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Evaluation of the End-of-Life of Electric Vehicles according to the State-Of-Health

Canals Casals, L. [1], Rodríguez, M.[1], Cristina, C.[1], Carrillo, R.[2]

[1] *Canals Casals, Lluc (corresponding author) IREC (Energy Research Institute of Catalonia), jardins dones de negre 1, pl.2, 08930, Sant Adrià de Besòs, lcanals@irec.cat*

[2]*CSEM PV-Center, Rue Jaquet-Droz 1, 2000, Neuchâtel, Switzerland*

Summary

As a result of monitoring thousands of electric vehicle charges around Europe, this study builds statistical distributions that model the amount of energy necessary for trips between charges, showing that most of trips are within the range of electric vehicle even when the battery degradation reaches the End-of-life, commonly accepted to be 80% State of Health. This study analyses how far this End-of-Life can be pushed forward using statistical methods.

Keywords: battery ageing, battery SoH (State of Health), EV (electric vehicle), sustainability, vehicle performance.

1 Introduction

Electric vehicles (EV) are constant and steadily increasing the cleaner mobility market share in the world. Year after year the number of sold EVs increase and the expectations are quite optimistic for future years to come [1]. As it happens with any other technology that is accepted by the society, the higher the deployment, higher its overall impact will be in many different fields. In the case of EV, these fields are, for instance, household consumption, electricity grid balancing and load management or the environment among others.

Regarding households, as most common EV batteries have a capacity of 24 kWh, which is more than the average household daily consumptions, it seems obvious that the impact of EVs on daily energy consumption curves will be more than considerable. To evaluate and reduce the effects of EVs in buildings, it is important to count on smart energy management systems capable to optimize the EV charges according to the instantaneous and the expected energy consumption of the building. These systems might also bring environmental and economic benefits to the building, which is the main goal of the SABINA project, framework of this study described in more details in the methodology section.

On the other side of the meter, from an electricity grid perspective, uncontrolled and unexpected EV charges might bring to grid voltage variations, overloads and network congestion [2] and, in consequence, the need for load management strategies appears, such as the use of distributed energy resources with demand-side response capabilities. In this case, EVs might be part of the problem and of the solution at the same time thanks to vehicle-to-grid (V2G) technologies.

Nonetheless, apart from technical aspects, the entrance of EVs also carries environmental burdens to analyze. When dealing with environmental analysis of EVs, the majority of Life Cycle Assessments (LCA) are launched on the base that vehicles will run for around 100,000 and 150,000 km [3]. This overall mileage is aligned with the warranties given by car manufacturers, which nowadays go from 8 to 10 years within this range of mileage [4], and incidentally, with the expected lifespan of batteries for traction purposes. In fact, batteries degrade among time and use due to many factors, such as temperature, intensity of use, depth-of-discharge (DOD), working voltage and time (used or not) [5]. It is widely accepted that the battery is inappropriate for mobility purposes when its State-of-health (SoH) reaches 70-80% of its initial capacity [6]. This moment is commonly known as the End-of-Life (EoL) of the battery in the vehicle. Then, these batteries are either sent to recycle or re-used in stationary applications offering them a second life, as most car manufacturers are starting to evaluate and test [7], [8].

However, some researchers have already noticed that, according to travel needs, this EoL might go below this limit [9], which is said to be fixed by car manufacturers more due to commercial decisions rather than for real noticeable driving impacts [10]. These doubts regarding the EoL of EVs gain relevance seeing that the range of new EVs increase (without increasing the EV cost significantly) [11], as vehicles will keep doing the same regular trips but will have a wider autonomy. Therefore, it seems that it makes sense to study the possibility to go beyond the generally accepted battery EoL of 70-80% SoH.

In order to answer this question, this paper analyzes thousands of EV charges done by hundreds of electric vehicles around Europe to obtain representative statistical curves that may be used to estimate EV charge events distribution in relation to the plug-in hour. These raw data are the result of the Green eMotion FP7 project [12] that analysed several electric mobility issues. Then, data is used to determine the average energy consumption per trip within an acceptable uncertainty range. The study of the energy consumption distributions per trip is further used to determine an acceptable SoH limit that correctly indicates the real EoL of EVs.

