EVS28
KINTEX, Korea, May 3-6, 2015

Impact of smart charging on the EV battery ageing - Discussion from a 3 years real life experience

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Abstract

Smart charging is related to a possible adjustment of the charging sequences with some energetic constraints. It can be defined in different ways, namely depending on the specific objectives. However, they all result in similar consequences for the charging sequences, with regard to conventional charging: potential delay, interruption(s) and power modulation of the charging cycles.

It is commonly admitted that smart charging will be necessary to face the growing deployment of EVs, namely for the local grid operators. Moreover, from the user point of view, smart charging can be seen as an additional motivation for the choice of an EV instead of a conventional car, if e.g. lower electricity tariffs are proposed for charging flexibility.

In this paper, a quantitative evaluation is performed of EV battery ageing, in function of the charging conditions, with a special focus on the smart charging specificities. The study is based on real data from a three years continuous monitoring of five Peugeot iOn cars, a first of a kind campaign that was performed in Belgium in the Brussels area during the period 2011-2014. Different use profiles and charging patterns were observed. Among other elements, battery capacity and battery efficiency and their evolution in time were calculated, taking into account various factors, such as the seasonal impacts.

It will first be highlighted that, whatever their charging patterns, all the considered cars are showing a significant flexibility potential, making them good candidates for smart charging. The impact of smart charging on battery ageing will then be discussed, with a focus on the charging frequency, the average state of charge and the impact of faster versus slower charge on battery capacity. This long time monitoring period allows to clearly identify the time evolution trends, leading to unique conclusions from the real life.

Keywords: smart charging, battery ageing, monitoring

1 Introduction

Smart charging is related to a possible adjustment of the charging sequences with some energetic constraints. It can be defined in different ways, namely depending on the specific objectives. However, they all result in similar consequences for the charging sequences, with regard to conventional charging: potential delay, interruption(s) and power modulation of the charging cycles.

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Moreover, from the user point of view, smart charging can be seen as an additional motivation for the choice of an EV instead of a conventional car, if e.g. lower electricity tariffs are proposed for charging flexibility.
In this paper, a quantitative evaluation is performed of EV battery ageing, in function of the charging conditions, with a special focus on the smart charging specificities. The study is based on real data from a three years continuous monitoring of five Peugeot iOn cars, a first of a kind campaign that was performed by GDF SUEZ in the Brussels area (Belgium) during the period 2011-2014, with support from the Vrije Universiteit Brussel.

2 Test conditions

2.1 Three-years field test with five cars

Five Peugeot iOn cars (16kWh LMO batteries) were used continuously as personal leasing cars and/or as service or business pool cars. Some of the cars were used in the same context/by the same person since the beginning of the tests, while other cars have known a change in their attribution during the three years (Figure 1). A dedicated monitoring system was developed by the Research & Technology Division of GDF SUEZ.
The cars show very different consumption profiles, depending on their use. Some key figures are given in Table 1 below.

Table 1: Key data of the cars

	Total distance (km)	Urban distance (%)	Extra-urban distance (%)	Highway distance (%)	Avg. consumption (kWh_{AC}/100km)
EV1	8583	72.2	25.7	2.1	18.0
EV2	33919	40.3	43.5	16.2	20.9
EV3	25362	41.5	48.2	10.3	15.5
EV4	16712	24.3	40.4	35.3	18.1
EV5	5901	55.1	34.9	10.0	18.6

2.2 Laboratory tests

In parallel to the field test study, the Battery Innovation Center of Vrije Universiteit Brussel performed an extended experimental analysis on cell level of different lithium-ion chemistries for battery electric vehicles. The lab exists of several state-of-the-art battery test devices (± 250 test channels), which can be used at cell and module levels. Then, the lab has also extended types of climate chambers and impedance spectroscopy test channels.
In this paper, the experimental field tests will be compared to laboratory results at cell level.

3 Charging flexibility potential

The energy content of the charging sequences is shown in Figure 2 below for the five considered cars.
The energy content was found to take a wide range of values, with an important number of small charging sequences (<2kWh), and another concentration around 8..9kWh, being about 50% of the battery capacity. Given the available and needed charging time, all the considered cars were showing a significant flexibility potential, making them good candidates for smart charging.
Note that, at the time of the monitoring campaign, only conventional charging was applied by the five cars considered.

