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Optimal Life-Cycle Costs of Batteries for Different Electric Cars

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***Abstract*—As a consequence of the remarkable increase in the production of electric cars, the cost per kWh of battery packs is more decreasing, although it still has a considerable impact on the purchase price of these vehicles.**

This paper describes the optimal cost analysis of battery packs for different electric cars among full battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs) and autonomous vehicles (AVs). In fact, the cost optimization of battery use also depends on the type of electric vehicle and not only on battery pack type, operating conditions and driver's style. Thus, the proposed analysis aims to optimize battery costs over time by considering battery life degradation for various types of electric cars. The results indicate a greater degradation of a PHEV battery, for urban trips with many stops, with respect to a BEV battery, with the consequence of an expected early replacement of the PHEV battery before the warranty expires. In this context, the usage rate of a BEV battery is about 50% of that of a PHEV battery.

***Index Terms*—Battery pack, cost analysis, electric vehicles.**

NOMENCLATURE

C_{deg}	Actual cost of battery life degradation.
C_{opt}	Optimal cost of the life degradation after N_d days.
C_{opt}^{d}	Optimal daily cost of battery life degradation.
C_{tot}	Total cost of battery pack.
C_{AV}	Energy cost of an autonomous vehicle.
C_{BEV}	Energy cost of a full battery electric vehicle.
C_{PHEV}	Energy cost of a plug-in hybrid electric vehicle.
E_e	Electrical energy consumption.
E_g	Gasoline energy consumption.
N_d	Number of days of battery life.
p_e	Electricity price.
p_g	Gasoline price.
Q_f	Capacity fade.
$Q_{f_{max}}$	Maximum capacity fade in battery life.
Q_{nom}	Nominal capacity.
Q_{Ah}	Total ampere-hours during service time.
α	Battery degradation index.

I. INTRODUCTION

One of the main goals of this modern society is to reduce air pollution. This effort has been leading to (i) the development of motor vehicles with different power supply with respect to those with internal combustion engine (ICE) using petroleum products, and (ii) the increasing use of renewable energies (e.g., photovoltaics, wind). In both cases, one of the general common effects has been the increasing use of batteries: mainly as energy source for traction in electric vehicles, and energy storage for the electricity generated by renewable energy plants. Therefore, one of the most research subjects during the last two decades has been the development of batteries of various chemistries and the analysis of their life degradation [1], [2]. Furthermore, the consequent and notable increase in the production of batteries has led to their rapidly decreasing price per kilowatt-hour [3]. However, the cost of batteries still weighs heavily on the total cost of an electric car (in this work, the generic term "vehicle" refers to "car").

In the literature, the analysis of the degradation costs in batteries usually only considers cycle life (i.e., the number of cycles at certain working and operating conditions) and calendar life (i.e., the maximum number of years of service) [4], [2]. However, the real cost of a battery pack degradation also depends on the time interval for the battery to reach its *end of life* (EOL). This is commonly defined to be the condition of a state-of-health (SOH) of the battery equal to 80%, that is an irreversible capacity (energy) loss of 20% with respect to the nominal capacity [5]. In addition, this real-time cost analysis changes when considering battery packs installed on electric vehicles of different types, such as full battery electric (BEV), plug-in hybrid electric (PHEV) and autonomous (AV) vehicles. In fact, the cost of the total energy used, which is the real parameter of interest for the analysis of the expenses actually incurred, is closely connected to vehicle characteristics.

Furthermore, the total cost of battery energy is not simply based to a single battery pack, but also to the period that elapses from the replacement of a pack in EOL status to another new one. For this reason, the real life-cycle cost of a battery should include also a temporal analysis considering the degradation over time. Thus, the aim of this work is to present a life-cycle cost analysis for batteries of today's leading EVs, for possible optimization of battery use.

The paper is organized as follows: Section II reports the current status of the optimal cost analysis for batteries in EVs, Section III describes the various life-cycle cost models, and Section IV reports data statistics on the battery usage in EVs and related costs; finally, Section V draws some conclusions.

