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Cycle-Life Curves Determination and Modelling of Commercially Available Electric Vehicle Batteries

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Abstract. In recent decades, there has been a growing concern about the trend of global emissions, and in particular those of the transport sector. In this context, the electric vehicle is a promising technology, with some barriers still to be overcome. Among these deficiencies everything related to storage technology is found. In this sense, lithium-ion batteries are one of the options to be considered, although it is necessary to continuously monitor the state of health. Cycle life vs DoD curves are very useful for characterizing profitability in any application that considers battery storage, as well as life cycle optimization studies. Cycle life refers to the number of charge-discharge cycles that a battery can provide before performance decreases to an extent that it cannot perform the required functions (e.g., 80% compared to a fresh one in electromobility applications). In this paper, a model for calculating the Cycle Life vs DoD curves is proposed, applied to a commercially available electric vehicle, the Renault Zoe. Modelling results show R squared coefficient of determinations above 0.9890.

Key words. Battery, Degradation, Model, Li-Ion-NMC, Electric Vehicle.

1. Introduction

In 2019, Greenhouse Gas (GHG) emissions from fossil fuels reached 36.81 gigatons of carbon dioxide equivalent (GtCO2e), increasing between 0.4% and 2.1% over the previous year. Moreover, it is estimated that GHG emissions will double by 2050 if actions are not taken [1,2]. The transport sector was responsible for 35% of the total energy consumed in 2014, of which 21% corresponded to passenger transport, with an average consumption of 1.9 MJ/pKm [3]. Passenger transport by road accounted for 49.7% of total energy consumption from oil in 2015 with 1908.48 MToe and 5553.34 MtCO_2 [3]. Considering all mentioned data, there is still a long way to reach the scenario of zero net emissions by 2060 from IEA [2]. In this scenario, the energy and transport sectors play a fundamental role in achieving the zero emissions goal, through the development and implementation of new technologies such as Electric Vehicles (EV) and the improvement of energy generation processes

Nowadays, electric vehicles (EVs) are booming, due to the existing environmental problems. Among the different storage technologies in electromobility, batteries stand out the most. Although there are other alternatives such as hydrogen storage, a battery is also required for DC bus voltage stabilization and switching on of other essential or auxiliary devices of the fuel cell system [4]. High capital costs, limited lifetime, and relatively poor performance at low temperatures are the most important issues in EVs [5–8]. Therefore, the development of efficient storage technologies is an essential part for electromobility [9].

Lithium technology is highlighted for electromobility among the studied batteries options [10]. Its specific power and energy density are the highest, with the lowest self-discharge ratio [11]. In addition, voltage by cell is higher, which is the major drawback of the low overcharging tolerance. Therefore, a specifically designed charging system is required for this type of battery.

Battery performance and health are also important factors from the perspective of a life cycle. Battery health has a direct impact on the maximum usable range of an EV and also affects its residual value because the battery is the most expensive component in it. In this context, a battery is assumed to have reached its end-of-life (EoL) when its health-accounting capacity retention falls under 80% [1]. Unfortunately, the lifetime of even state-of-the-art battery systems is considered too low, and further research is needed on this matter [2]. Therefore, increasing useful battery life and reducing the cost of the cells are determining factors in achieving a massive integration of EVs.

2. Battery cycle aging model

Based on the results of some experimental tests, the degradation model considered battery degradation by cycling in capacity fade terms [15]. Later, this degradation model was used to characterise the EoL of these cells, which is the aim of this paper.

The studied cell is the commercially available "Pouch" cell LG Chem E63, which was engineered for high-demanding applications and installed in Renault Zoe EVs. This high-capacity lithium-ion cell includes a nickel-manganese-cobalt cathode and a graphite anode.

Testing procedure has been as follows: These cells were cycled at a specified temperature while the measurements were performed, generally in 200 cycle steps. The cells were discharged at 32.5 A constant current, i.e., at C/2 C-rate, until 2.50 V was reached. Then, the cells were charged at constant current in two stages: the first at 21.6 A (C/3) and the second at 13 A (C/5), until 4.05 V and 4.20 V were reached, respectively. Both processes were realized at 25 ºC, with 60 minutes resting time between them.

In the development of the model, the following assumptions were made:

- Battery degradation can be classified as cycling aging and calendar aging. These phenomena can be decoupled.
- DoD=0 and/or C= 0 cycles produce no degradation by cycling aging, as in these conditions, there is no cycling and all degradation produced can be assumed to be calendar aging.
- As this model is based on interpolations, the highest confidence bounds are defined by the available data, as shown in Table 1. However, using this model to calculate battery degradation out of these confidence bounds is also possible.

