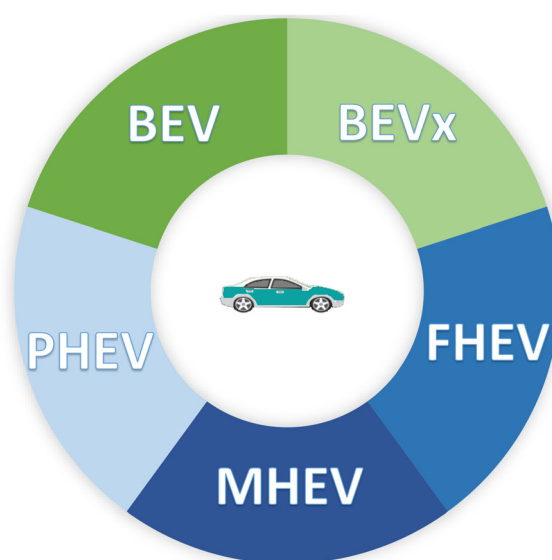

Fig. 1 The main electric and hybrid vehicles in the market

For light-duty vehicles, such as passenger cars, the energy size of the battery packs in EVs generally differs greatly depending on the type of vehicle: (1) usually less than one kilowatt-hour for MHEVs, (2) up to about 20 kWh for FHEVs and PHEVs, and (3) in general several tens of kilowatt-hours for BEVs, even up to or greater than 100 kWh (Blomgren 2017). However, the size of battery packs tends to increase with later-model EVs in order to achieve an ever-greater autonomy of distance that more closely approaches that of traditional vehicles. This impressive use of batteries in EVs, has also led to the search for ways to repurpose these batteries after their use in electric vehicles. This research activity has been ongoing during the last decade to reduce the total life cycle costs of these batteries (Neubauer et al. 2015). Most battery packs consist of lithium-based cells due to their high specific energy [Wh/kg] and the large availability of lithium on the Earth (Nitta et al. 2015).

The analysis of the performance, aging and cost of battery cells has captured the attention of both car manufacturers and researchers (Nykvist and Nilsson 2015; Larcher and Tarascon 2015; Duffner et al. 2020). For example, many battery simulation models have been proposed in the literature, from electrochemical and mathematical models to equivalent electrical circuits (Seaman et al. 2014). They are populated by using direct experimental data and/or manufacturers' data. In the latter case, the model accuracy depends on the amount and quality of information reported in public datasheets (Petricca et al. 2013). However, these models are directly concerned with performance only. Conversely, cost models are obviously more concerned with the economic, rather than the technical aspects. An overall analysis of the costs related to battery wear is indeed very important from an owner's perspective.

At system level, the models of the capacity fade in batteries (i.e., the reduction in the maximum available energy) due to cycle life generally consider average state-of-charge, temperature, depth of discharge, and C-rate (i.e., battery current normalized to nominal capacity) (Millner 2010; Yuksel and Michalek 2012; Bocca et al. 2015). Accurate models also include the analysis of calendar aging.

The Urban Dynamometer Driving Schedule (UDDS) is a test defined by the EPA for analyzing the performance, especially the CO_2 emissions of vehicles in urban mobility, which usually includes many start-and-stop phases (https://www.epa.gov/emission-standards-reference-guide/epa-urban-dynamometer-driving-schedule-udds). In this context, the authors in Duoba et al. (2012) and Chen et al. (2018) analyzed the energy performance of some BEVs and PHEVs in real-world driving, but they did not consider battery aging. Similarly, electrical energy and fuel consumption for these vehicle types were analyzed in Wang et al. (2015), resulting in some interesting conclusions regarding the optimal size of the battery packs from an energy perspective, especially in the case of PHEVs.

In Peterson et al. (2010), the authors state that vehicle-to-grid (V2G) service increases capacity fade more quickly and, therefore, this auxiliary service should generally be avoided in order not to further aggravate the degradation of batteries due to the normal operation of BEVs.