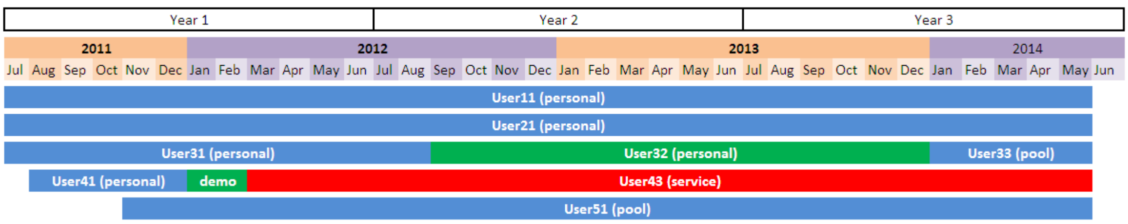


Figure 1: Distribution of the cars to the different users

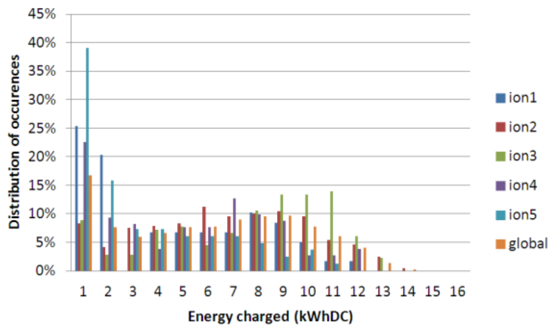


Figure 2: Distribution of the energy per charging cycle for the five cars

4 Impact of time on battery capacity evolution

4.1 Overview of the battery degradation

The battery pack of the Peugeot iOn is a lithium ion graphite manganese 16kWh pack that was developed by Mitsubishi and Yuasa in 2008.

In the following analysis, the battery capacity is calculated as the following ratio, for each trip:

Battery capacity (kWh) = energy consumed (kWh) / SOC decrease (%) (1)

A filtering is performed on the raw data, as developed in [1].

The battery capacity time evolution is evaluated for the 5 cars (Figure 3). A clear decrease of the battery capacity is observed with time, for all the cars.

The average battery degradation of the 5 cars, for the total three years monitoring period, is between 0.33 and 0.97kWh/year, depending on the car.

4.2 Time evolution of the battery degradation

Besides the global, three years results, an other approach is chosen, based on a sliding window along the time axis, for each car. The evolution of the battery degradation can then be obtained.

In this paper, we focus on the long term battery evolution. For that reason, and in order to limit the impact of numerical noise, all the following trends will be considered with a two years sliding window. By doing so, the seasonal effects are also eliminated from the results.

The time evolution of the battery degradation is illustrated in Figure 4 below.

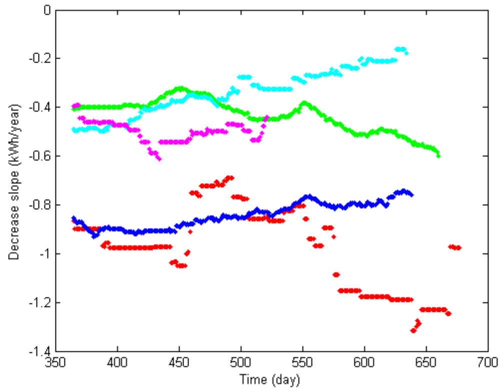


Figure 4: Average battery capacity evolution (kWh/year), with a two-year sliding window centered on the day mentioned on X-axis (red: EV1; green: EV2; blue: EV3; cyan: EV4; magenta: EV5)

The EV3 (blue) and EV4 (cyan) cars show a reducing degradation speed with time (globally increasing curves in Figure 4). On the other hand, the EV1 (red) and EV2 (green) cars show an increasing degradation speed with time (globally decreasing curve in Figure 4).