Table I. - Confidence bounds for cycle aging.

Temperature (T)	DoD	FEC	C-Rate
[25-45] ºC	[20-80] %	[0-1800] cycles	[0.3786-0.6710] C

After collecting all experimental test results, data treatment and normalization were undertaken to get a normalized data matrix comprising all possibilities. Although the experimental tests were realized at concrete values of DoD, temperature, and C-rate, the developed model can obtain degradation values using any value of these factors. For every test performed, an equation describing degradation was determined considering every DoD, N, T, and C, following (1).

$$SoH_C = 100 - a_C \cdot (DoD, C.T) \cdot N^{bc(C,T)} \quad (1)$$

where SoH_C is the state of health, a_C is a prepotential factor, N is the number of full equivalent cycles [FEC], and b_C is a potential factor that better fits available data.

For every data set, a linear regression adjustment was calculated, considering the following:

- All data sets were adjusted to (11) or (12).
- All data sets for the same temperature and C-rate were normalized using nonlinear square regressions of multiple data sets, and the *b* factor was set to a constant along DoD in order to obtain non-crossed curves. Consequently, *a* factor varies along operating DoD, T, and C, while the *b* factor varies along operating T and C.

The degradation model results and validation are shown in Figure 1, where it can be seen the simulated surface and measured experimental values. The maximum error when simulating CF was 3.74%, given when DoD=0.8, N=100 cycles, T=45 ºC, C=0.3786, while average RMSE was 1.12%.

3. Cycle-Life vs DoD

The model explained in the previous section has been evaluated along different DoDs, temperatures and currents, in search of the number of FECs necessary in each condition to reach an EoL of 80%. If said number of cycles is plotted as a function of the cycling DoD, the so-called Cycle-Life vs DoD curve is obtained, which is especially useful for evaluating different situations under identical energetic conditions. It has been experimentally determined that these curves follow the equation defined in (2):

$$CL\,[FEC] = a(C,T) \cdot DoD^{b(C,T)} + c(C,T) \quad (2)$$

where CL is the Cycle-Life [-], *a* is a prepotential coefficient, *b* is a potential coefficient [-], *c* is an offset coefficient [-] and DoD is the depth of discharge [-].

Knowing the CL in terms of FEC, it is possible to calculate the number of cycles at a certain DoD, according to expression (3).

$$CL\,[N\ @\ DoD] = \frac{CL\,[FEC]}{DoD} \quad (3)$$

where CL is the Cycle-Life expressed in number of cycles at a certain DoD and DoD the depth of discharge [-].