2 Methodology

The origin of this study comes from the developments done in the EU-H2020 funded SABINA project (http://sabina-project.eu). The main goal of SABINA is to maximize local renewable energy consumption of buildings by developing a Building Algorithm (BA) that manages the energy consumption of the building.

The Model Predictive Controller (MPC) BA aims at enhancing renewable self-consumption at building level. In order to achieve this objective, the BA has several means of actions. First, the building envelope is used to store thermal energy, by performing over heating or cooling by using heat-pumps (HP) or chillers. Second, by using batteries. The latter can be in house batteries (i.e. fixed) or EV batteries. To control these elements, the MPC self-constructs models of the considered elements. For the thermal behavior of the building, long-short term memory (LSTM) neural networks are used, which are trained by combining data from realistic EnergyPlus models and real data. For the batteries, basic models considering losses are employed. Finally, an optimization problem is posed where the objective function minimizes the total energy exchanged from/to the grid (aiming at maximizing self-consumption), as well as constraints associated to heating, cooling and batteries. The decision variables of the model are:

- the load associated to HVAC and base load (W).
- the state of charge of the battery (%).
- the state of charge of the EV battery (%).
- the temperature at zone i, $i=1,\ldots,O$ (°C).

And control (optimization) variables are:

- the charge power linked to the EV battery (W).
- the charge/discharge power linked to the battery (W).
- the set-point temperature at zone i, $i=1,\ldots,R$ (°C).
- the set-point temperature for tank i, $i=1,\ldots,Q$ (°C).
- the set-point temperature for the HP (°C).

The function model predicts the building state for the horizon H (24 hours) considering the state of the building for the past 6 hours and where the PV power production is forecasted (W).

Taking a 105 m2 building as base case, the BA manages its energy flows under five scenarios:

a) Heavy thermal inertia + Heat, Ventilation and Air Conditioning (HVAC) systems
b) Heavy thermal inertia + HVAC + Battery
c) Heavy thermal inertia + insulation + HVAC + Battery
d) Low thermal inertia + insulation + HVAC + Battery
e) Heavy thermal inertia + HVAC + Battery + Electric Vehicle

Although the main BA government function is the same for all scenarios, this study focusses the attention in the last one (e), which includes the integration of several EVs.

Knowing that EVs have a high impact potential on energy consumption of buildings, the MPC acts on the P_{ev}, while taking into account usage constraints to ensure that the EV is charged with the right amount of energy (or more) at the time of departure (or before). Moreover, the BA adjusts the set-points of the elements (HVAC, batteries, EVs…) in the building regarding the expected generation and foreseen events to maximize self-consumption. Therefore, it is relevant to include a forecasting system that would allow the BA to modify the behaviour of such load following smart charge practices.

The forecasting of the EV energy consumption in the building has been built taking data from thousands of EV trips and charges around Europe resulting from the Green eMotion FP7 project. From all the data, this study is based on the information of EV charges instead of trips, as several small trips could come one after the other without any charge between them and because EV charges give more accurate information of the real needs of EVs and of what to expect from a building energy consumption perspective. All the data analysis is carried out using R software (V 3.5.2).

The study analysed four EV charging parameters to decide which one provided more trustable and realistic information to facilitate the forecasting of the energy demand of the vehicle in the building:

- Charge duration
- Initial State of Charge (SoC)
- Energy of the charge
- Charge ratio, understood as the total amount of energy divided by the duration of the charge.

EV charge duration indicates the time needed per charge. Nonetheless, it is hard to know the reasons that end the charge. It could be either that the charge is complete or that there is a need for a sudden trip and it is stopped at a middle of a charge. Moreover, it gives few information of the amount of energy needed per charge, as charges at high SoC perform slower than charges at low SoC.

Similarly, the initial SoC does not gives information of the end of charge, that is, the charge could finish at 100% SoC or lower. This issue can be easily corrected by having the final SoC and taking the difference. However, that would mean to also know the capacity of the battery. Supposing that the BA could effectively know the EV model and battery capacity, the battery ageing, and its consequent loss of capacity, would mean that the error in the charge energy estimation would increase along time. Additionally, note that SoC is an estimated parameter that, although its accuracy is improving with recent research in the field, relying on it means assuming an uncertainty from the very beginning.