An annualized total cost of ownership of electric passenger cars was analyzed in Bubeck et al. (2016). The proposed model also includes investment cost, maintenance cost, and insurance cost. However, battery cost is changing considerably in EVs during these recent years and, therefore, it truly affects the fluctuating cost of ownership. In general, the cost of depreciation of a battery pack over time is commonly included in maintenance costs (Bösch et al. 2018).

3 Cost model

The basic equations of the proposed cost model for battery usage are defined hereafter. The minimal or optimal daily cost of battery usage is given by:

$$c_{d_{min}} = \frac{c_{tot}}{N_{d_{max}}}. \tag{1}$$

where c_{tot} is the total cost of a fresh battery pack and $N_{d_{max}}$ is the estimated maximum number of days of service. Then, the minimal cost of battery usage after N_d days of service is given by:

$$c_{min} = c_{d_{min}} \cdot N_d. \tag{2}$$

Then, the actual cost of battery use is defined as follows:

$$c_a = c_{tot} \cdot \frac{Q_f}{Q_{f_{max}}}. \tag{3}$$

where Q_f and $Q_{f_{max}}$ are the actual capacity fade and maximum capacity fade of a battery, respectively.

Battery usage index, or cost index, after N_d days of service is given by:

$$\alpha = \frac{c_a}{c_{min}}. \tag{4}$$

Therefore, this index has three main results:

$$\alpha = \begin{cases} < 1 & : \text{battery is underused} \\ = 1 & : \text{battery is used optimally} \\ > 1 & : \text{battery is overused} \end{cases}$$

Therefore, if $\alpha < 1$ then the replacement of the battery will take place as a consequence of the expiry of the warranty rather than the achievement of the maximum number of

equivalent cycles, and vice versa in the case of $\alpha > 1$. Although this basic usage cost analysis is the same for all-electric vehicles, the total cost for the energy consumption in BEVs and PHEVs differs as reported below.

3.1 Battery electric vehicle (BEV)

In BEVs, the energy cost is defined as follows:

$$c_{\text{BEV}} = \sum_{i=1}^{N_d} E_e(i) \cdot p_e(i) + c_a. \tag{5}$$

where E_e and p_e are the energy and unit price of electricity, respectively, for each day of use i.

3.2 Plug-in hybrid vehicle (PHEV)

PHEVs use two different energy sources: electricity and gasoline. Therefore, the degradation of battery life over time tends to differ from that in BEVs. Furthermore, the energy cost is also affected by fuel price as follows:

$$c_{\text{PHEV}} = \sum_{i=1}^{N_d} (E_e(i) \cdot p_e(i) + E_g(i) \cdot p_g(i)) + c_a. \tag{6}$$

where E_g and p_g are the energy (in this case, "amount") and unit price of gasoline, respectively, for each day of use i.

3.3 Simulation setup

There are several vehicle simulators, in both academia and industry, for the analysis of the energy consumption and/or gas emission of vehicles. Among them, ADVISOR (ADvanced VehIcle SimulatOR), a MATLAB-/Simulink-based open-source simulator, is widely used for research studies in academia because of several merits (Markel et al. 2002). First, ADVISOR is free and supports various frameworks for ICE vehicles, PHEVs, and BEVs that are sold successfully in the market. Second, it also allows access to detailed simulation codes and vehicle simulator updates in an easy way. For these reasons, we adopted ADVISOR as a tool for simulating EVs. In this context, the simulation of the overall energy flow of such vehicles is carried out by considering the vehicle powertrain model, drivetrain model including power transmission system, and battery SOC estimator. ADVISOR includes detailed model coefficients of engines, electric traction motors, controllers, converters, energy storage systems, shapes of chassis, etc. We carefully scaled and tuned the specification and efficiency of the components in order to simulate the following vehicles.