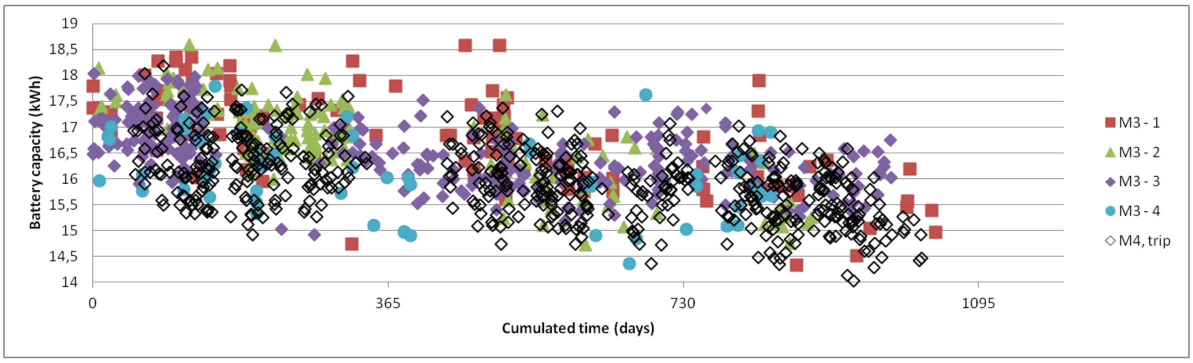


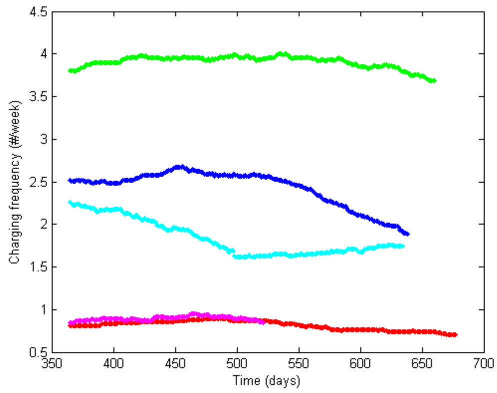
Figure 3: Battery capacity evolution in time, for the three considered years, based on SOC evolution and energy consumption during trip [1] (M3-1 = EV1; M4,trip = EV2; M3-2 = EV3; M3-3 = EV4; M3-4 = EV5)

5 Impact of charging frequency on battery capacity evolution

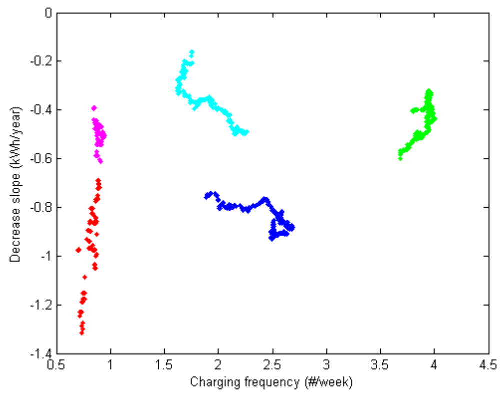
Smart charging can involve the decomposition of charging sequences into several blocks, to e.g. better follow a local, intermittent renewable energy production or to properly follow the consumption peaks.

At the beginning of the monitoring campaign in 2011, the considered cars and charging stations were not able to interrupt and restart the charging sequences. The impact analysis of the charging frequency that is proposed here is based on complete charging cycles, as programmed by the users, with no interruption.

The time evolution of the charging frequency and the relation between the charging frequency and the battery degradation are shown in Figure 5 (a) and (b) below, respectively.



(a)



(b)

Figure 5: (a) Time evolution of the charging frequency; (b) battery capacity evolution (kWh/year) in function of the charging frequency; two years sliding window centred on the day mentioned on X-axis (red: EV1; green: EV2; blue: EV3; cyan: EV4; magenta: EV5)

EV2 (blue) and EV3 (cyan) cars show the highest time evolution of their charging frequency, because of a change in the use of the cars (reduction of the driven distance).

When considering the general position of the data sets of each car in Figure 5 (b), less negative degradation values are globally observed when the charging frequency is higher. However, this trend is not unique, since EV2 (blue) and EV3 (cyan) cars show very distinct battery degradation values, while their charging frequencies are in the same range.

Within the data sets of each car, the trend is also unclear: for EV1 (red), EV2 (green) and EV5 (magenta) cars, an increasing charging frequency leads to a lower battery capacity decrease, while the EV3 (blue) and EV4 (cyan) cars show a stronger battery degradation when the charging frequency is higher.