Contrarily, the energy accumulated from each charge eliminates the uncertainties of previous parameters. It is true that it gives no information of the final SoC, so it is difficult to know if the charge is completed or if, as it happens with the duration of the charge, the EV is unplugged prior to fully charge the battery.

Finally, the charge ratio gives an overview of the amount of energy delivered per hour. It is useful to know if the charge takes place at high SoCs (lower values) or if a fast charge was performed. However, it is impossible to extract the amount of energy per charge that is the most valuable parameter from a building perspective, as it happens with the duration of the charge.

The BA has a module that studies and forecasts stochastic events in the building it controls, such as the arrival or departure of an EV. The BA assumes, with a confidence range, the available amount of time in which the EV is plugged-in. Having that, and after analysing the results of all the mentioned parameters (see results and discussion section), the most interesting parameter to count on for our purpose is the amount of energy per charge.

Once decided that the Energy of the charge is the parameter to look at, the EV charge information is decoupled by hours to determine similarities between charges among hours using Kruskal Wallis test. Having that, it is possible to group the intervals according to the distribution of the amount of energy per charge. This process results in 6 clusters of plug-in hours based on the charge events. Then, it was possible to obtain representative mathematical distribution of the EV charges in relation to the hour when the EV is plugged-in.

This charging distribution is then used by the BA to prepare the building for the expected charge having, in advance, a forecast of the arrival hour and the amount of energy to be charged. Moreover, as the BA also estimates the hour when the car will be disconnected, it can modify the power set-points of the charger to increase the overall benefits of the building.

Moreover, these distribution functions are then related to the available energy of EV batteries at the EoL, that is, when batteries in EVs reach 80% SoH to determine the amount of times that the EV would not comply with the mobility needs. As the capacity of batteries change among EVs, this study analyses the impact on 16, 24 and 30 kWh batteries, which are the most common capacities among commercial non-luxury EV. The evaluation will even go deeper in the EoL analysis, by calculating what would happen if the SoH at the EoL is defined at lower values, such as 70 or 60%.

3 Results and Discussion

The methodology section already advanced some of the inconveniences and advantages of considering one or another charging parameter to forecast the total amount of energy EVs would need to charge when they plug into the building's premises. This first part of the section presents the histograms resulting of the data analysis.

Figure 1 shows the empirical and theoretical density function of the duration of the charges (in minutes). It can be appreciated that most of charges concentrate in the range between 2 and 4 hours. Knowing that common EV charges work at 3.7kW maximum power, these results give the idea that most of charges correspond to half battery charges.

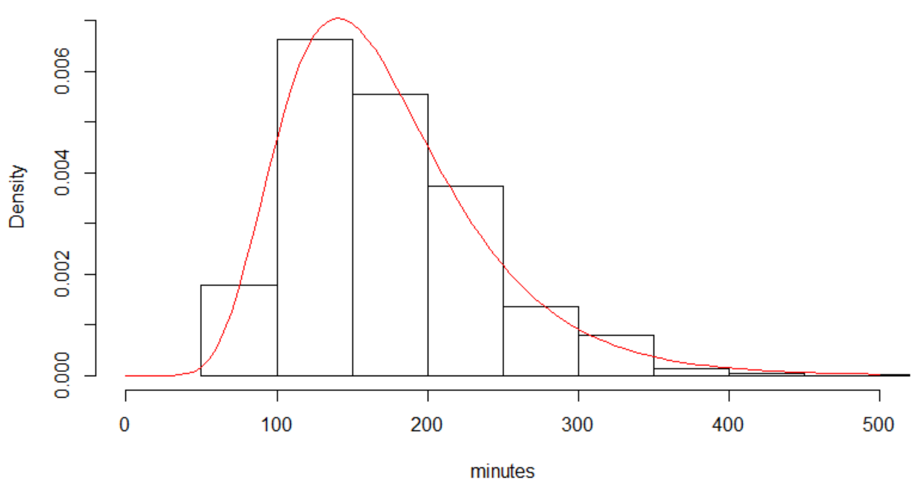

Figure 1: Histogram of the EV charge duration reported by the data analysed and theoretical density in red (minutes on the x-axis).

This first conclusion is confirmed after observing Figure 2, which shows the initial SoC of the EV battery when plugged-in. This parameter clearly indicates that charges begin, more frequently, at a 70% SoC. That is, the battery has still more than 2/3 of its capacity when the car is plugged-in to recharge, leaving a huge amount of unused energy.