II. Background and Related Work

Nowadays, there are various hybrid electric vehicle types in addition to full battery electric vehicles (BEVs), such as full hybrid (HEV), plug-in hybrid (PHEV), mild hybrid (MHEV) and micro hybrid (μHEV) electric vehicles, as reported in Fig. 1. However, battery packs are still one of the main costs for plug-in electric vehicles.

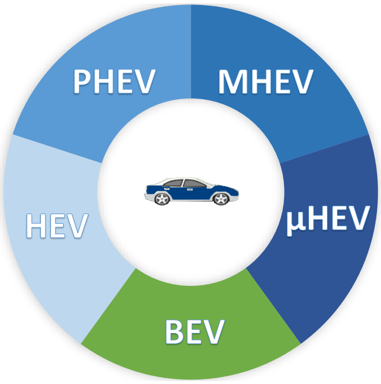


Fig. 1: The main electric vehicle types in the market.

As each EV generally wears out more than one pack during its lifetime, the costs due to the depreciation of a pack are generally included in the maintenance costs [6]. In order to reduce these costs, nowadays the research for new batteries is focusing especially on materials with high specific energy (Wh/kg), long calendar life, a very low degradation with cycling and fast charging, and with low environmental costs [1], [4].

Some system-level models may provide an accurate estimation of battery life degradation, in order to avoid the analysis through electro-chemical processes [7]. These models are generally based only on a few parameters such as state-of-charge (SOC), depth-of-discharge (DOD) at each cycle, temperature (T), and charge/discharge currents. In addition, they usually include degradation over time, that is calendar aging. However, a comprehensive analysis for optimal battery use should also include possible benefits, as well as degradation, from special services, for example vehicle-to-grid (V2G) applications [8].

In the literature, life degradation costs due to charging were analyzed extensively because, in general, charging is nowadays one of the most critical aspects in the evolution of electric car sales [9], [10].

In [11], the total cost C_{en} due to the energy consumption in PHEVs is simply defined by:

$$C_{en} = E_e \cdot p_e + E_g \cdot p_g \tag{1}$$

where E_e and E_g are the energy consumption of battery and gasoline, respectively, whereas p_e and p_g are the corresponding prices per unit. This model is useful when the depreciation cost of a battery pack is mostly a *fixed cost*. This is when the pack is rented by the car's manufacturer to the user instead of selling it with the vehicle. In fact, in this case the monthly cost of the battery is well defined and can therefore be considered separately. Conversely, the depreciation cost is a *variable cost* when the battery pack is a property of the car owner. In this context, the cost due to battery life degradation could be minimized as far as possible.

In [12], the cost of battery lifetime reduction is defined by two different components: the cost due to charging/discharging power and the one due to the fluctuations of the power between two consecutive time intervals. In both cases power is considered squared. However, the degradation cost due to calendar aging is not really included.

In [13], the life-cycle costs in EVs and PHEVs are described without an analytical approach except for a general formula from [14] regarding the net present value (PV) of a battery pack over years:

$$PV = \frac{C}{(1+D)^y} \tag{2}$$

In (2), C is cost, D is discount rate, and y is the number of years. However, this general approach does not consider the current state of the degradation and, therefore, the real perspective regarding the true number of years of service of a battery pack, a parameter that is essential when analyzing actual costs.

A more comprehensive cost analysis is provided in [15], although for the use of batteries in renewable energy storage applications. This work reports annualized life cycle costs, which are the most interesting data also for a car owner in a cost-benefit analysis. In addition, the authors reports the replacement costs of batteries as proposed by [16], where self-discharge loss is considered in the overall system efficiency (η_{sys}) as well as other losses such as, for instance, the one due to DOD. However, a more practical analysis would make an easier effort for a user to examine the actual costs for battery use, that is, a cost model should be considered separately from any aging model for a sake of simplicity. In fact, including the system-level parameters for battery degradation in cost analysis makes it really more complex and, therefore, more easily incomplete.