We selected Tesla Model 3 and Toyota Prius for the simulation because they were the best-selling BEV and PHEV in the United States in 2019, respectively (U.S. Plug-in Electric Vehicle Sales by Model 2020). Furthermore, Model 3 is the first plug-in electric car to reach one million sales in June 2021 (Huang et al. 2022).

1. BEV: The curb weight of Tesla Model 3 is 1611 kg, and the drag coefficient is 0.23 (https://www.tesla.com/model3). Model 3 is a rear-wheel-drive car and includes a maximum 211 kW AC permanent magnet motor and a 50-kWh lithium-ion battery pack. We updated model coefficients based on specifications and driving data provided by the manufacturer. Then, we validated the performance and electric fuel economy of Model 3.
2. PHEV: Toyota Prius Prime is based on the XW50 model (the fourth-generation Prius) (https://www.toyota.com/prius). It is a front-wheel-drive car, the curb weight is 1526 kg, the drag coefficient is 0.24, and the powertrain is 1.8 L (1798 cc) Atkinson cycle engine with an electric motor. The maximum power and torque of the motor are 53 kW and 163 Nm at 4000 RPM, respectively. This car includes an 8.8 kWh lithium-ion battery pack, which we assume of lithium-ion cells of the same type used in Model 3, in order to coherently compare the battery SOC and battery aging of the selected PHEV and BEV under the same battery characteristics.

Indeed, the degradation of the battery of a PHEV operating in *charge-depleting* mode is comparable to that of a BEV, as the traction energy is provided exclusively by the battery in both cases. Conversely, the degradation of the battery of a PHEV changes considerably in the case of *charge-sustaining* mode, where a traditional ICE provides traction energy to the vehicle. For this reason, the comparison of battery costs is here based on the analysis of the selected BEV and PHEV under charge-depleting and charge-sustaining operating mode, respectively.

4 Results

4.1 Analysis of driving simulation results

Initially, we performed the driving simulation test on a typical city driving condition with the Urban Dynamometer Driving Schedule (UDDS) defined by EPA and analyzed the operation and related energy consumption of the electric cars considered in this work. Figure 2 shows the simulation results for the BEV and PHEV under the UDDS cycle. The overall driving time of UDDS is about 22.8 min to drive 12 km, so that the average speed is 31.5 km/h during 17 stops and goes. The maximum speed is 91.2 km/h.

Fig. 2 The simulation results of the UDDS test cycle

(a) BEV power consumption.
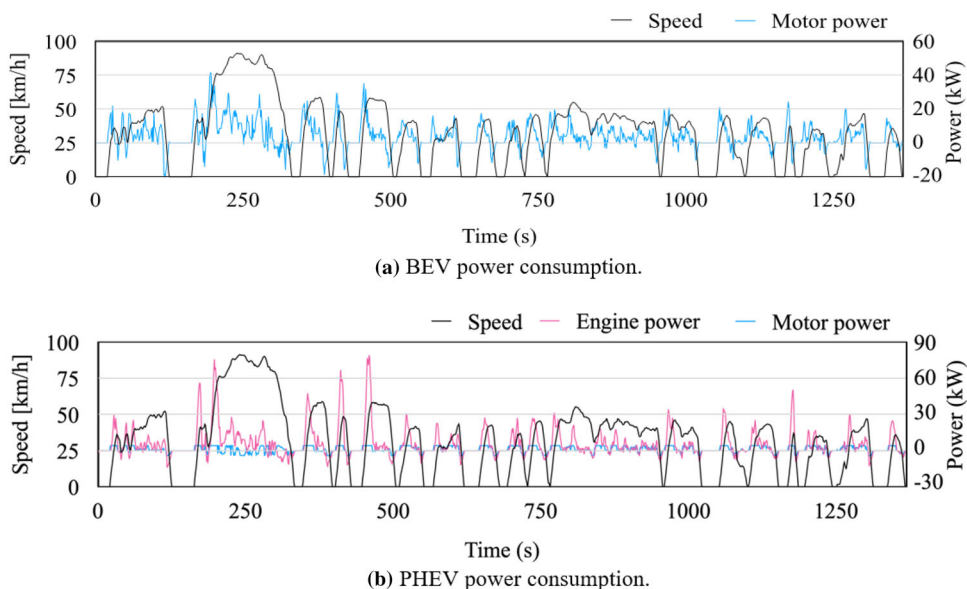

(b) PHEV power consumption.