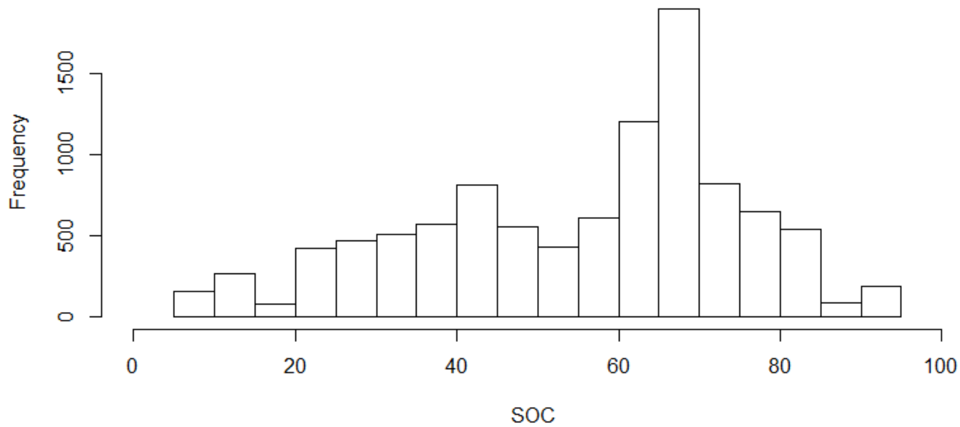

Figure 2: Histogram of the EV initial SoC reported by the data analysed.

However, the analysis of the real amount of energy per charge is the parameter that provides a clearer picture of what really occurs in EV charge distributions.

The statistical analysis showed that the hours with fewer charges are those at late hours in the night (from 0 to 6), while at dawn or during the hours at the beginning of the night where those where more charges started. Differences in the central values (median) and dispersion of the amount of energy per charge distribution per hour are visible in the boxplot shown in Figure 3**Error! Reference source not found.**. However, it already shows that most charges concentrate around 5 kWh and only phew of them go beyond 10 kWh. The minimum median in energy per charge is found between 9 and 10 in the morning (coinciding with the shorter charges) and the maximum median amount of energy charged on EVs is found at 22 hours.