III. EV models and Battery Cost Analysis

As replacement costs really affect the life-cycle costs of battery packs [16], the cost analysis here described focuses on the minimization of such costs for three different electric vehicles: BEV, PHEV and AV. Although BEV and AV are basically full electric vehicles, they truly differ for the number of sensors, software size, and the capability for a more balanced drive [17]. Therefore, the battery energy consumption of these vehicles also basically differs.

In the market there are various PHEV types, which are mostly characterized by their drive train architecture. In this case, the hybridization factor depends on the power size of electric motor and ICE motor [18]. However, we simplified the context by considering only the main property of these vehicles, that is, the use of gasoline and electricity as possible sources of energy for traction, and independently from the vehicle's maximum driving range.

After considering the total cost C_{tot} of a fresh battery pack and the estimated maximum number of days of service N_{dmax}, then the minimal or optimal daily cost of battery life degradation is the following:

$$C_{opt}^{d} = \frac{C_{tot}}{N_{dmax}} \quad (3)$$

The optimal degradation cost for battery use after N_d days of service is therefore given by:

$$C_{opt} = C_{opt}^{d} \cdot N_d \quad (4)$$

Actual degradation cost for battery use:

$$C_{deg} = C_{tot} \cdot \frac{Q_f}{Q_{f_{max}}} \quad (5)$$

Then, the degradation index of a battery pack after N_d days of service is defined as follows:

$$\alpha = \frac{C_{deg}}{C_{opt}} \quad (6)$$

From (6), there are three possible main results:

- α <1 battery is underused so that its replacement will occur before reaching the maximum number of equivalent cycles;
- α =1 battery is used optimally from a degradation point of view;
- α >1 battery is overused so that its replacement will be anticipated.

Although the basic degradation cost and this analysis are the same for all electric vehicles, the actual cost for the energy consumption in BEV, PHEVs and AVs differs as reported here below.

A. Battery Electric Vehicle (BEV)

In BEVs, the energy cost is defined as follows:

$$C_{BEV} = \sum_{i=1}^{N_d} E_e(i) \cdot p_e(i) + C_{deg} \quad (7)$$

B. 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, in this case the energy cost is also affected by fuel price as follows:

$$C_{PHEV} = \sum_{i=1}^{N_d} (E_e(i) \cdot p_e(i) + E_g(i) \cdot p_g(i)) + C_{deg} \quad (8)$$

C. Autonomous Vehicle (AV)

$$C_{AV} = C_{BEV} + \sum_{i=1}^{N_d} E_a(i) \cdot p_e(i) \quad (9)$$

In (9), E_a is the energy consumption due to the automatiion devices (e.g., sensors) and communication systems (e.g., radio) to send/receive data to/from infrastructures and other vehicles. In fact, the remarkable presence of a complex electronic system in AVs, although it is also present in other modern cars but not in such an expensive and voluminous way, is the true difference between BEVs and AVs regarding energy consumption in the case of similar weight and electrical motor.

IV. Results

A. Simulation Setup

Firstly, we adopted ADVISOR (ADvanced VehIcle SimulatOR), a MATLAB/Simulink based open-source simulator, for the analysis of the energy consumption and/or gas emission of vehicles [19]. ADVISOR carries out the simulation of the overall energy flow of an EV through a vehicle drivetrain model and a battery SOC estimator. This tool considers various kinds of engine, electric traction motor, controller, converter, energy storage system, shape of chassis, etc. There are default vehicle frameworks for BEVs, HEVs, and PHEVs based on vehicles that have been sold successfully. We carefully scaled the size of key components (engine, motor and battery) or tuned the efficiency to match specification of vehicles we want to simulate.

1) EV: we selected Tesla Model 3 as a BEV under simulation test. Model 3 is one of the best-selling electric cars in the market during recent years. The curb weight of this car is 1611 kg, and the drag coefficient is 0.23.

