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Electric vehicle range and battery lifetime: a trade-off

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Abstract

Extended range of electric vehicles is seen as a mean to accelerate the market penetration of electric vehicles. However, putting more and more battery cells in a pack may lead to an unsuitable usage regarding battery lifetime. In this paper, we assess the impact of oversizing batteries in their lifetime and their total cost of ownership. Simulation results reveal a reduction in battery lifetime of larger batteries when charge is not adapted, dramatically increasing the total cost of ownership. On the contrary, optimisation of the charging strategy preserves the battery's performances for a longer time and lead to important cost savings.
Keywords: EV (electric vehicle), battery ageing, battery management, LCC (life cycle cost).

1 Introduction

Electric vehicles constitute a part of the solutions to stop climate change and reduce air pollution. The market penetration of electric vehicles is increasing fast in many developed countries [1]. Governments encourage purchasing this type of vehicles by using tax exemptions, subsidies and other. However, the increase of electric vehicles sales since 2010 is also due to the manufacturing cost reductions mainly performed in the battery. As the battery pack size increases, electric vehicles' range is growing. For example, Renault Zoe had a battery pack of 22kWh in 2012 and of 41kWh since 2016; other electric car models have increased their battery size (Nissan Leaf from 24 to 40kWh, BMW i3 from 22 to 42kWh) expanding ranges from about 150 to more than 300km. With ranges up to 350km, electric vehicles could replace internal combustion engine vehicles in most of cases. However, the daily required range is most often less than 50km [2]. With larger batteries, state of charge may be often higher leading to faster battery degradations. Size and charging of batteries can be optimised to a minimal range in order to prolong their lifetime.

Despite of advances in cost and performances, batteries are still the weak point of electric vehicles because they limit their range and have a significant impact on the total cost of ownership. For these reasons, battery management to reduce its degradation sparks much interest in the scientific community. For example, some authors aimed to optimise the charging protocol of lithium-ion batteries to minimise charging time and/or maximise battery's lifetime [3–5]. Other works, for example [6, 7], studied the influence of V2G (vehicle to grid) applications in battery degradation.

In this work, we are exploring the consequences of increasing electric vehicles' battery size on its lifetime. We are considering two distinct scenarios: first one, consists in fully charging the battery every day (worst-case scenario); second scenario consists in charging the battery to a defined state of charge ensuring a reduced range.

2 Battery ageing

A battery allows to reversibly store energy by transforming electricity into chemical energy. The main characteristics of a battery are energy (capacity) and maximum power (impedance). Batteries are complex systems: their performances depend on the composition of their parts (electrodes, current collectors, electrolyte, etc.) and on the reactions occurring between them.

Batteries' performances degrade over time because of ageing mechanisms. These mechanisms are parasitic physico-chemical reactions causing capacity fade and impedance rise [8]. Battery ageing is classified in two types: calendar and cycling ageing. Calendar ageing is the degradation during rest times whereas cycling ageing is the degradation induced by charging and discharging the battery. In this work, we are considering the electric vehicle application where average current rates are very low, about C/2 in discharge (during the vehicle use) and C/5 in charging. Moreover, private owned vehicles are parked most of time (more than 95% of time). For this reasons, in this paper we will consider only calendar ageing. So cycling ageing with little solicitation will be neglected. The main calendar ageing factors are temperature (T) and state of charge (SoC).

3 Modelling

We are focusing in battery degradation as a consequence of the electric vehicle use. As explained above, T and SoC are the main factors for calendar ageing. Calendar ageing will be computed by using a degradation model based on Eyring relationship [9].The following expression is used to calculate the capacity fade as a function of T and SoC:

$$Q_L = A \cdot e^{(-E_a/kT + B \cdot SoC)} \tag{1}$$

To obtain the SoC profile, we need to define a use scenario; that is a daily speed profile and a charging strategy.

The chosen mission profile is shown in Figure 1. From Monday to Friday, two WLTC (World-wide harmonized Light duty Test Cycle) class 3 [10] speed profiles are used to represent a daily trip home-to-work (at 8 a.m.) and work-to-home (at 5 p.m.). The WLTC class 3 is 23km long and it includes four phases (low, medium, high and extra-high speed) corresponding to different road types (urban, rural, motorway). The cycle length corresponds approximately to the average daily travelled distance in the French case (25km) [11]. On Saturday, we supposed that a longer trip is made mainly for leisure activities. For this reason, WLTC class 3 speed profile is used twice at each trip (at 9 a.m. and 9 p.m.), making the travelled distance (46km) two times higher compared to the preceding case. Finally, on Sunday, a WLTC class 1 is performed at 10 a.m. and 5 p.m. as we supposed less leisure activities. The WLTC class 1 is 8km long and it includes two phases (low and medium speed). These choices are arbitrary, but sufficiently realistic for the purpose of the work.