Figure 2a shows the power consumption by the electric motor of the BEV under test. All the power consumption is directly related to battery SOC. It is worth noting that the electric motor in the BEV regenerates electricity during deceleration through regenerative braking; this is identified by negative power in the figure. On the other hand, Fig. 2b shows the power consumption by the engine and electric motor of the PHEV under the same driving profile. Most of the power for PHEV accelerations comes from the engine, whereas the electric motor only assists as a sidekick. Although energy recovery from regenerative braking is possible in PHEVs, the amount of such energy is generally less than that obtained in BEVs because of the smaller size of the motor.

Figure 3 enlarges the time period from 250 s to 500 s of the simulation test depicted in Fig. 2. Figure 3a refers to the speed profile. Figure 3b shows the power of the BEV motor and the battery SOC, which decreases when the power is positive (energy consumption) and increases when the power is negative (recovered energy) during regenerative breaking; these braking periods are highlighted in light blue color. Figure 3c shows the engine power, motor power and battery SOC of the PHEV. In this case, the battery is charged by (1) the electricity generation from the engine, and (2) the electricity generation from the electric motor through regenerative braking. The charging periods are highlighted in magenta color and marked from 1 to 5. The first, third and fifth period (i.e., 1, 3 and 5) resulted from the electricity generation of the engine, whereas the second and fourth periods (i.e., 2 and 4) resulted from the regenerative braking.

Fig. 3 Battery charging by **b** regenerative braking by a motor and **c** regenerative braking by a motor and electricity generation by an engine
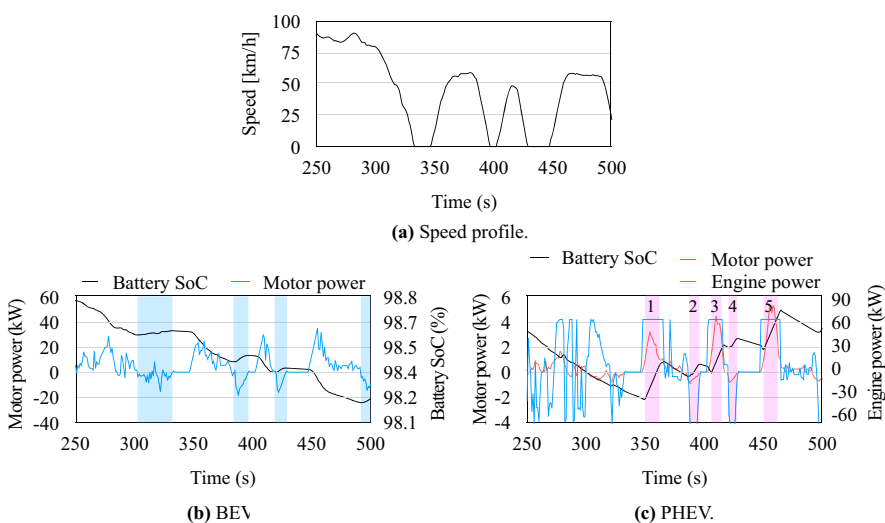

(a) Speed profile.

(b) BEV

(c) PHEV.