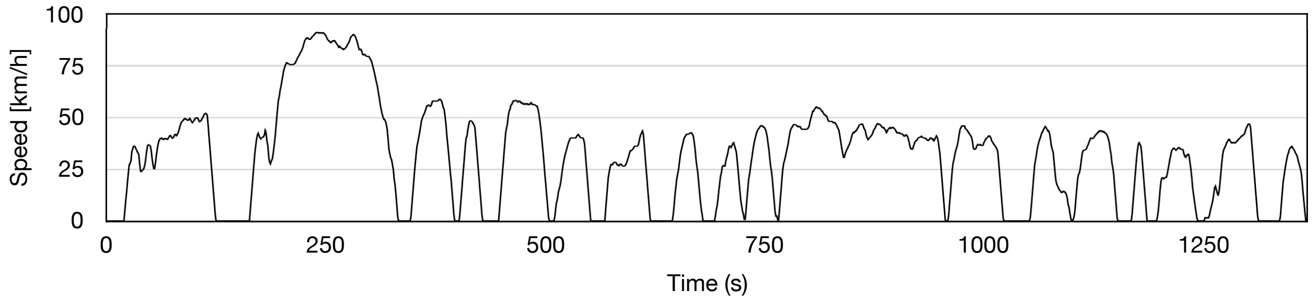
Model 3 standard plus version is a rear-wheel-drive car with an AC permanent magnet (PM) motor and a 50 kWh lithium-ion battery pack [20]. We picked a default EV framework in ADVISOR and set the key components: motor type, motor size, battery cell specification, battery pack size, vehicle shape, etc.

2) PHEV: we selected Toyota Prius hybrid (XW50) as a PHEV in our simulation. XW50 is the fourth generation PHEV released by Toyota, and it is also one of the best sold cars in the world. This is a front-wheel-drive car; the curb weight is 1397 kg, and the drag coefficient 0.24. XW50 has a 1.8 L (1,798 cc) Atkinson cycle engine. The maximum power and torque are 53 kW and 163 Nm at 4000 RPM, respectively. This car includes an 8.87 kWh lithium-ion battery pack [21]. In order to coherently compare the energy consumption and the battery aging of PHEV and BEV under the same characteristics during the simulation test, we assume that a battery pack for WX50 consists of the lithium-ion battery cells used in Model 3.

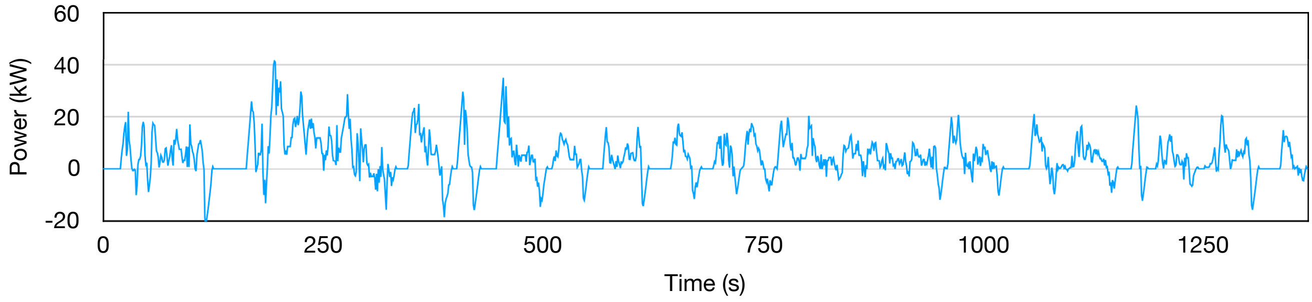
B. Analysis of Driving Simulation Results

We performed the driving simulation test on a city driving cycle, according to Urban Dynamometer Driving Schedule (UDDS) [22]. This is one of a series of tests defined by the US Environmental Protection Agency (EPA) to measure tailpipe emissions and fuel economy of passenger cars in city driving conditions. In this context, the overall driving time is about 22.8 minutes to drive 12 km, so that the average speed is 31.5 km/h.

