Empirical Electrical and Degradation Model for Electric Vehicle Batteries

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ABSTRACT Battery degradation is one of the key barriers to the correct deployment of electric vehicle technology. Therefore, it is necessary to model, with sufficient precision, the State of Health (SoH) of batteries at every moment to know if they are useful as well as to develop operating strategies aimed at lifetime maximization. This paper presents a commercial electric vehicle with a nickel-cobalt-manganese (NCM) battery cell model that is composed of electrical and degradation submodels given by cycling aging. The studied cell is an LG Chem E63 cell, which is used in Renault Zoe electric vehicles. This degradation model is based on experimental results that are interpolated in the Hermite Cubic Interpolation Polynomial (PCHIP), with the exception of the number of cycles, whose impact is determined by a potential law. Temperature and C-rate are found to be the most influential factors in the aging of these batteries. The degradation model developed presents an RMSE of 1.12% in capacity fade and 2.63% in power fade. Furthermore, an application of the model is presented, in which high demanding (highway), average demanding (mixed), and low demanding (urban) driving environments are analyzed in terms of degradation.

INDEX TERMS Battery degradation, lifetime model, lithium-ion battery, electric vehicle.

I. INTRODUCTION

Battery lifetime as well as with its range and charging equipment are among the key factors to consider when acquiring an electric vehicle (EV). 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.

The aging of lithium-ion batteries is a highly complex and multidisciplinary process [3]–[8]. Calendar aging and cycling aging can be distinguished, and while looking at the effects, capacity fade (CF) and power fade (PF) can be determined. Calendar aging is the degradation independent of the use of the cell. It is linked to the cell structure itself and strongly depends on the State of Charge (SoC), temperature, and time lapsed during battery storage [9]–[11]. Cycling aging depends on current rate (C-rate), temperature of cycling, depth of discharge (DoD), and the number of cycles performed [12]–[14]. Cycling aging is an important source in the degradation of batteries allocated to an EV as driving and charging are high power demanding processes that are usually linked to a relatively high temperature—generally limited by passive or active cooling methods—that is high enough to accelerate the aging process. For example, Tesla controls battery temperature to remain below 55°C.

CF is the loss of capacity of a cell when compared to a fresh one, while PF is the decrease in the maximum power a cell can deliver, caused by an increase in internal resistance. Battery degradation is a natural process that permanently reduces the amount of energy a battery can store as well as the amount of power it can deliver. The batteries installed in EVs are...
form EIS diagnostics are complex and expensive, therefore for EV technology. Furthermore, the devices used to per-
tions [35], [36], which makes them somewhat inappropriate
temperature, and even the impedance of wire connec-
However, EIS measurements are very sensitive to SoC,
operation is limited since they cannot operate accurately
parameters and neglect-
are determined by combining
EIS models or by other

The parameters related to battery aging are internal vari-
ables, making them difficult to measure with sensors. Thus,
it is of vital importance to study degradation behaviors and
construct a degradation model to estimate the State of Health (SoH) [16]. Aging occurs due to diverse microscopical chem-
ical and electrochemical processes [6], [17]–[20]. The promi-
ient mechanism is usually considered to be the formation of
the so-called solid electrolyte inter-phase (SEI) [21], [22].
The SEI is a thin (nm-scale) layer on the graphite active
material particles, growing over time, but its composition
is not well known. This SEI formation is the cause of loss
of capacity and increase in internal resistance. Therefore,
battery lifetime can be maximized by appropriately selecting
or controlling operating conditions in order to avoid over-
stressing the battery.

According to existing literature, SoH estimation, and thus
remaining useful lifetime (RUL) prediction methods, can
be categorized into model-based, data-driven, and hybrid
approaches [16]. Model-based approaches establish a math-
ematical model based on battery physics and dynamics to
describe the degradation trajectory. Generally, they are based
on algebraic and differential equations, or they build an empirical
model based on a simple empirical equation. How-
ever, there is a trade-off between prediction accuracy related
to model complexity and speed of convergence. Meanwhile,
data-driven approaches use statistical theories or machine
learning techniques to derive a predictive model directly from
the measured data, so they can extract hidden correlations
from the data and predict the RUL, without a mathema-
tical model of the battery [23], [24]. A data-driven approach
does not require analyzing the system mechanism and is
feasible and practical, but a large amount of data is neces-
sary for the same. Hybrid approaches, which combine the
model-based and data-driven approaches, have also been
proposed.