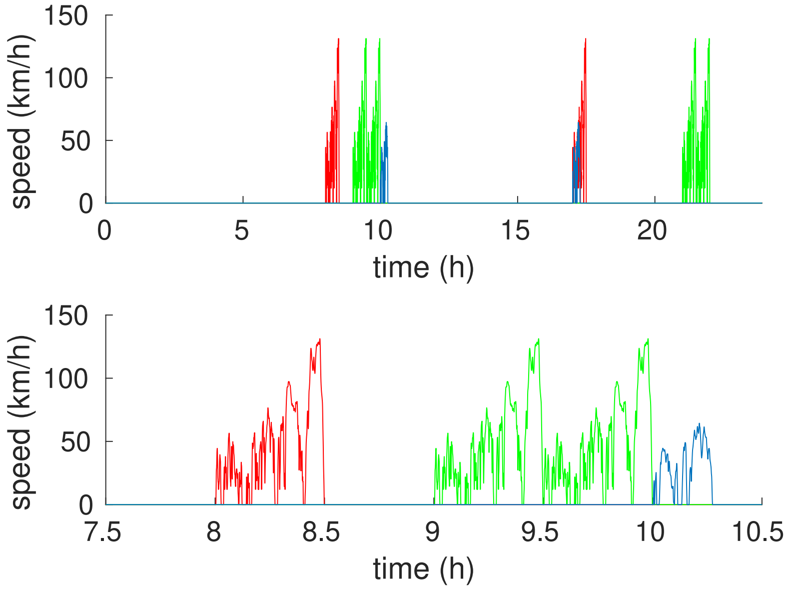

Figure 1: Speed profile (red = Monday to Friday, green = Saturday, blue = Sunday).

The VEHLIB library [12] is used to assess the electric power going upstream from vehicle's speed to battery power (P_{bat}). Vehicle chassis is modelled considering its total weight (including battery) and the drag forces due to aerodynamics and tires. Electrical machines are modelled considering efficiency maps and battery behaviour by an electric equivalent circuit.

Note that P_{bat} is the output battery power. In order to properly quantify the amount of available energy in the battery, the net power $P_{bat,0}$ must be calculated by adding the power losses inside the battery. This is achieved by using the relations given in Appendix (Useful equations).

Finally, the charging strategy consists in defining some rules to make the decision of charging the battery. For example, some users may decide to completely charge their batteries every day, but other may adapt the battery charge to the expected distance to travel the day after. The charge time is fixed to 9 p.m. from Sunday to Friday and 11 p.m. on Saturday.

In this paper, a small city car is considered (47kW, 945kg excluding batteries). Battery mass is calculated for each battery size from 20 to 60kWh. Temperature is constant and equal to 25 °C.

4 Simulation results: effects of oversizing the battery depending of the charging strategy

Depending on the charging strategy, battery lifetime and total cost of ownership may change according to the size of the battery. Indeed, according to equation 1, ageing is amplified by high temperature and high SoC. In this work, we consider constant temperature all along the year but scenarios differ on the value of the daily average SoC. Consequently, different capacity fade rates occur.

We will consider two charging scenarios. In the first one, there is no charging strategy depending on the next day's travelled distance: the battery is fully charged each night independently the needed range for the day after. On the contrary, in the second scenario, the charging strategy will take into account the expected next day's travelled distance.

For each scenario, the mission profile and the charging strategy will be repeated until end of life (EoL) of the battery (i.e. capacity fade = 20%). Different battery sizes from 20 to 60kWh are simulated to measure the impact of the battery size on its lifetime (in number of days) and cost (in €/ day) for each charging scenario.

4.1 Scenario 1: charging the battery to a maximum SoC level

In this scenario there is no charging strategy: the battery is fully charged every day regardless of the travelled distance. Real world use shows that this situation of charging "as soon as possible" occurs frequently [13].

In figure 2, the SoC level for a Monday is shown for three battery sizes: 20, 40 and 60kWh. The battery is charged to 100% every day. Depending on the battery size, the SoC range is different. For example, at beginning of life (BoL), with 60kWh the SoC level varies from 100 to 90% whereas it varies from 100 to 69% with a 20kWh battery. At end of life (EoL), as capacity decreases, the SoC range is larger: minimum SoC is 86 and 61% for 60 and 20 kWh respectively.