With smart charging and decomposition of charging cycles into several blocks (i.e. more, smaller charging cycles), much higher charging frequencies could be expected, that could lead to more incisive trends.

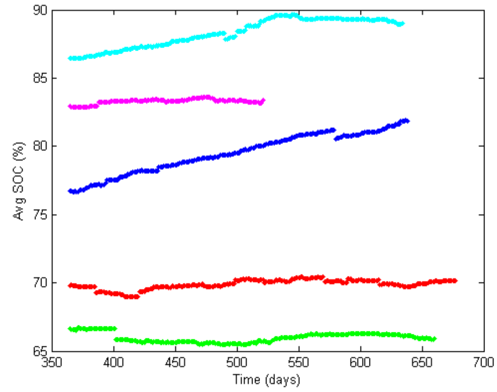
6 Impact of the average state of charge

Smart charging can involve the delay of the charging sequence, e.g. to wait for the end of a consumption peak, or to wait for the availability of solar energy. Waiting more before charging means having a lower state of charge for a longer time.

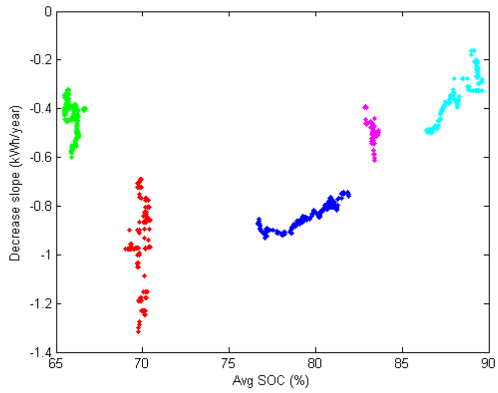
The average state of charge is calculated based on the total time, including driving, charging and no-action periods. Lower average state of charge are expected with smart charging than with conventional charging.

The time evolution of the average state of charge and the relation between the state of charge and the battery degradation are shown in Figure 6 (a) and (b) below, respectively.

When considering the general position of the data sets of each car in Fig. 6 (b), a higher battery degradation is found for the cars showing an average state of charge around 70..80% (EV1 (red) and EV3 (blue) cars). Below and above this range (EV2 (green), EV4 (cyan) and EV5 (magenta) cars), the battery degradation is less negative.



(a)



(b)

Figure 6: (a) Time evolution of the average SOC ; (b) battery capacity evolution (kWh/year) in function of the average SOC; two years sliding window centred on the day mentioned on X-axis (red: EV1; green: EV2; blue: EV3; cyan: EV4; magenta: EV5)

Within the data sets of each car, two different trends are found. The EV1 (red), EV2 (green) and EV5 (magenta) cars show an almost constant 2 years average state of charge throughout the whole monitoring period. The EV2 (green) and EV4 (cyan) cars show a more significant time variation of their average state of charge; their battery degradation is less important when the average state of charge increases.

7 Impact of charging power

Smart charging can involve the modulation of the charging power during the charging cycle, in order to properly follow a dynamical constraint.
The impact of charging power was investigated in [1], leading to useful results for the present discussion.
An intensive use of Mode 4 fast charging (50kW DC) was made with the EV2 (green) car during several months (period centered around day 640 in Figure 4), while the other cars only charged in Mode 3 (3.7kW AC). The intensity of Mode 4 use is shown in Figure 7 hereunder.

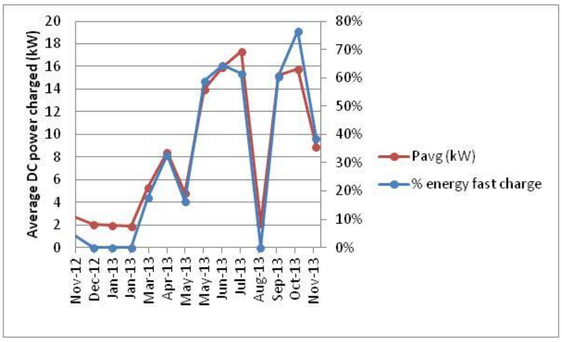


Figure 7: Proportion of Mode 4 charging and average power of the Mode 4 cycles per month