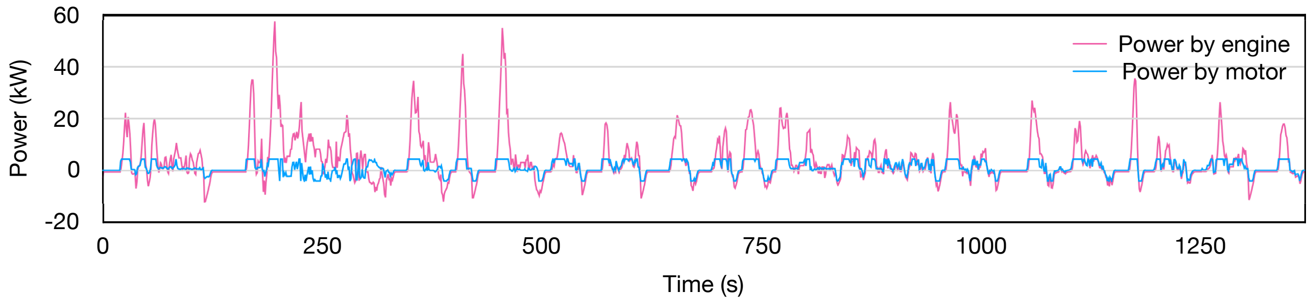
Fig. 2 shows the simulation results of the driving cycle for the PHEV and BEV under test on UDDS. Fig. 2(a) shows the driving profile of UDDS, including 17 stops, during the time



(a) UDDS driving profile.



(b) BEV power consumption.



(c) PHEV power consumption.

Fig. 2: Simulation results of the UDDS test cycle.

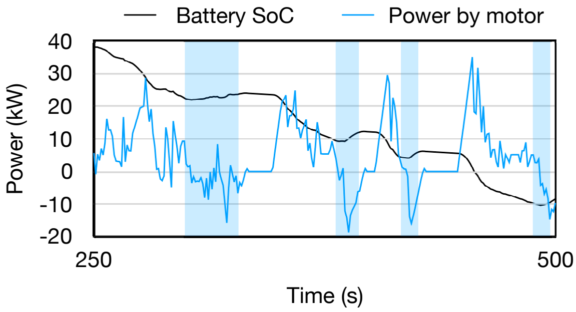
interval of 1369 s; the maximum speed for this test is 91.2 km/h. Fig. 2(b) shows the power consumption of BEV. In this case, all the power consumption occurs by the electric motor and the related energy consumption directly reduces battery SOC. It is worth noting that BEV regenerates electricity using its motor during deceleration through regenerative braking; this is identified by the negative power in Fig. 2(b).

Figure 2(c) shows the power consumption of PHEV by its engine and electric motor. Most of the power required for acceleration comes from the engine, whereas the electric motor helps the engine as a sidekick. Energy recovery also occurs in PHEVs during deceleration. However, in this case the energy obtained by regenerative braking is less than that of BEVs, as a consequence of the size of the motor.

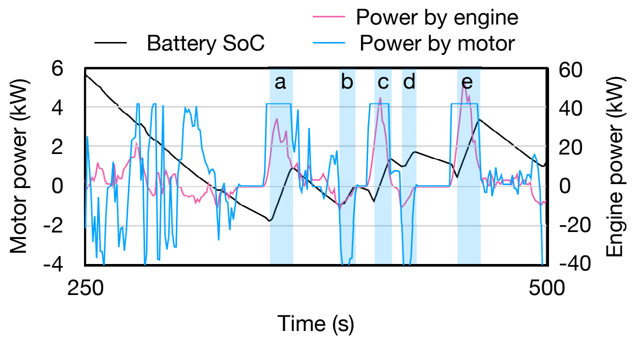
Figure 3 enlarges the time period from 250 s to 500 s of the simulation test depicted in Fig. 2. Fig. 3(a) shows the battery SOC and the motor power of the BEV under test. Battery SOC decreases when motor power is positive and increases when power is negative during regenerative breaking, whose time periods in the test are highlighted in blue.