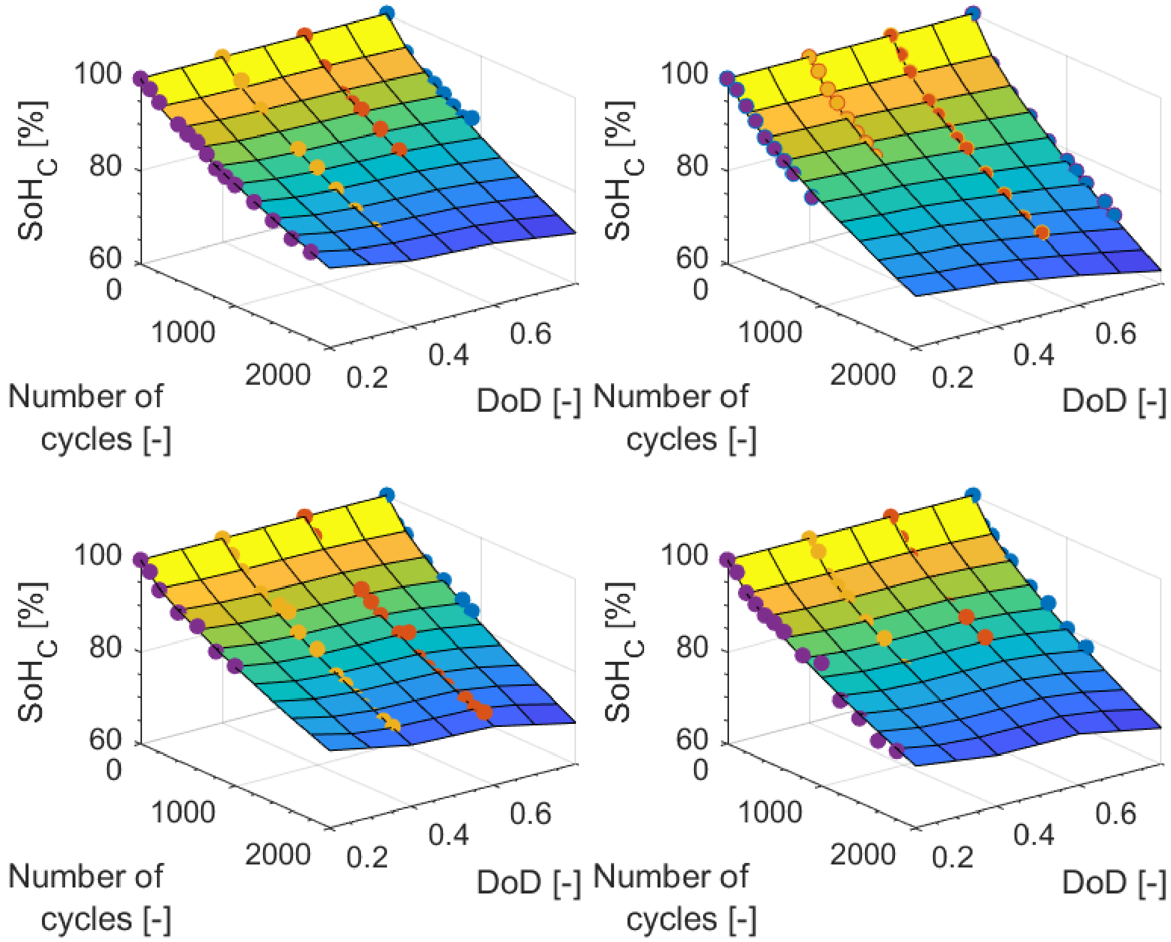
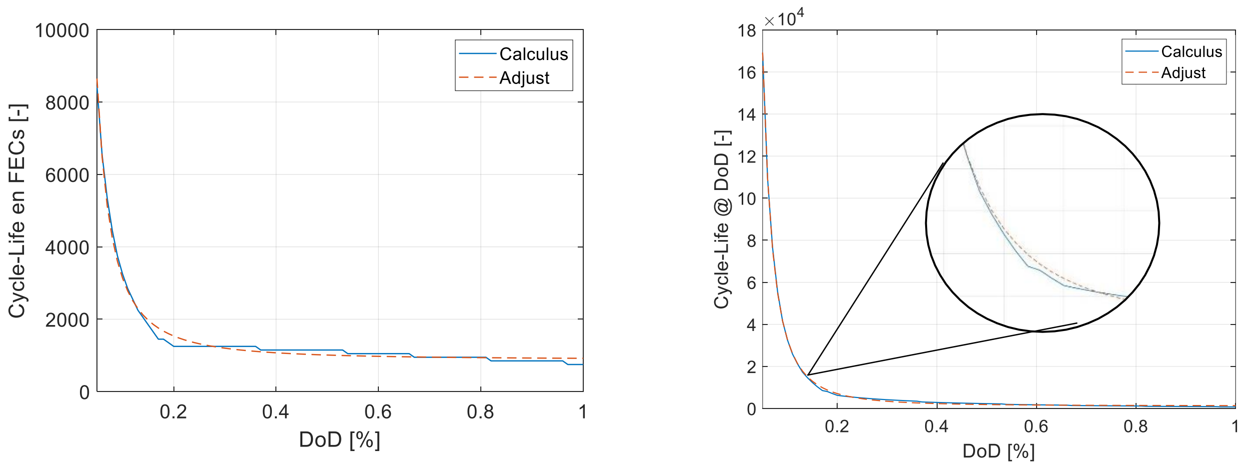


Fig. 1. Capacity degradation for a) 25C 0.3786 C, b) 45C 0.3786 C c) 25C 0.4812 C d) 25C 0.6710 C.



a) b)

Fig. 2. Cycle-Life, as a function of the DoD at 45ºC and C-Rate = 0.4C, a) expressed in FECs and b) expressed in number of cycles @ DoD.

After having calculated all cycle-life data, a model which represents cycle-life according DoD has been developed.

The model has been observed to adjust another potential law, which is expressed according to (4), and parameters values are provided in Table II.

$$CL\ [N\ @\ DoD] = a(C,T) \cdot DoD^{b(C,T)} + c(C,T) \quad (4)$$

where CL is the Cycle-Life expressed in number of cycles at a certain DoD and DoD the depth of discharge [-].