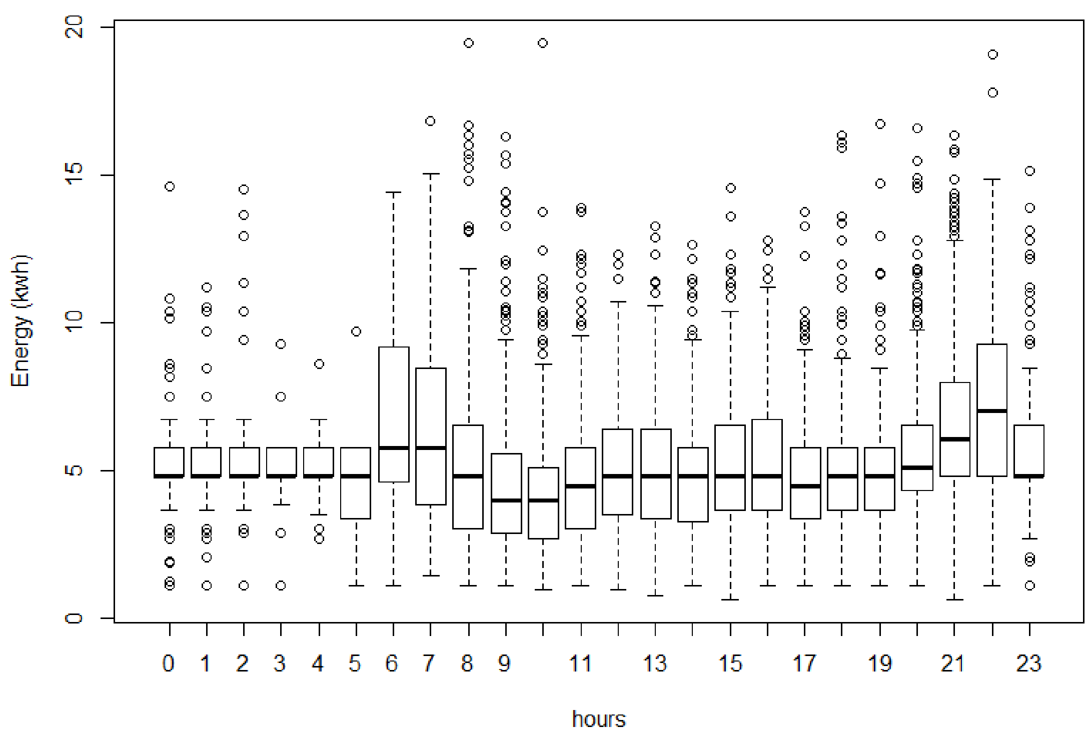

Figure 3: Boxplot of the amount of energy of charges within each hour of the day.

Figure 3 already anticipates the hours in which, presumably, battery charges behave in a similar manner.

However, this EV charge distribution grouping should be confirmed following statistical methods, such as the Kruskal-Wallis test. With that, hours having similar distribution were grouped based on the significant differences, passing from 24 lots (one per hour) to only 6. Thus, hours were grouped as follows:

- Group 1: 9 and 10h;
- Group 2: 8, 11, 13, 14, 17 and 19h;
- Group 3: 12, 15, 16 and 18h;
- Group 4: 20 and 23h;
- Group 5: 21h
- Group 6: 22h and from 0 to 7h in the morning.

Table 1: Share (or percentage) of charges per hours

Group	1	2	3	4	5	6
Share	14%	28%	18%	10%	13%	17%

It is important to note that there were too few data during late night hour charges to have reliable indicators and they were added to group 6. Also note that the distribution of charges per group (Table 1) is quite homogeneous. In fact, only group 2 has a relevant amount of charges in comparison to the others, but it is also the group that has more hours in it.

The statistical analysis of these 6 groups separately served to obtain the density functions that better fit to the experimental data. Figure 4 presents an overlapping of the density that real data presents (red line) in contrast with the density function (black line) for each group. Density functions of groups 1, 2 and 6 follow a gamma distribution, while groups 3, 4 and 5 follow a Lognormal distribution.

From Figure 4 it can be extracted that, except for groups 5 and 6, the energy per charge density distribution is centred below 5 kWh, while between 21h and 22h charges the centre of the distributions tend to be greater.