Most theoretical models that represent the electrochemical
reactions taking place in a battery cell are electrochemi-
cal models [25]–[29]. These models are known to have the
highest precision, but they require several parameters and
variables that must be known in advance. Therefore, real-time
operation is limited since they cannot operate accurately
without data and are not easily adaptable.

Several publications deal with Electrochemical Impedance
Spectroscopy (EIS) measurements for cell SoH characteri-
zation and degradation mechanism identification [30]–[34].
However, EIS measurements are very sensitive to SoC,
temperature, and even the impedance of wire connec-
tions [35], [36], which makes them somewhat inappropriate
for EV technology. Furthermore, the devices used to per-
form EIS diagnostics are complex and expensive, therefore
EIS measurements are usually only implemented in laboratories [37].

A theoretical description of battery aging as a function of
operating conditions can be achieved by empirically param-
eterized equivalent circuit models (ECMs). Generally, they
only consider the main variables and parameters, neglect-
ing others that have less influence on the main effects to
be modeled. ECMs are widely used in battery management
systems (BMSs) [38] for their capability to operate on few
parameters and low computational speed with sufficient pre-
cision [39]. Their parameters can be determined by combin-
ing them with electrochemical or EIS models or by other
techniques generally based on experimental tests.

Aging experimental studies are time intensive and only
focus on certain discrete aging conditions (temperature, DoD,
and so on). Therefore, they do not provide a complete under-
standing of the entire range of conditions [10], [38]. Further-
more, a model with physical correspondence is required to
be applicable in a vehicle, making models in the frequency
domain unsuitable for this purpose [37]. Therefore, models
that can calculate degradation at any operating conditions,
independent of the discrete experimental trials performed, are
needed.

Taking into account the information mentioned above,
section 2 of this paper introduces related works in bat-
tery degradation modeling, while section 3 shows the stud-
ied cell data. Section 4 describes the modeling techniques
used to develop the battery electrical model, and section
5 describes the degradation model developed. Additionally,
section 6 presents an application of the model, comparing
three typical scenarios. Finally, the conclusions and summary,
including some research gaps, are presented in section 7.

II. RELATED WORKS
Degradation models of electric energy storage systems are
gaining interest among academia since several advances
depend on them. EVs and battery energy storage sys-
tems (BESSs) providing ancillary services and contributing
to grid stability are a clear example of their utility. Thus,
the number of papers focusing on battery SoH has increased
considerably in recent years.

Several authors have focused on finding the origin of bat-
tery degradation under different operating conditions. Some
works can be found in [13] and [40], where authors attempt to
identify the main degradation factor. Most of them conclude
that operating conditions related to EVs and BESS are related
to SEI growth, although other mechanisms gain relevance at
certain conditions [41], [42].

Several authors have proposed new battery degradation
models. Wang et al. studied lithium battery aging at sev-
eral DODs (10–90%), temperatures (10–43°C), and C-rates
(C/2 to 6.5 C), resulting in 60 different aging conditions [43].
The tests under low current (C/2) and DOD (10%) were
assumed to represent calendar aging since very low cyclic-
ing was performed. However, the C/2 current is not too low
and may correspond to the ranges of currents used in EV
applications. As demonstrated in this paper, currents as low as C/3 have an important aging effect and further work is thus needed.

It is common to represent degradation based on an exponential decay function of degradation [44], especially in a BESS simulation, but this approximation must be adapted to the commercial battery cell used in each case. Therefore, experimental tests are also necessary. Moreover, it is important to account for temperature, DoD, and C-rate in degradation models since lithium-ion batteries do not match traditional cycle life vs. DOD and Ah throughput models [45]. Consequently, exponential decay models are not very suitable when high accuracy is needed.

In [46], the degradation of 18650 type cells considering both CF and PF was modeled. Based on this degradation model, an LIFEPO cell characterization was performed in [47] for voltage and SoC estimation. However, the authors performed cycling aging tests at a single temperature and at a single C-rate, which makes the results’ applicability more limited. A similar problem occurs in [44], where the degradation model developed aimed at BESS did not take into account the C-rate influence, making its application in EV very limited. Studies such as [48] focus on characterizing electrochemical differences and their influence on fading in order to upgrade their model parameters while depending on operating conditions to improve the accuracy of the model, whose simulation time was 15 min for 1000 cycles simulation with 1s per step. Probabilistic works have also been carried out [49], [50], where a model-based Bayesian approach or a data-driven approach is used to express battery SoH as a probabilistic function.