On the other hands, the battery of a PHEV is charged by electricity generation by the engine as well as by the regenerative braking by the electric motor. Figure 3(b) shows the battery SOC profile during the driving test of the PHEV. The first, third and fifth battery charging periods (i.e., a, c and e of the highlighted areas) occurred by the electricity generation by the engine, whereas the second and fourth battery charging periods (b and d) occurred by the regenerative braking by the electric motor.

In addition to the BEV simulation results, we considered a fully autonomous driving system with no steering wheel and no pedal driving. This can be achieved by considering NVIDIA DRIVE AGX Pegasus^{TM}, an AV platform performing 320 trillion operations per second [23] and having a thermal design power of 500 W. However, the remarkable current investments for a continuous development of self-driving cars, suggests to consider at present only a partial analysis of AVs until automotive industry and researchers will reach a stable technology under regulated legislation. Nevertheless, a preliminary comparison is included here.



(a) BEV.



(b) PHEV.

Fig. 3: Battery charging by (a) regenerative braking by a motor and (b) regenerative braking by a motor and electricity generation by an engine.

TABLE I: Energy consumption and cost.

	PHEV	BEV	AV
Electrical energy, E_e (Wh)	248.9	1972.4	1972.4
Energy for self-driving, E_a (Wh)	0.0	0.0	190.3
Gasoline energy, E_g (g)	541.0	0.0	0.0
Electricity cost, $(E_e + E_a) \cdot p_e$ (\$)	0.089	0.706	0.774
Gasoline cost, $E_g \cdot p_g$ (\$)	0.796	0.0	0.0
Total cost, C_{en} (\$)	0.885	0.706	0.774

Table I shows the overall energy consumption and costs for the UDDS driving cycle after simulating the different electric cars: BEV, PHEV and AV. Electricity price p_e and gasoline price p_g are 0.358 \$ per 1 kWh and 1.472 \$ per 1 kg, respectively, as reported in [24], [25]. In general, PHEVs spend much more money for charging gasoline than electricity (0.649 \$ vs. 0.104 \$) and, therefore, currently the total energy cost for a PHEV is higher than the total costs for a BEV.

C. Battery Usage Analysis

There is not a large variation in battery SOC during the test driving, for both BEV and PHEV, as a consequence of the numerous charging and discharging periods, as shown in Fig. 3. Nevertheless, the battery pack is degraded by both charging and discharging phases. For this reason, battery usage Q_{Ah} is defined as the total number of ampere-hours during service time, by the following equation:

$$Q_{Ah} = \int_0^T |I(t)| dt \tag{10}$$

TABLE II: Battery usage analysis.

	PHEV	BEV	AV
Discharged energy (Wh)	589.9	2260.9	2425.2
Charged energy (Wh)	341.0	288.5	262.5
Total energy (Wh)	930.8	2549.4	2687.8
Battery usage rate (%)	10.6	5.1	5.4
Total SOC variation (%)	3.10	3.24	3.41

where I is the battery current and T is the overall driving time. The maximum number of ampere-hours in battery life depends on working and operating conditions.

Table II shows a comparison of the battery energy for the driving test. BEV and AV consume nearly four times more electrical energy than PHEV, which charges more energy in its battery through its engine and motor. However, the PHEV under test shows a higher battery usage rate (10.6%), which is the percentage value of the ampere-hour ratio Q_{Ah}/Q_{nom}, the latter term being the nominal capacity of battery pack. In addition, the SOC variation (3.1%) is the smallest among these vehicles, as a consequence of the frequent charging process and, in general, of the lower discharged energy of a PHEV battery.