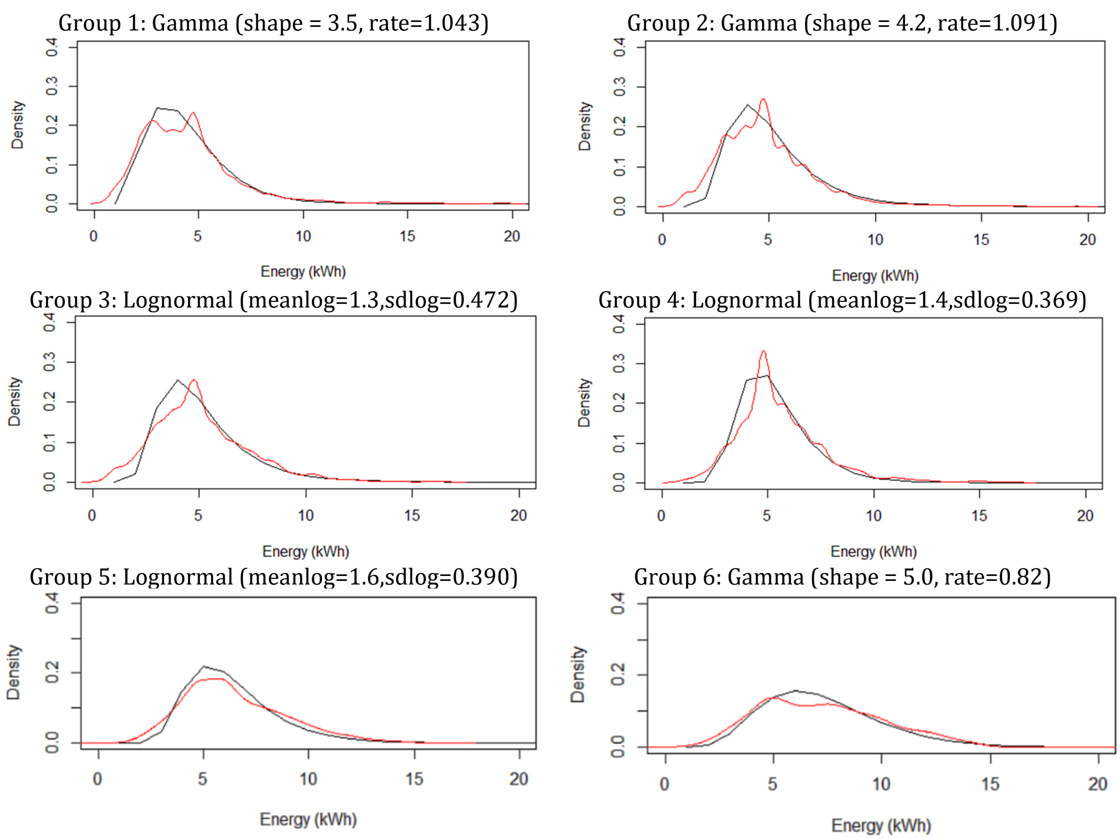

Figure 4: Charge density distributions per group of hours

Similarly, in all groups except group 6, there are generally almost no charges beyond 10 kWh, only in group 6 it seems to be a significant number of charges (8,87% from Table 2) after this point. However, even within this group it seems clear that only a residual number of charges take more than 15 kWh.

Additionally, although the study focuses the attention on EV charges, Figure 4, somehow also reflects the variabilities from the factors concerning EV energy consumption, such as the effect of driving behaviour [13], temperature, loads [14] and urban-highway trips [15] as data is taken from different drivers in different geographical places.

Taking these charging distributions and assuming that the battery EoL is fixed at 80 % SoH it is possible to determine if EVs would be capable of positively respond to the owner's mobility needs.

To do so, the study first considers more common EV battery capacities, which are around 16 and 24 kWh for first EV models in the market and 30 kWh for models sold since 2017 or 2018. For these cases, at the generally accepted EoL, their available capacity should still be 12.8, 19.2 and 24 kWh respectively. Notice that, in the first place, the capacity of batteries at EoL of newer EV models (30 kWh) is equal to the capacity of most of the EV models that are nowadays running in our streets (24 kWh). Table 2 presents the values corresponding to the percentage of charges, derived from the 6 groups of charging density functions, that are higher than the available capacity in the battery at EoL. Note that it presents the results for different values of SoH at EoL to determine which would be the one that better fits to real driving needs.

Under these circumstances, all EVs seem to perfectly fit the driving needs at 80% SoH. However, when going beyond this point and the EoL is fixed at 70 or 60% SoH, the percentage of charges in group 5 and 6 begin to be critic, revealing that around 5 or 10% of the energy needed between charges is higher than the available capacity of the battery (in red in Table 2). However, note that these two groups are responsible of 13, and 17% of all charges (Table 1), which implies that the global percentage of energy needed between charges that fail to comply with the owner's needs reduces to 0.58 and 1.83% (group 5 and 6 respectively), which makes that, in overall, the percentage of charges that fail short is only 2.5%.

Table 2: Share of charges with higher amount of energy than the capacity of EV batteries at different EoL's SoH

Batt. Initial Capacity (kWh)	SoH (%)	Capacity at EoL (kWh)	Share of non-reachable charges					
			Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
16	60	9.6	0.55	0.92	2.08	0.98	4.49	10.72
16	70	11.2	0.15	0.25	0.90	0.29	1.82	4.91
16	80	12.8	0.04	0.06	0.41	0.09	0.75	2.11
24	60	14.4	<0,01	0.02	0.19	0. 03	0.31	0.87
24	70	16.8	<0,01	<0,01	0.06	<0,01	0.09	0.21
24	80	18	<0,01	<0,01	0.04	<0,01	0. 05	0.10
30	60	19.2	<0,01	<0,01	0.02	<0,01	0. 03	0.05
30	70	21	<0,01	<0,01	0.01	<0,01	0. 01	0.02
30	80	24	<0,01	<0,01	<0,01	<0,01	<0,01	<0,01
-	-	10	0.40	0.67	1.68	0.72	3.58	8.87

These results indicate that, the EoL of 80% SoH might be mostly acceptable for small capacity EVs (16 kWh) having the opportunity to reduced it to less than 70% and even 60% without much effect on daily needs. For medium and higher capacity EVs (24 and 30 kWh) this SoH could go even below 60% in terms of capacity without having a noticeable impact on daily mobility needs.