In [51], an empirical electrothermal model was developed, which was upgraded by an empirical CF model. However, the authors only considered temperature and C-rate when modeling CF, neglecting the influence of DoD and neglecting PF as it was not considered relevant. The results show a 5% mean error since the maximum error rises to 14%. In [52], a cell model validated by three chemistries and a wide range of temperatures (−5–45°C) was presented. This was based on second-order Thevenin ECM and had errors up to 8%. In [53], a combined cycle and calendar aging model for 20-Ah NCM cells was proposed. Although they only considered CF, the results show a good SoH estimation since errors are below 5%, but no data about simulation time is provided. Later, the same authors published a PF model of the same cells [54], which was aimed at investigating the degradation caused by high currents related to fast charging, with 2°C error in the temperature estimation.

The model developed consists of two linked submodels (Figure 1). The first is a degradation submodel that allows the estimation of degradation at determined conditions by performing a set of interpolations based on experimental data. It accounts for all the important factors, namely DoD, temperature, number of cycles, and C-rate, with 1.12% of root-mean-square error (RMSE) in CF and low execution time. The second is an electrical submodel that is able to represent the terminal voltage at every time step and whose parameters are upgraded by the degradation model results.

### III. STUDIED CELL DATA (LG E63)

The battery cell (LG Chem E63, Figure 2) selected is a “Pouch” cell, which is installed in a Renault Zoe EV. The basic data of this cell is shown in Table 1. It is a high-capacity nickel-cobalt-manganese (NCM) cathode and graphite anode lithium-ion cell.

The NCM cathode and nickel-cobalt-aluminum (NCA) cathode in combination with graphite anode cells are considered high specific energy cells, with a good specific power—some of the best types of lithium-ion cells that can be used in EVs. NCM cells provide better safety compared to NCA cells. In contrast, the cost of NCA cells is lower [38], [55].

It is known that the capacity of a battery follows a nonlinear law with temperature [56], [57]. Temperature is a catalyst, as higher temperatures favor the speed of reactions taking place in charging and discharging processes. These higher speeds are translated into higher useful capacity. In this case, this relationship is notified in the technical product specification report [58] and is graphed in Figure 3. The modelling curve is obtained based on Hermite Cubic Interpolation Polynomial (PCHIP).
TABLE 1. Basic data of LG E63 cell.

| Parameter                      | Value                      |
|--------------------------------|----------------------------|
| Nominal Voltage                | 3.60 V                     |
| Voltage                        | 2.50 – 4.20 V              |
| Continuous operation temperature| 10 °C – 45 °C              |
| 1st over voltage limit         | 4.40 V @ Normal            |
| 2nd over voltage limit         | 4.30 V @ Charging          |
| Under voltage limit            | 2.00 V                     |

FIGURE 3. Actual capacity at several temperatures.

FIGURE 4. Internal resistance model.

IV. ELECTRICAL MODEL

The electrical model developed corresponded to an internal resistance model. In this model, only an internal voltage source and resistance were considered. The internal voltage source was dependent on capacity (given by temperature), SoC, and SoH. The resistance, however, was different for the charging and discharging processes, both of which were dependent on SoC and SoH. The capacity state of health (SoH_C) related to capacity retention and the resistance state of health (SoH_R) related to internal resistance increase were also considered, allowing CF and PF to be decoupled. The internal resistance model used is shown in Figure 4.

Terminal voltage is calculated as (10):

\[ V_T(t) = V_{OC}(SoC) - R(\text{SoH}_R, \text{SoC}) \cdot I(t) \]  

where \( V_T(t) \) is the terminal voltage in each time step, \( V_{OC}(SoC) \) is the open circuit voltage according to SoC, \( R(\text{SoH}_R, \text{SoC}) \) is the internal resistance value according to SoH_R and SoC, and \( I(t) \) is the current value in each time step.