Table 1 Energy consumption and cost

	PHEV	BEV
Electrical energy, E_e (Wh)	128.3	1972.4
Gasoline energy, E_g (gram)	645.3	0.0
Cost by electricity, $E_e \cdot p_e$ ($)	0.048	0.740
Cost by gasoline, $E_g \cdot p_g$ ($)	0.950	0.0
Total cost	0.998	0.740

Table 2 Battery usage analysis

	PHEV	BEV
Discharged energy (Wh)	544.0	2261
Charged energy (Wh)	415.7	288
Total energy (Wh)	959.8	2549
Ah_{index} (%)	10.9	5.1
Total SOC variation	1.5	3.9

Table 1 shows the overall energy consumption and related costs by electricity and gasoline for the BEV and PHEV under the UDDS driving test. In this analysis, the electricity price p_e is 0.375 $ per 1 kWh, whereas the gasoline price p_g is 1.472 $ per 1 kg (https://www.globalpetrolprices.com, https://money.cnn.com/pf/features/lists/global_gasprices/) . In general, PHEV owners spend much more money on gasoline than electricity. One of the reasons is that a part of the electrical energy is generated by the engine in addition to regenerative braking. On the other hand, BEV uses only the electrical energy, and part of this energy is recovered by regenerative braking with a relatively large motor. Therefore, the total energy cost for a PHEV is higher than the total energy cost for a BEV.

4.2 Battery usage analysis

The battery SOC of the BEV and PHEV is discharged or charged during the test driving because of energy consumption for accelerating or continuing vehicle speed and energy regeneration as shown in Fig. 3. Because the degradation of the battery pack is strongly dependent to the charging and discharging cycles, battery usage is defined as the total number of absolute ampere-hours Ah during service time, as set forth in the following equation:

$$Ah = \int_0^T |I(t)| \mathrm{d}t \tag{7}$$

where I is battery current, and T is driving/charging time. Accordingly, the maximum number of ampere-hours in battery life is Ah_{max}. We assume that the ratio of battery fade Q_f and $Q_{f_{max}}$ in (3) could be approximated as the ratio of battery usage A_h and $A_{h_{max}}$.

In addition, we define Ah_{index} as the ratio of the total ampere-hours Ah in a certain period of service time to the nominal capacity Ah_b of battery pack:

$$Ah_{index} = \frac{Ah}{Ah_b} \tag{8}$$

The consumption and generation for the driving test and battery usage during the driving test is summarized in Table 2. The BEV consumes nearly four times more electrical energy than the PHEV, which also uses gasoline energy. However, the PHEV shows a higher battery usage than the BEV, although the total variation in SOC is smaller due to the frequent charging phases and the lower discharged energy of the PHEV battery.

4.3 Battery cost analysis

In this subsection, we analyze and discuss the battery costs for a sake of comparison based on the battery usage data reported in Table 2 for the UDDS test cycle. For the conversion of battery usage to battery cost, we referred to the lithium-ion battery price survey results by Bloomberg New Energy Finance (BNEF) as shown in Fig. 4. Battery prices are steadily falling due to mass production and advance in lithium-ion manufacturing technology. The battery price including cell price and cell-to-pack price becomes 132 $ in 2021. So, we assume that the replacement cost of a whole battery pack of Model 3, which consists of four battery modules, is 6600 $.

Conversely, the replacement cost for the PHEV battery (8.8 kWh) is assumed to be 1162 $ by scaling down. The battery warranty period is 8 years for Model 3 (https://www.tesla.com/support/vehicle-warranty). The minimal daily cost $c_{d_{min}}$ is obtained by dividing the total battery cost
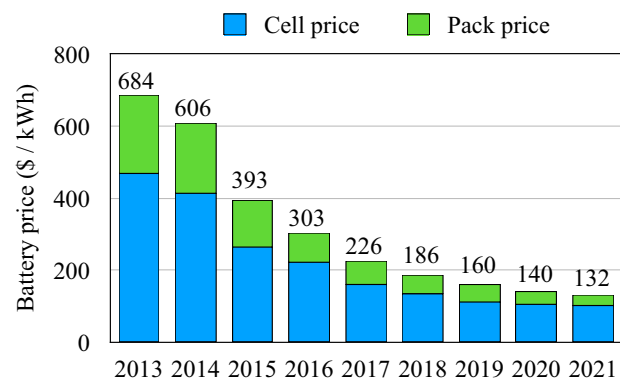
Fig. 4 Lithium-ion battery price survey result. Data source: (https://about.newenergyfinance.com/blog/battery-pack-prices-fall-to-an-average-of-132-kwh-but-rising-commodity-prices-start-to-bite/)

by the warranty period. We assume two driving tests a day in order to obtain the actual cost per day. Results are summarized in Table 3.