However, although the capacity decrease does not suppose a limitation in daily electric mobility, there are other aspects that can certainly have an impact on it. One is the exponential increase of the internal resistance of the battery with aging. In fact, the internal resistance at 80% SoH increases only by 20% while at 60% SoH it rises up to 200% [16], which might suppose additional losses on power and on efficiency. The other aspect is that, beyond the 60% SoH, the chances to fall into the ageing knee (a sudden acceleration of battery aging) increase dramatically, shortening considerably the expected lifespan after this point [17]. These two issues should be another issue to inspect in future works

From and environmental perspective, EV LCA should consider clearly fixed aspects before performing the environmental analysis. First, these analysis should fix the SoH at the EoL. For instance, if the EoL is considered to go up to 60% SoH, mileage during the first life should be enlarged to 225,000 km or more, increasing the EV emissions of CO_2 during the use phase by more than 50% but saving the emissions of building new EVs, which can be the principal emission factor depending on the electricity mix of the country where the EV runs. Second, according to the definition of the SoH at the end of the first life in the vehicle, LCA should consider the incorporation of second life applications, as, in some cases, they can offer interesting economic and environmental opportunities [18].

4 Conclusions

The definition of 80% SoH as the EoL of batteries in EVs seems to be statistically reasonable only for small battery capacity EVs (16 kWh), being able to decrease it even below 70% without relevant risks. For higher battery capacity EVs this SoH can be reduced to 60% or below with a high probability that this won't represent an inconvenient to EV owners.

In fact, statistically and considering only the term of capacity fade, it would be even reasonable to go down to a 50% SoH in new high capacity EVs (30 kWh). However, going below a 60% SoH might risk to enter into the ageing knee (an acceleration of the battery ageing phenomena) and power limitations might be significant below these values.

These new SoH limits suppose a rethinking of the second life opportunities, as the paradigm changes and it might be no longer possible if EV owners decide to expand the EV battery life down to these values (even if they are out of warranty from car manufacturers).

Moreover, environmental analysis should also consider these changes in the studies, as lower SoH values represent higher mileage at the end of life and they suppose an impact in second life scenarios, which should always be in the scope of critical environmental studies.

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Authors

Lluc Canals Casals: Industrial engineer (2005) that worked for the automotive industry until 2013, moment in which he leaves the production sector and begins his PhD on Modelling Li-ion battery aging for second life businesses (SEAT-UPC). Doctor by the UPC in 2016 and Post-Doc researcher in IREC since 2017 in the Energy System Analytics group working in the field of energy aggregators for the grid.

Marta Rodríguez graduated in Mathematics at the University of Santiago de Compostela in 2013 and did a Master's Degree in Statistics and Operations Research between 2014 and 2016 in which she specialized in Operations Research. Right after that she started working for Tecnocom Telecomunicaciones y Energía where gained experience with databases. Now, since 2017, she works as Junior Researcher at IREC in the Energy System Analytics Group

Cristina Corchero: Head of the Energy Systems Analytics research group in IREC. Doctor by Universitat Politècnica de Catalunya in 2011 on Statistics and Operations Research. . Her research focus on the application of statistical and mathematical modelling knowledge to energy systems. She is also operating agent on the Hybrid and Electric Vehicle Technology Collaboration Program of the IEA.

Rafael E. Carrillo received the B.S. and the M.S. degrees in electronics engineering from the Pontificia Universidad Javeriana, Colombia, in 2003 and 2006, respectively, and the Ph.D. degree in electrical engineering from the University of Delaware, USA, in 2011. He was a lecturer from 2003 to 2006 at the Pontificia Universidad Javeriana, and a research assistant at the University of Delaware, from 2006 to 2011. From 2011 to 2016, he was a postdoctoral researcher in the Signal Processing Laboratory (LTS5) at École Polytechnique Fédérale de Lausanne (EPFL), Switzerland. Since 2016 he is with CSEM where he is now a Senior R&D Engineer. His research interests include signal and image processing, inverse problems, machine learning and convex optimization.