The open circuit voltage \( (V_{OC}) \) according to SoC is graphed in Figure 5 using PCHIP. This interpolation method was selected for showing great robustness as data monotonicity was respected. The PCHIP interpolation polynomial \([59],[60]\) used is shown in (1).

\[ y(x) = h_{00}(t) y_k + h_{10}(t) (x_{k+1} - x_k) m_k + h_{01}(t) y_{k+1} + h_{11}(t) (x_{k+1} - x_k) m_{k+1} \]

for \( k = 1, \ldots, n \)  

(2)

where \( x \) is the discrete value entered; \( y(x) \) is the interpolated value; \( x_k \) and \( x_{k+1} \) are the values before and after \( x \), respectively; \( y_k \) and \( y_{k+1} \) are the values before and after \( y(x) \), respectively; \( m_k \) and \( m_{k+1} \) are the tangents evaluated at points \( k \) and \( k+1 \), respectively; \( h_{ij}(t) \) is the basic Hermite functions; and \( t \) is the point at which each \( h_{ij}(t) \) is evaluated. \( t \) and \( m_k \) were respectively determined using (2) and (3).

\[ t = \frac{x - x_k}{x_{k+1} - x_k} \]

(3)

\[ m_k = \frac{\Delta_{k-1} - \Delta_k}{2} \]

(4)

where \( \Delta_{k-1} \) and \( \Delta_k \) are the slopes of the secant lines between successive points, which can be obtained using (4).

\[ \Delta_k = \frac{y_{k+1} - y_k}{x_{k+1} - x_k} \]

(5)

The basic Hermite functions \( h_{ij}(t) \) are shown in (5)–(8).

\[ h_{00}(t) = B_0(t) + B_1(t) \]

(6)

\[ h_{10}(t) = \frac{1}{3} B_1(t) \]

(7)

\[ h_{01}(t) = B_1(t) + B_2(t) \]

(8)

\[ h_{11}(t) = B_0(t) + B_1(t) \]

(9)

where \( B_i \) are the elements of the Bernstein polynomials of order 3 used to compose \( h_{ij}(t) \) and are given by (9).

\[ B_i(t) = \binom{3}{i} \cdot t^i \cdot (1 - t)^{3-i} \]

(10)
The open circuit voltage curve was only tested at 25°C and so the characterization of the open circuit voltage was not performed according to temperature.

The internal resistance values according to SoC in charging and discharging are graphed in Figure 6 using PCHIP. It can be seen that the resistance increases greatly at low SoCs.

The values shown in Figures 5 and 6 correspond to those of a fresh cell. As time goes by and more cycles are performed, the capacity decreases and internal resistance increases. The evolution rate of these parameters is dependent on operating conditions and can be calculated with the degradation model from the next section. The coupling of both models is performed as follows: the degradation model calculates the actual capacity and internal resistance values after every cycle performed, which are then applied to the electrical model.

V. DEGRADATION MODEL

The degradation model developed considered battery degradation by cycling in CF and PF terms. Based on the results of some experimental tests, a reference matrix was created and the degradation of the desired variables was calculated by interpolation. A general overview of this model is shown in Figure 7.

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.
- \( \text{DoD} = 0 \) 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 2. However, using this model to calculate battery degradation out of these confidence bounds is also possible.

A. TEST MATRIX

The cells under study were tested experimentally in [39], and the test matrix is shown in Table 3. The charging powers expressed in the table correspond to that of the battery organization in the Renault Zoe, which is described in section 6.

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…

| Table 2. Confidence bounds for cycling aging. |
|---|---|---|---|
| **Temperature (T)** | **Depth of Discharge (DoD):** | **Cycles Number (N):** | **Current (C-rate)** |
| \([25-45] °C\) | \([20-80] \%\) | \([0-1800]\) cycles | \([0.3786-0.6710]\) C |

| Table 3. Cycling aging test matrix. |
|---|---|---|
| **Charging Power – Charging Current** | **Temperature** | **DoD** |
| 14.6 kW – 1/3 C | 25 °C | 20 % |
|  | 45 °C | 40 % |
|  | 60 % | 60 % |
|  | 80 % | 80 % |
| 22 kW – 0.5012 C | 25 °C | 20 % |
|  | 40 % | 40 % |
|  | 60 % | 60 % |
|  | 80 % | 80 % |
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°C, with 60 minutes resting time between them.