D. Battery Cost analysis

Tesla announced that the replacement cost of a battery module is between 3,000 and 7,000 \$ [26]. So, for a price of 6,000 \$, the total replacement cost of the whole battery pack, which includes four modules in Model 3, is assumed as 24,000 \$. The battery warranty period N_{nmax} is 8 years for Model 3 [27]. On the other hand, the replacement cost for the PHEV battery (8.8 kWh) is scaled down to 4,224 \$.

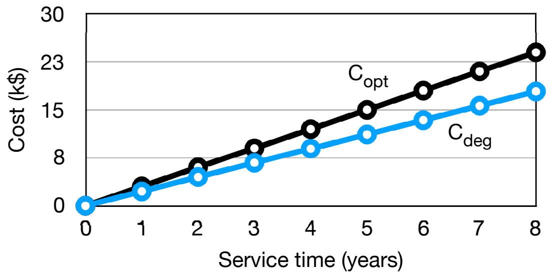
The optimal daily cost C^d_{opt} is obtained by dividing the total battery cost and the warranty period. We assume two driving tests during a day in order to obtain the actual degradation cost C_{deg} per day. Results are summarized in Table III.

TABLE III: Battery price and warranty.

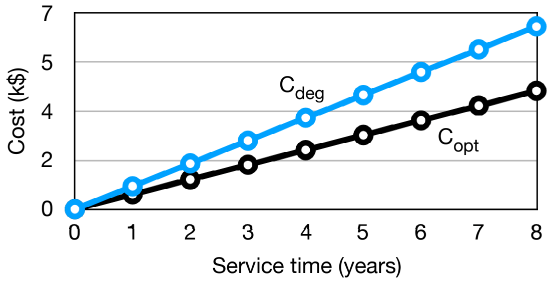
	PHEV	BEV	AV
Battery price, C_{tot} (\$)	4224	24000	24000
Battery capacity (kWh)	8.8	50	50
Battery warranty, N_{dmax} (year)	8	8	8
Optimal daily cost, C^d_{opt} (\$)	1.349	8.219	8.219
Actual degradation cost, C_{deg}, per day (\$)	2.234	6.119	6.451

Fig. 4 shows a comparison between C_{deg} and C_{opt} for the different EVs considered here. C_{deg} is always lower than C_{opt} in the case of BEV and AV, as shown in Fig. 4(a) and Fig. 4(c), respectively; this means that their batteries are underused ($\alpha < 1$). A daily driving of 45.6 minutes is, however, suitable for the warranty period of BEV and AV.

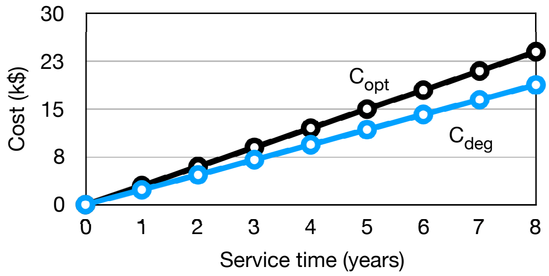
On the other hand, a PHEV battery could be more easily overused ($\alpha > 1$), as shown in Fig. 4(b). In fact, C_{deg} is higher than C_{opt} in the simulation test as a consequence of the more frequent charging and discharging cycles, which accelerate battery degradation. In this case, a battery replacement is expected before the warranty expires.



(a) BEV.



(b) PHEV.



(c) AV.

Fig. 4: Battery cost comparison between C_{deg} and C_{opt} in (a) BEV, (b) PHEV and (c) AV.

V. Conclusion

This work presented an analytical approach for the cost analysis of battery life-cycle degradation for BEVs, PHEVs and AVs. Simulation results of a standard driving test are reported for a Tesla Model 3, as a full battery electric car, and a Toyota Prius XW50, as a plug-in hybrid electric car, in addition to some preliminary results for an AV. From the results, the life degradation of a PHEV battery is greater than that of a BEV battery in urban mobility because of the more frequent charging and discharging cycles from both PHEV engine and motor. In this scenario, the battery usage rate of a BEV battery is about 50% of that of a PHEV battery.

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