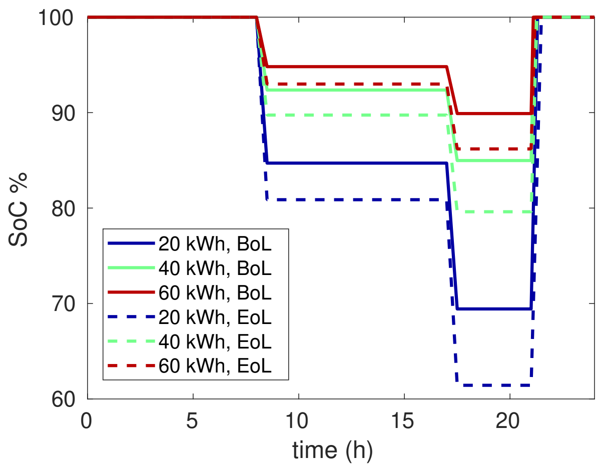

Figure 2: Monday's SoC profile in scenario 1 for different battery sizes at beginning of life (continuous lines) and at end of life (dashed lines).

These differences in the SoC profile have a direct consequence in battery ageing according to equation 1: with higher SoC levels, battery degradation is faster. So, in big batteries, as their SoC remains higher than in small ones, degradation will be faster if no charging strategy is used.

An alternative variant of this scenario is to modify the value of the target SoC (SoC_{max}) in the daily charge (90, 80 or 70% instead of 100% for instance). By decreasing the average SoC, this is expected to limit the capacity fade.

4.2 Scenario 2: charging the battery to the required SoC level

In this scenario the charging strategy consists in dynamically calculate SoC_{max} as a function of the expected next day's travelled distance.

First we need to calculate the required energy ($E_{required}$) in the battery as the product of the average energy consumption (Ec, in Wh/m) and tomorrow's trip length. A security margin should be included to avoid excessive depth of discharge and to cope with unexpected trip overlength. The auxiliary devices consumption (P_{aux}) can also be considered. This energy consumption is very dependent of ambient temperature:

$$E_{required} = Ec \cdot (distance + security\ margin) + P_{aux} \cdot duration \quad (2)$$

Then, the target state of energy (SoE_{max}) is computed as :

$$SoE_{max}(p.u.) = SoE_{end\ of\ trip} + \frac{E_{required}}{E_{bat}} \quad (3)$$

Finally, SoC_{max} can be calculated with relations included in Appendix (Useful equations).

Figure 3 illustrates the SoC profile during a week following the mission profile given in the preceding section with this charging strategy for a 40kWh battery. In contrast to scenario 1, maximum SoC is not the same every day, but it depends of the subsequent daily trip. At beginning of life, the initial SoC (fixed by the preceding day's SoC_{max}) is 26% from Monday to Friday, 43% on Saturday and 14% on Sunday. These levels ensure that the minimum SoC is about 10%. The minimum SoC directly depends of the security margin. In these simulations security margin was fixed to 20 km, although it could be adjustable by the user. SoC levels change progressively with battery ageing. For example, the initial SoC from Monday to Friday raised from 26% at BoL to about 31% at EoL.

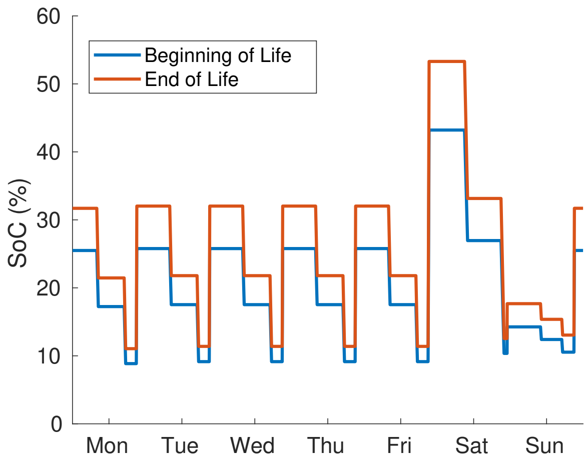

Figure 3: SoC profile of the 40kWh battery during a week with charge optimisation at beginning of life (blue) and end of life (red).

4.3 Comparison between scenarios

4.3.1 Daily state of charge levels

Notice that, as illustrated by figures 2 and 3, SoC levels change with battery's capacity fade because weekly mission profile is the same but stored energy in the battery decrease. For example, in scenario 1 (figure 2), the maximum SoC is constant but average and minium SoC levels decrease.

Table 1 shows the values of the daily SoC levels (maximum, average, minimum) for each scenario at beginning of life for a 40kWh battery. From these values, one could predict that the ageing would be lower in scenario with lower SoC.