B. DATA TREATMENT AND NORMALIZATION

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 (11) and (12).

\[ \text{SoH}_C = 100 - a_C(\text{DoD}, C, T) \cdot N^{b_C(C,T)} \]  
\[ \text{SoH}_R = a_R(\text{DoD}, C, T) \cdot N^{b_R(C,T)} \]

where \( \text{SoH} \) is the state of health, \( a \) is a prepotential factor, \( N \) is the number of cycles, and \( b \) is a potential factor. \( \text{SoH}_C \), \( \text{SoH}_R \), \( a_C \), \( a_R \), \( b_C \), and \( b_R \) are distinguished for CF and PF, respectively. The actual capacity and resistance of a cell was determined by (13) and (14).

\[ \text{Cap}(\text{SoH}_C) = \text{Cap}_N \cdot \text{SoH}_C \]  
\[ R(\text{SoC}, \text{SoH}_R) = R(\text{SoC}) \cdot (1 + \text{SoH}_R) \]

where \( \text{Cap}(\text{SoH}_C) \) is the actual capacity depending on \( \text{SoH} \) \( \text{Cap}_N \) is the nominal capacity, \( R(\text{SoH}_C, \text{SoH}_R) \) is the actual resistance depending on SoC and SoH, and \( R(\text{SoC}) \) is the resistance depending on SoC in a fresh cell.

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, the \( a \) factor varies along operating DoD, T, and C, while the \( b \) factor varies along operating T and C.

The values determined for these parameters as well as each \( R^2 \) correlating factor value are presented in Table 4. The average \( R^2 \) values for CF and PF modeling are 0.9780 and 0.9755, respectively.

The results for 45°C are shown in Figure 8, indicating the discrete points obtained from the experimental tests and the continuous curves obtained by applying (11), (12) using the data from Table 4.

Two boundaries were applied to the model in order to omit capacity data points over 100% and internal resistance increase data points below 0%.

From the \( a \) parameter value analysis, it was adjusted based on PCHIP. Following the example from Figure 8, 45°C case
TABLE 4. Values of Parameters got for Data Normalization under Cycling aging.

| C<sub>Carge</sub> | T     | DoD | Capacity | Resistance |
|-------------------|-------|-----|----------|------------|
|                   |       |     | a<sub>C</sub> | b<sub>C</sub> | R<sup>2</sup> | a<sub>R</sub> | b<sub>R</sub> | R<sup>2</sup> |
| 20 %              | 25 ℃  | 20% | 0.0890  | 0.7287    | 0.9887    | 0.00077  | 1.5691  | 0.9831  |
|                   |       | 40% | 0.1010  | 0.7287    | 0.9903    | 0.00081  | 1.5691  | 0.9883  |
|                   |       | 60% | 0.1049  | 0.7287    | 0.9629    | 0.0009   | 1.5691  | 0.9821  |
|                   | 0.3786 C | 80% | 0.1147  | 0.7287    | 0.9314    | 0.0015   | 1.5691  | 0.9826  |
|                   |       | 20% | 0.1291  | 0.7113    | 0.9685    | 0.0186   | 1.1247  | 0.9029  |
|                   |       | 40% | 0.1371  | 0.7113    | 0.9807    | 0.0219   | 1.1247  | 0.9812  |
|                   |       | 60% | 0.1507  | 0.7113    | 0.9976    | 0.0282   | 1.1247  | 0.9618  |
|                   |       | 80% | 0.1671  | 0.7113    | 0.9876    | 0.0374   | 1.1247  | 0.9882  |
| 20%               | 45 ℃  | 20% | 0.0964  | 0.7211    | 0.9858    | 0.0016   | 1.4563  | 0.9838  |
|                   |       | 40% | 0.1109  | 0.7211    | 0.9797    | 0.0018   | 1.4563  | 0.9830  |
|                   |       | 60% | 0.1133  | 0.7211    | 0.9826    | 0.0029   | 1.4563  | 0.9928  |
|                   |       | 80% | 0.1298  | 0.7211    | 0.9714    | 0.0031   | 1.4563  | 0.9632  |
| 20%               | 0.4812 C | 25 ℃ | 20% | 0.1375  | 0.6918    | 0.9741    | 0.0009   | 1.5531  | 0.9891  |
|                   |       | 40% | 0.1498  | 0.6918    | 0.9824    | 0.0011   | 1.5531  | 0.9448  |
|                   |       | 60% | 0.1502  | 0.6918    | 0.9809    | 0.0012   | 1.5531  | 0.9849  |
|                   |       | 80% | 0.1679  | 0.6918    | 0.9837    | 0.0014   | 1.5531  | 0.9966  |

A parameter factor values along DoD are shown in Figure 9. A point corresponding to a<sub>C</sub> = 0 for DoD = 0 and a set of points corresponding to C = 0 were added to the results’ available data. These points were not available in the experimental test results; they were added following the cycling and calendar aging decoupling assumption made and helped in smoothing the trend in range DoD = [0,0.2] and C = [0,0.3786]. Therefore, null cycling aging degradation was obtained for DoD = 0 and/or C = 0 cycling.