Given the rapidly decreasing shape of the fast charging curves, the average charging power per cycle is much lower than 50kW, and most of the time below 16kW (i.e. below 1C or 1It).
The time evolution of the battery capacity degradation slopes was shown in Figure 4.
The EV2 (green) car (having experienced intensive fast charging) shows an increasing degradation speed with time (globally decreasing curve in Fig.X(b)). However, this phenomena is already observed during the period before the use of intensive fast charging and can therefore not be linked to the use of fast charging. Moreover, the EV1 (red) car shows a similar increasing degradation, with no use of fast charging at all. In other words, no relation can be shown between the battery capacity degradation and the charging power [1].

8 Laboratory results

8.1 Average SOC

The behaviour of lithium-ion batteries during calendar life at different storage conditions is not well identified because the investigation works are only performed at high operating temperatures. A comprehensive analysis was performed in laboratory, whereby the experimental data has been combined with numerical tools and post mortem analysis for having a clear overview of the battery behaviour [2].
In Figure 8, the evolution of capacity degradation as function of storage time at different state of charge levels and temperatures is evaluated for LFP cells. As one can observe, the capacity degradation is higher at higher SOC levels.

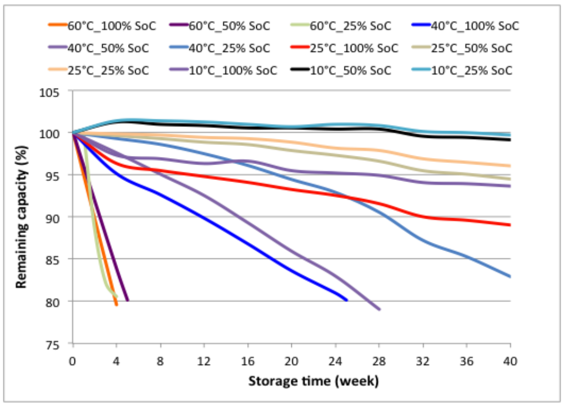


Figure 8: Battery capacity evolution as function of operating temperature and storage time

This observation is favourable to smart charging. It differs however from the field results presented before, where different trends were emphasized, depending on the car. Moreover, the battery cell technologies are not the same (LMO vs LFP).
The laboratory results show that the battery capacity degradation is also strongly impacted by the operating temperature. This parameter was not considered in the field analysis, since the seasonal impacts (including temperature) were cancelled by the sliding window approach.

8.2 Charging power

The cycle life of a battery is strongly dependent on the applied charging current rate. The main reason for the obtained evolution is related to the formation of lithium plating at high current rates [3]. This process is not fully reversible where lithium ions form metallic lithium at the surface instead of the intended intercalation. This results into decrease of the active material and further degradation of the battery capacity. This process is more important with higher charge current rates, as shown in Figure 9.

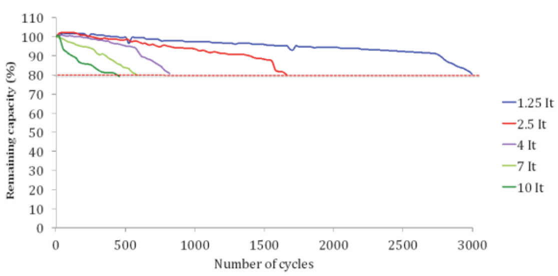


Figure 9: Evolution of remaining capacity versus cycle life for lithium iron phosphate battery type (2,3Ah, cylindrical)

During the field tests, the charging current used by all the cars (including EV2 when using the Mode 4 fast charging, as shown in Figure 7), was on average below 1It. The total number of charging cycles of each car was also far below 1000. With those conditions, the laboratory results show no difference between the capacity evolution, independent of the It value (up to 2.5It). This is consistent with the conclusions of the experimental results with Mode 4 smart charging.