Figure 5 shows a comparison between c_{min} and c_a for BEV and PHEV, respectively. Indeed, c_a is always lower than c_{min} in the case of the BEV as shown in Fig. 5a; this means that the BEV battery is underused in this test case. An additional daily driving time of about 15.7 min, at those test conditions, is required to achieve the optimal daily cost from a warranty perspective for the BEV under test. Conversely, the PHEV battery is overused, as shown in Fig. 5b. In fact, c_a is higher than c_{min} because of the more frequent charging and discharging cycles, which accelerate battery degradation. For this reason, the replacement of the PHEV battery is expected before the warranty expiration period.

4.4 Battery aging analysis by driving profiles

In this section, we compare the battery usage cost on various driving cycles listed in Table 4. In this work analysis, we tested six driving cycles in addition to the UDDS. These cycles are also defined by the EPA Vehicle Chassis Dynamometer Driving Schedules (https://www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules) to test a vehicle in the following scenarios:

1. Inspection and Maintenance (IM240), which is commonly used for roadside testing.
2. Federal Test Procedure (FTP) also known as EPA75. This test is based on the UDDS test, with the final part ($t = 505$ s) being the same as the initial one.
3. Highway Fuel Economy Test (HWFET), for testing highway driving conditions with a speed limit of 60 mph.
4. New York City Cycle (NYCC), for low speed and stop-and-go driving.
5. High acceleration, deceleration and speed driving (US06), as supplemental FTP driving schedule.
6. Air Conditioning supplemental FTP driving schedule (SC03).

Table 3 Battery price and warranty

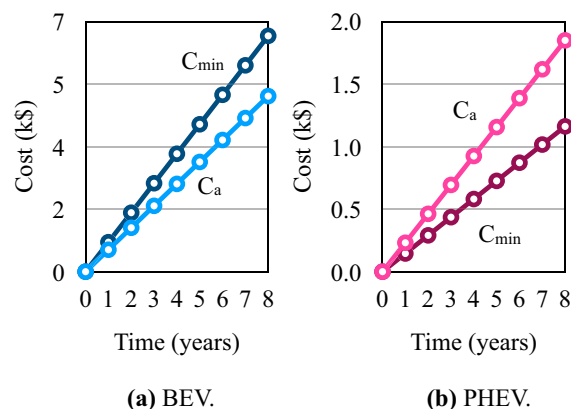|	PHEV	BEV
Total battery price ($)	1162	6600
Battery energy (kWh)	8.8	50
Warranty (year)	8	8
Optimal daily usage cost ($)	0.398	2.260
Actual daily usage cost ($)	0.633	1.683

(a) BEV. **(b)** PHEV.

Fig. 5 Battery cost comparison between c_a and c_{min} in **a** BEV and **b** PHEV

Table 4 List of driving cycles

Name	Distance (miles)	Driving time (s)	Avg. speed (mph)
UDDS	7.45	1369	19.59
IM240	1.96	240	29.38
FTP	11.04	1874	21.2
HWFET	10.26	765	48.3
NYCC	1.18	598	7.1
US06	8.01	596	48.37
SC03	3.58	596	21.55

Table 4 reports the total distance, driving time and average speed of each test. In this case, the distance and average speed are reported in miles and miles per hour (mph), respectively, in order to maintain the original units of measurement and avoid any approximation from converting miles to kilometers.