Table 1: Comparison of SoC levels of 40kWh battery depending of the chosen scenario at beginning of life.

(a) Monday to Friday

	Scenario 1 (SoC_{max} = 100)	Scenario 1 (SoC_{max} = 70)	Scenario 2
Maximum SoC	100	70	26
Average SoC	95	65	20
Minimum SoC	85	54	9

(b) Saturday

	Scenario 1 (SoC_{max} = 100)	Scenario 1 (SoC_{max} = 70)	Scenario 2
Maximum SoC	100	70	43
Average SoC	90	60	32
Minimum SoC	70	38	14

(c) Sunday

	Scenario 1 (SoC_{max} = 100)	Scenario 1 (SoC_{max} = 70)	Scenario 2
Maximum SoC	100	70	26
Average SoC	99	69	14
Minimum SoC	97	67	12

4.3.2 Lifetime

Figure 4 shows the battery lifetime (days to EoL) depending on battery size for scenarios 1 and 2.

For scenario 1, when SoC_{max} is 100% the battery lifetime is between 2380 and 2100 days. By reducing SoC_{max}, the battery lifetime is increased for every battery size. For example for 40kWh, battery lifetime is 2170, 2630, 3210 and 3910 days with SoC_{max} = 100, 90, 80 and 70% respectively. In other words, battery lifetime is multiplied by a factor of 1.2, 1.5 or 1.8 when SoC_{max} is 90, 80 and 70% respectively compared to SoC_{max} = 100.

When the charging strategy of scenario 2 is used, the battery lifetime varies from 5320 to 9950 days when battery size varies from 20 to 60 kWh. Compared to scenario 1 with SoC_{max} = 100%, lifetime is 2.2 to 4.7 times greater (for 20 and 60kWh respectively). This demonstrates that this strategy can be used to preserve the battery's life.

Another interesting result appears in figure 4. In fact, with this charging strategy, in contrast to scenario 1, bigger batteries lead to longer longevities, as the average SoC becomes lower when the size increases.

4.3.3 Battery cost

Figure 5 shows the daily battery cost, i.e. the purchase cost divided by the lifetime, assuming that the battery's purchase cost is proportional to its size and equal to 500€/kWh. We also neglected in the cost estimation an eventual resale of the batteries for second life applications.

For every case of scenario 1, the battery's daily cost grows rapidly with battery size. For example, for SoC_{max} = 100%, a 20 kWh battery costs about 4€/day while a 60 kWh one costs about 14€/day (3.5 times more).

By limiting SoC_{max}, the battery cost is reduced: for example, in the case of a 60kWh battery,limiting the SoC to 70%, instead of 100%, reduce the cost from 14 to 8€/day.

But the charge optimisation leads to considerable higher cost reductions. In fact, when a charge optimisation strategy is applied, the battery cost is 3€/day for 60kWh batteries.

Figure 5 shows that increasing the battery size could drastically increase the cost per day in case of scenario 1 (full charging every day). On the contrary, when considering a charging optimisation like in case scenario 2, the influence of the size on the battery cost is minimised. It could be deduced that increasing the battery size could be a not so good idea if no care to SoC is taken.

Finally, the following rules could be concluded from the results in figures 4 and 5:

- Increasing the battery size with no adapted strategy accelerates the battery ageing.
- Limiting the maximum SoC of the battery decreases the capacity fade.
- Management of the charging target SoC according to the expected actual need decreases the capacity fade.

It must be noticed that the present work only dealt with one specific type of lithium-ion battery (LFP/graphite) for which the ageing parameters were identified [14]. But the tendency for ageing laws of any lithium-ion is similar to Equation 1. This allows to generalise the results by keeping the general rules: lower SoCs allow to prolong the battery lifetime.

Depending of the technology, batteries can be more or less sensitive to charge optimisation. For example, from results in [14], SoC sensitivity to calendar ageing is higher in NMC cells compared to LFP, then charging optimisation could be more interesting in NMC cells. In another work LFP cells were more sensitive to different charging strategies than NCA cells [6].

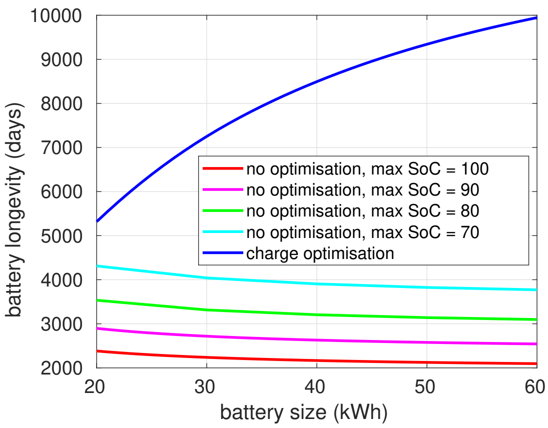

Figure 4: Battery lifetime for different sizes from 20 to 60kWh.