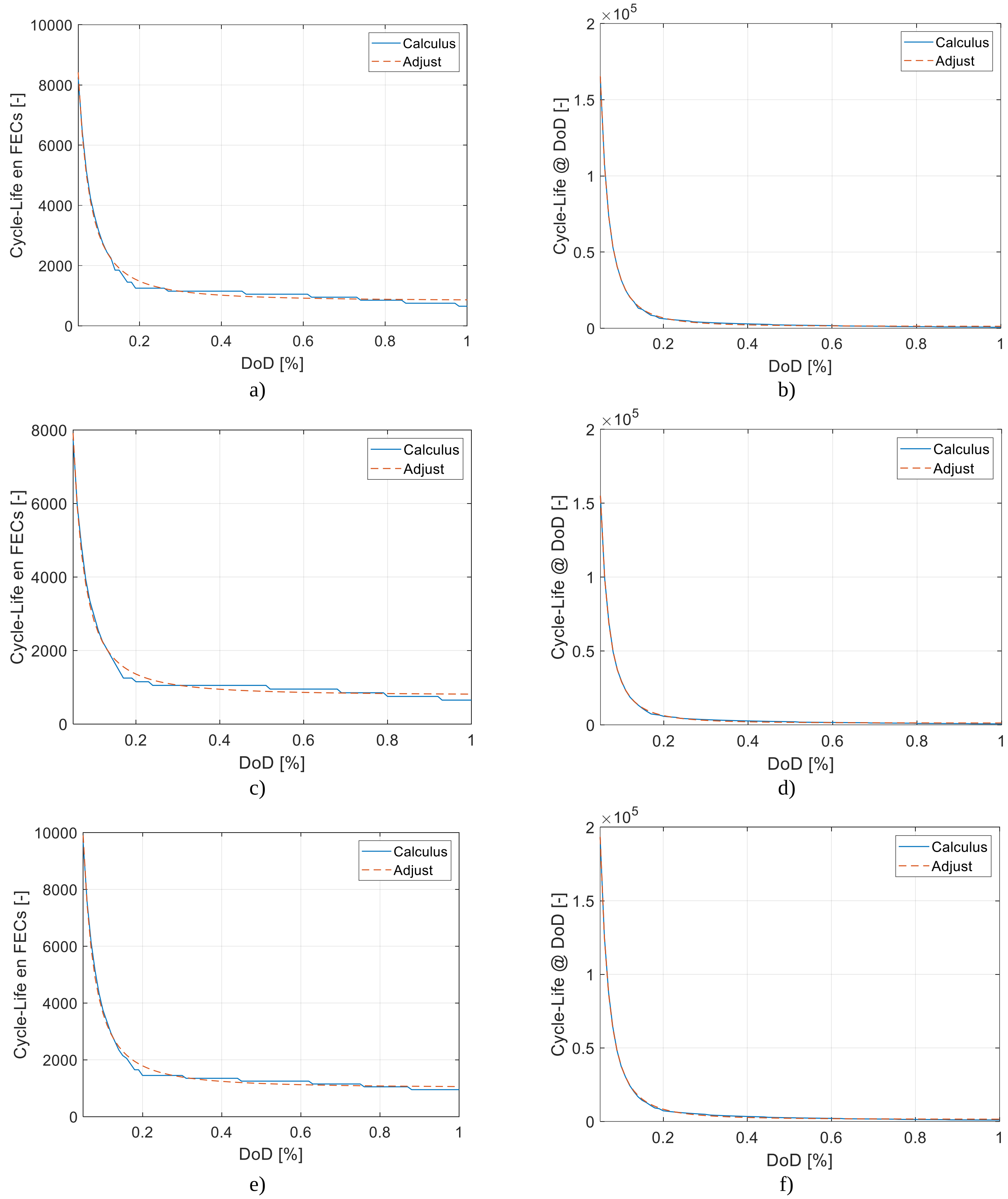
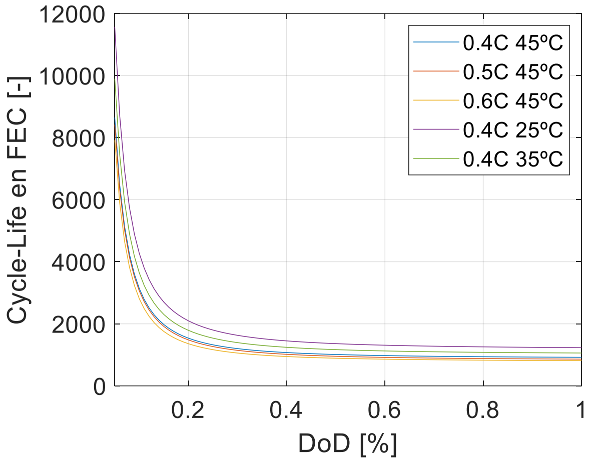