Similar to the UDDS test, for the battery usage cost analysis we assumed two driving tests for each daily driving cycle. Figure 6b shows the relationship among the driving cycles with respect to the driving distance and PHEV battery usage. The dashed line refers to a baseline passing UDDS, which is a typical city driving. Most driving cycles are on or near the dashed line, except US06 and HWFET. The latter requires less battery energy because of the long driving time without high acceleration/deceleration. So, in this case, there is less battery charging by regenerative braking and battery discharging due to vehicle acceleration. US06 is between the dashed line and HWFET because this driving cycle is a mix of highway driving and city driving.

Figure 6a shows the battery energy consumption by the BEV, which corresponds to the energy for driving. The battery usage for the US06 test is higher than the dashed

Fig. 6 Driving cycle comparison by battery energy versus travel distance

(a) BEV.

(b) PHEV.

line because the battery consumes energy with acceleration, deceleration and high-speed driving on highway.

Figure 7 shows the battery cost comparison only for the following driving cycles: FTP, HWFET, NYCC and US06. The reason is that the IM240 test is the "Inspection & Maintenance Driving Schedule," whereas SC03 is the Air Conditioning supplemental FTP driving schedule, that is "Speed Correction Driving Schedule." Accordingly, the details of these two tests are not included in Fig. 7, although the main results are reported in Fig. 6.

The FTP is a 31-min light-duty vehicle driving test. In this case, the usage of the BEV battery is just slightly higher than the optimal one. Therefore, the battery warranty is almost adequate. Conversely, the PHEV battery is extremely overused, so that a replacement will be required twice during the warranty period. In fact, the acceleration and deceleration phases are even more frequent than in the UDDS test.

HWFET is a short (less than 13 min) highway vehicle driving test. In this case, because the usage of PHEV and BEV batteries is less than optimal the related costs are also less than optimal. For the PHEV, the battery usage cost is lower than optimal because there are fewer acceleration and deceleration phases during highway driving than during city driving.

NYCC is a 10-min driving test under low speed and stop-and-go traffic conditions. Due to the short driving time, the degradation of PHEV and BEV batteries is less than optimal. However, the use of these batteries is relatively high because of the frequent stop-and-go driving patterns.

US06 is also a 10-min driving cycle but, compared to NYCC, US06 consists of greater acceleration, deceleration and, in general, speed. In this case, the use of the BEV battery is close to optimal from a cost perspective. This is true also for the PHEV battery, but as a consequence of the short driving time. In fact, the greater stress on the PHEV battery from city traffic conditions, tends to increase the aging of the battery and, therefore, the related costs.