9 Combined impact of parameters

The results obtained in the previous sections show no evidence of a general, unique impact of the parameters on the battery degradation. The laboratory results give an additional insight, but do not explain all the observations.
In the following, a multi-regression analysis is performed, in order to evaluate the role of different parameters on the long time battery degradation, and their potential combined effect.
The coefficient of determination R^2 is calculated for each car between the real battery degradation and a linear combination of one up to five parameters, as follows:

Degradation (kWh/year) = A0 + A1[CumulatedTime] + A2*[ChargingFrequency] + A3*[AverageSOC] + A4*[YearlyDistance] + A5*[ChargingEnergy]* (2)

In equation (2), the cumulated time represents the number of calendar days since the first use day of the considered car. The charging frequency and the average SOC are taken as defined in section 5 and 6, respectively. The charging energy is the average energy charged per charging cycle. The charging frequency, average SOC, yearly distance and charging energy are taken as the average values on the 2 years window centered on each value of the considered cumulated time.
The best combination is identified for each number of parameters, as the one with the highest R^2 (the more R^2 is close to 1, the better the regression).
In Figure 10 below, the evolution is shown of R^2, for each car and each number of parameters.

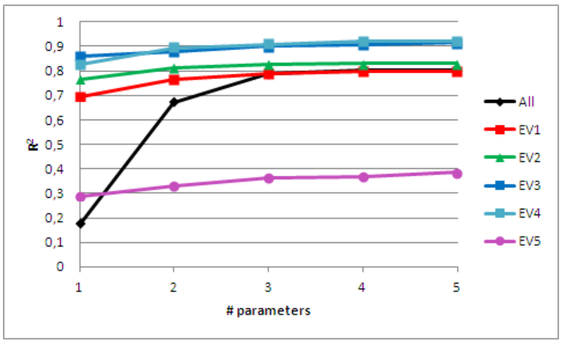


Figure 10: Evolution of R^2 with the number of parameters considered in the interpolation of the battery degradation

Except for the EV5 (magenta) car, all cars are reaching a high R^2 value with already 2 or 3 parameters. This means that the most important factors for the long term battery degradation are well included in the evaluation.
In Table 2 hereunder, the order of importance of each parameter is given for each car. Parameters in green (resp. red) have a positive (resp. negative) impact on the battery degradation. The three first parameters by order of importance are highlighted in orange for each car.

Table 2: Influencing parameters, by importance

	Charging Freq	Avg SOC	Charging Energy	Cumul Time	Yearly Distance
EV1	1	2	4	5	3
EV2	1	3	4	2	5
EV3	3	5	4	1	2
EV4	3	2	5	1	4
EV5	5	1	3	2	4

Note that the results for EV5 are of lower quality, due to a smaller useful data set after filtering, and low variation of the parameter values; it will therefore not be discussed hereunder.
The ranking order of the parameters is very different from one car to another one. No global trend can be observed regarding the parameters of influence. However, some trends appear.
For each car, the first parameter of influence has a positive impact on the battery degradation.
For EV1 and EV2, a higher charging frequency (more charging cycles) corresponds to a lower battery degradation: this is of particular interest when smart charging is concerned.
For EV3 and EV4, a higher cumulated time corresponds to a lower battery degradation.
For each car, the yearly distance (or the total energy consumption) has a positive influence on the battery capacity degradation.
For each car, the second or the third parameter of influence has a positive impact on the battery degradation, while the other one has a negative impact, respectively.
Among the parameters involved in a smart charging approach (charging frequency, average SOC and charging energy), charging frequency and average SOC are the most impacting factors.

10 Conclusions

The long time monitoring that was performed on five cars allows to clearly identify the time evolution trends, leading to unique conclusions from the real life.
It was found from the monitoring data that a higher average state of charge of the cars had no negative effect on the battery degradation. This result is not in phase with the laboratory results at cell level, and should be further investigated with more cars.
The impact of the charging energy per cycle was found to be limited on the battery degradation.
The impact of the charging frequency is unclear, and should be further investigated, in real smart charging conditions.
Finally, the influence of the charging power level was found to be negligible, in real conditions and at lab scale.
The present study gave a first flavor of what could be expected from smart charging, on battery degradation evolution, based on the first commercial EVs available and conventional charging conditions.
In a next step, the evaluation of the battery capacity degradation will have to be performed with new EVs and in real smart charging conditions, meaning shift-able, interruptible and modulating cycles. Laboratory results with other battery technologies will also help to better understand the potential and limits of lithium ion batteries for smart charging.

Acknowledgments

The authors would like to thank Electrabel for their active support, funding and steering.

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