This adjustment was applied to obtain the value of a<sub>C</sub> prepotential factor for every value of DoD at 25℃ and 45℃ and 0.3786 C, 0.4812 C and 0.6710 C. Combining these adjustments with (11)–(12), cycling aging modeling expressions were obtained. After sorting them, a reference normalized matrix was obtained, which is shown in Table 5.

As seen in the test matrix (Table 3), the available testing data displayed different temperatures at the same current.
For those combinations of temperature and current values for which no data was available, a proportional fit was performed, as given in (15) and (16).

\[
\begin{align*}
    a_{C_{T2}} &= a_{C_{T1}} \cdot a_{C_{T2}} \\
    a_{R_{T2}} &= a_{R_{T1}} \cdot a_{R_{C1}}
\end{align*}
\]

where \(a\) is the prepotential factor, \(C_2\) is the current at which calculation is intended, \(T_2\) is the temperature at which calculation is intended, \(C_1\) is the available data current, and \(T_1\) is the available data temperature.

From the linearizing data of \(a_C\) shown in Figure 9, three major ranges of DoD were distinguished and applied to the 25°C data:

- [0–20%] DoD, where degradation grew rapidly when DoD was increased, with a degradation rate of 0.0044%(degradation)/%DoD.
- [20–60%] DoD, where degradation grew slowly when DoD was increased, with a degradation rate of 0.0004%(degradation)/%DoD.
[60–100%] DoD, where degradation grew a little quicker when DoD was increased, with a degradation rate of 0.0006%(degradation)/%DoD.

In the case of higher temperatures, the degradation rates along DoD increased and a narrow middle range was observed. No quantitative comparison was made regarding temperature or C-rate since these were highly non-linear factors. This non-linearity was represented in the variation of parameter $b_C$.

For every value to be interpolated, the model calculated PCHIP interpolating parameter values that fit the available data better. Thus, the model considered a dynamic interpolating algorithm that recalculated every PCHIP parameter value depending on the operating conditions.

The cycling aging interpolation was performed in 4 dimensions or variables, namely DoD, number of cycles, temperature, and C-rate. The determination of every variable was performed based on PCHIP instead of the number of cycles, N, which reconstructs (11) and (12). The 4D resulting reference matrix structure is shown in Figure 10.

This model had a low computational demand and high speed, running in as much as 2.03s to calculate CF and PF for the desired conditions on an intel i7 processor at 2.80 GHz. This maximum resource demanding case corresponded to the case in which all variables had to be interpolated. The validation of the model results is shown in Figure 11 for CF and Figure 12 for PF.

The maximum error when simulating CF was 3.74%, given when DoD=0.8, N=1, 100 cycles, T=45°C C=0.3786, while average RMSE was 1.12%. Regarding PF simulation, the maximum error obtained was 8.65%, given when DoD=0.2, N=100 cycles, T=45°C C=0.3786, while average RMSE was 2.63%.

**VI. APPLICATION**

The developed model was used to evaluate differences in battery degradation terms at the cell level among various driving environments. For this, three environments or scenarios were selected: urban, mixed, and highway. Each one was given a test procedure.

- Federal Test Procedure 75 (FTP75) was selected for urban driving. This procedure is defined by the American Environment Protection Agency (EPA). In this test, frequent stops are performed, considering a maximum speed of 91.25 km/h, while the average speed is 25.86 km/h.
- Worldwide Harmonized Light Vehicles Test Procedure (WLTP3) was selected for mixed driving. This test is defined by the United Nations Economic Commission for Europe (UNECE) based on the real driving profiles and habits of drivers. It was chosen to replace the common NEDC test as it is more realistic. It is composed of four parts according to the maximum speed: low,
medium, high, and extra-high, reaching a maximum speed of 135 km/h, with 46.52 km/h as the average speed.

- Highway Fuel Economy Driving Schedule (HWFET) was selected for highway driving. This test is also defined by the EPA and does not include any stop, reaching a maximum speed of 95 km/h, with 77.68 km/h as the average speed.

In this study, data from the commercial EV Renault Zoe 2020 R110 was used. The energy demand was calculated considering traction power, rolling friction losses, and aerodynamic friction losses. In this context, Renault Zoe had a 41-kWh battery, approximately, and could be charged up to 50-kW power. DC bus nominal voltage was 360 V and 400 V during charging. The battery was organized in 2 parallel strings of 96 cells in series in each one [61].