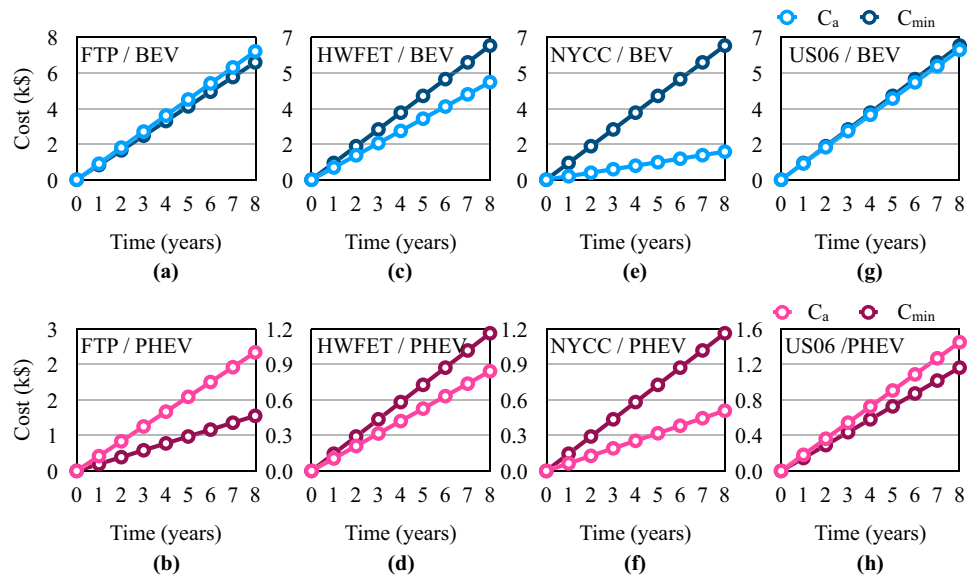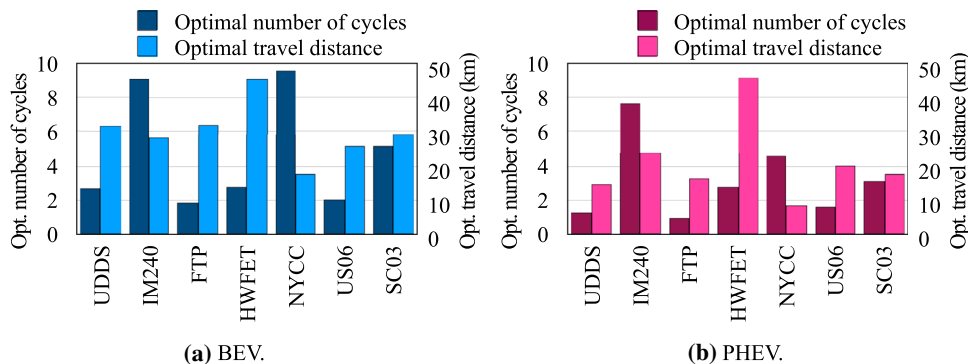**Fig. 7** Battery cost comparison between c_a and c_{min} for four different driving cycles

Fig. 8 Optimal number of cycles and travel distance

(a) BEV.

(b) PHEV.

In summary, the usage cost of a PHEV battery is greater than optimal in all situations in which frequent stops and acceleration/deceleration phases occur. Conversely, the usage cost of a BEV battery pack is close to optimal in all driving conditions. However, this result depends on daily travel distance, whose optimal value depends on driving condition and scenario. Accordingly, a further step is required to evaluate the best use of these batteries. Figure 8a, b shows the optimal number of cycles and travel distance in a day in order to use the battery optimally for the BEV and PHEV, respectively, under test conditions.

In general, the number of cycles of a driving test is inversely proportional to its driving distance: if this distance is too short, we need to drive more times to consume the battery optimally. The optimal number of cycles for PHEVs is generally less than that for BEVs, especially in the case of UDDS and NYCC, except for HWFET. In fact, HWFET requires less frequent acceleration and deceleration phases, with respect to the other tests. Conversely, UDDS and NYCC have so many starts and stops that, in these two cases, the optimal number of cycles for PHEVs is about half of that for BEVs.

5 Conclusion

This paper proposed a simple cost analysis model and reported the results of the optimal usage cost of batteries in EVs as the main outcomes. The analysis was based on the accurate vehicle driving simulator and survey data. For an optimal cost of ownership of batteries in BEVs and PHEVs, this work presented a usage cost analysis of these batteries. Simulation results from various EPA standard driving tests applied to these electric vehicle types were then reported for Tesla Model 3 under charge-depletion mode and Toyota Prius Prime under charge-sustaining mode, respectively. Significantly, the degradation of a BEV battery is generally less than 50% of that of a PHEV battery in city traffic, but it is slightly greater in highway driving. It follows that driving a PHEV with the use of a traditional

combustion engine is strongly discouraged on routes with frequent starts and stops, not only for the harmful effects on environment, but also for the greater degradation of the battery. Furthermore, battery wear in BEVs is generally more correlated to travel distance than other driving characteristics, whereas in PHEVs it largely depends on the frequency of high-speed variations involving acceleration and braking phases.

Declarations

Availability of data and material The simulation data generated by ADVISOR are available under request.

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