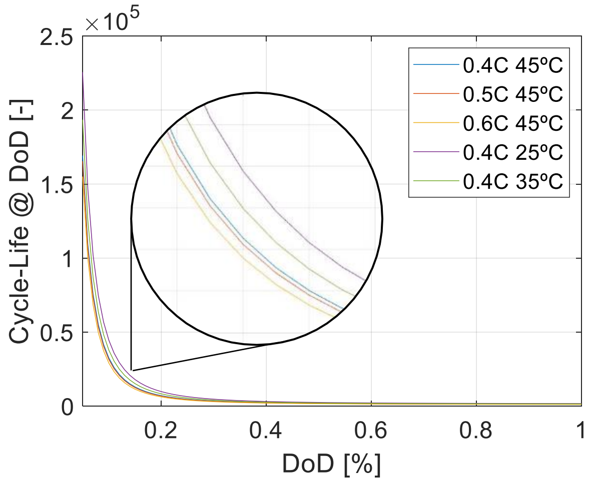
Fig. 3. Cycle-Life adjusts studied, a) 45ºC and C-Rate = 0.5C expressed in FECs, b) 45ºC and C-Rate = 0.5C expressed in number of cycles @ DoD, c) 45ºC and C-Rate = 0.6C expressed in FECs, d) 45ºC and C-Rate = 0.6C expressed in number of cycles @ DoD, e) 35ºC and C-Rate = 0.4C expressed in FECs and f) 35ºC and C-Rate = 0.4C expressed in number of cycles @ DoD.

Table II. Data of the adjustments performed and correlation coefficients.

C_{Carga}	T	FEC				N @ DoD			
		a	*b*	*c*	R^2	*a*	*b*	*c*	R^2
0,4C	25 ºC	55,18	-1,749	1175	0,9934	178,6	-2,382	1559	0,9997
	35 ºC	45,82	-1,758	1012	0,9925	146,2	-2,397	1384	0,9996
	45 ºC	36,88	1,786	883,4	0,9904	117,9	-2,424	1242	0,9995
0,5C	45 ºC	38,26	-1,766	823,2	0,9900	110,6	-2,438	1190	0,9995
0,6C	45 ºC	31,03	-1,815	781,3	0,9890	96,8	-2,461	1125	0,9996



a)



b)

Fig. 4. Cycle-Life adjusts studied, a) expressed in FECs and b) expressed in number of cycles @ DoD.

Figure 2 shows this adjustment for the case of 45ºC and C = 0.4C, where the influence of the DoD on the CL can be appreciated. The adjustments for the rest of the cases studied are included in Figure 3. Note the difference between FEC and cycle @ DoD, the CL being expressed in FEC and in number of cycles at certain DoD, respectively. It is observed that very shallow cycling is highly beneficial in terms of cycling degradation.

However, the minimum DoD will be determined by the range need of the EV user, while the total useful life will also be influenced by degradation due to calendar aging, among others. Table II shows the adjustments and correlations for the different cases studied, while these cases are graphed in Figure 4.

In provided Table II, it can be seen that the model fits very well to data in N @ DoD terms, given by a minimum R^2 correlating factor of 0.9995. Furthermore, it is observed how the cycling temperature is a key variable in the useful life of a battery, comparable to the working current-rate. In this context, under operating conditions of DoD=40%, C-Rate=0.4C and T=45 ºC, studied cells last 2328 cycles, or 1072 FEC; under C-Rate=0.6C and T=45 ºC, studied cells last 2048 cycles, or 945 FEC; while under C-Rate=0.4C and T=25 ºC, studied cells last 3142 cycles, or 1448 FEC. Although measuring cycle-life in FEC is very useful for accounting for total energy throughput or kilometres driven, number of cycles at certain DoD (N @ DoD) has to be checked as well, as it defines the maximum number of trips before cells reaching their end-of-life in that application, for example.

4. Conclusion

Battery degradation is one of the main problems of energy storage, in automotive applications as well as in stationary applications. Knowing the rate of degradation of a battery under a known working cycle is necessary for technology general deployment and performance improvement, as well as life cycle assessment since the usage optimization improves life cycle. Therefore, research on how to maximize batteries' lifetime is being encouraged. Concerning electric vehicles, people do want to know, as accurately as possible, how often they will need to replace the batteries installed in their vehicles. For this purpose, it is necessary to directly monitor, or indirectly estimate, the state of health.

In this context, with the aid of this paper, and the lifetime model here presented, the trade-off between working current and temperature in batteries applications can be correctly assessed.

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