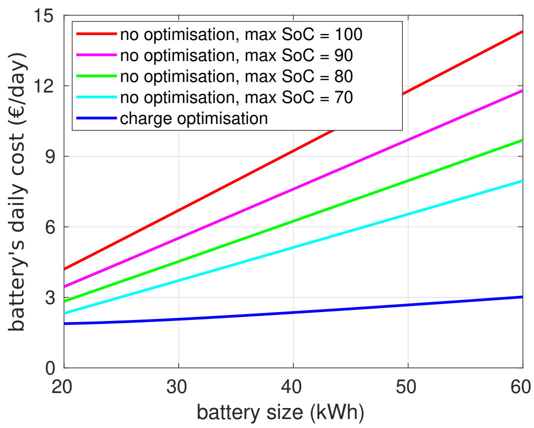

Figure 5: Battery cost (€/day) for different sizes from 20 to 60kWh.

5 Conclusions

Battery size is growing as a direct consequence of manufacturing costs diminutions allowing higher range of electric vehicles. However, if charging strategies are not considered, this oversizing leads to a reduction of lifetime of batteries and relatively higher total ownership costs. Simulation results show that, if charging strategies are not adapted to higher battery sizes, lifetime of batteries decreases. This dramatically affects the total cost of ownership.

With an optimised charging strategy, the ownership costs still moderately rise with battery size but the battery lifetime greatly increases: having a bigger battery allows higher electric vehicle range for a little ownership costs increase. From a practical point of view, BMS (battery management systems) must provide a mean to charge the battery to a desired distance and to permit to fully charge the battery when the user needs to use the full range (e.g. holidays trips). However, the strategy proposed here supposes that the user knows exactly the driven distance the day after and accepts to limit the "operational" range of his/her vehicle. Studies about practical feasibility and user acceptability of this solution have to be conducted from a multidisciplinary point of view (engineering and human sciences together).

Further works will consider variable climatic conditions. A sensitivity analysis of battery lifetime to climate, trip conditions and user charging choices will be conducted. Global environmental impact of batteries (and the entire vehicle) will also be considered.

Appendix

List of symbols and units

Ec (Wh/m)	energy consumption of the vehicle
E_{bat} (Wh)	maximum energy of the battery
I_{bat} (A)	battery current (I>0 discharging)
P_{aux} (W)	power consumption of auxiliary devices (e.g. air conditioning)
P_{bat} (W)	output power of the battery
$P_{0,bat}$ (W)	net power of the battery
Q (Ah)	capacity
Q_L (Ah)	capacity fade
OCV (V)	Open Circuit Voltage
SoC (p.u. / %)	State of Charge
SoC_{max} (p.u. / %)	maximum State of Charge after charge
SoE (p.u. / %)	State of Energy
SoE_{max} (p.u. / %)	maximum State of Energy after charge

Useful equations

State of charge (in p.u.): $$SoC(t) = SoC_0 - \frac{\int I_{bat}(t)dt}{3600 \cdot Q}$$

State of energy (in p.u.): $$SoE(t) = SoE_0 - \frac{\int P_{bat,0}(t)dt}{3600 \cdot E_{bat}}$$

Maximum energy of the battery (with SoC in p.u.): $$E_{bat} = Q \cdot \int_0^1 OCV(SoC) \cdot dSoC$$

Net power in the battery: $$P_{bat,0}(t) = I_{bat}(t) \cdot OCV(t)$$

Output power of the battery: $$P_{bat}(t) = P_{bat,0}(t) - P_{bat,losses}(t)$$

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Pascal Venet was born in Aix-Les-Bains, France, in 1965. He received the Ph.D. degree in electrical engineering in 1993 from the Lyon 1 University, France. After postdoctoral positions, he joined the Lyon 1 University as Assistant Professor from 1995 to 2009.
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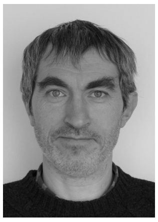
His current research interests include characterization, modeling, fault diagnostics, reliability and ageing of energy storage systems such as batteries, supercapacitors and capacitors.



Serge Pelissier was born in 1963. With a PhD in Electrical Engineering from the Institut National Polytechnique Grenoble, he first became Associate Professor and then Professor at the University of St. Etienne. In 2007, he joined INRETS (IFSTTAR since 2011). His work focuses on modelling, characterisation and ageing of batteries in automotive applications.