The average operating C-rate was calculated for each driving environment or scenario as well as for each C-rate corresponding to each charging power. The discharging C-rate while driving was calculated considering the energy throughput, i.e., considering regenerative braking. The equations to calculate these variables are given in (17)–(18).

$$ C_{RateDriv} = \frac{\int_0^1 |F(t)| \cdot [N] \cdot \cdot v(t) \cdot \frac{[\frac{t}{s}]}{N_{cells} \cdot C[Ah] \cdot V[V] \cdot t[s]} dt}{P_{charging}} $$

$$ C_{RateCh} = \frac{P_{charging}}{N_{cells} \cdot C[Ah] \cdot V[V] \cdot t[s]} $$

The driving average C-rate and charging C-rate were combined in order to get an average cycling C-rate, as given in (19).

$$ C_{Rate} = \frac{C_{RateDriv} \cdot t_{Driv} + C_{RateCh} \cdot t_{ch}}{t_{Driv} + t_{ch}} $$

The CF at a constant temperature of 45°C for all DoDs as a consequence of each driving environment or scenario is shown in Figure 13. The graphed cases match some of the most common studied charging powers. The top surface in each plot corresponds to the urban driving environment given by FTP75, the middle surface corresponds to the mixed driving environment given by WLTP3, and the bottom surface corresponds to the highway driving environment given by HWFET. It can be observed that the C-rate given by the driving environment and charging power had the greatest influence in battery degradation, while the DoD influence was quite linear. The greater the C-rate and/or DoD, the greater the degradation produced.

The PF at a constant temperature of 45°C for all DoDs as a consequence of each driving environment or scenario is shown in Figure 14, which can be observed as the increase in internal resistance. The top surface corresponds to the...
highway driving environment given by HWFET, the middle surface corresponds to the mixed driving environment given by WLTP, and the bottom surface corresponds to the urban driving environment given by FTP-75. A greater C-rate and/or DoD produced greater degradation in the PF as well. It can be observed how the C-rate given by driving environment and charging power had the greatest influence in the PF of these batteries, while DoD influence was quite linear but more pronounced compared to the CF degradation case.

Figures 15 and 16 show the CF and PF for DoD = 60% for each driving environment graphed along the charging power used and number of cycles.

As the C-rate is a determining factor in battery cycling aging, the choice of an adequate recharging power is highly relevant. This charging power must be high enough to meet the available charging time needs of the users but also as low as possible to prevent batteries from aging in excess. In this context, for the urban driving case, taking an 80% in SoH as EoL and supposing a 60% of DoD, the battery would last approximately 2,900 cycles with a 7-kW charger, 2,150 cycles with a 22-kW charger, and 925 cycles with a 43-kW charger. For the mixed driving case, the battery would last approximately 1,850 cycles with a 7-kW charger, 1,225 cycles with a 22-kW charger, and 1,075 cycles with a 43-kW charger. For the highway driving case, the battery would last approximately 1,600 cycles with a 7-kW charger, 1,050 cycles with a 22-kW charger, and 925 cycles with a 43-kW charger.

The results of this application have been derived from simulations and have not been experimentally validated. Therefore, the methodology for cell model to battery model extrapolation is considered by the authors to be an area for further research since several factors must be taken into account, such as contact resistances and battery cell balancing.

VII. SUMMARY AND CONCLUSION

Battery degradation is one of the major problems of energy storage in automotive applications as well as in BESSs. Knowing the rate of degradation of a battery under a known working cycle is necessary for technology deployment and performance improvement. Regarding EVs, clients want to know, as accurately as possible, how long the batteries of their vehicles will last. For this purpose, a SoH monitoring or estimation system is necessary. Moreover, research on how to maximize batteries’ lifetime is being encouraged; for instance, optimized strategies for BESS exploitation or the optimal choice of charging power for an EV are being sought.

This paper presents a simple but accurate electrical and degradation model for a battery that is already being used in a commercial EV. The model presents the degradation by
cycling with a RMSE of 1.2% in CF and 2.63% in PF under a wide range of DoDs, temperatures, and C-rates for the desired number of cycles. It is seen how the temperature and the C-rate, apart from the number of cycles, are the variables that have the highest impact on battery degradation, while DoD is linear in these cells, especially in CF.

The driving environment is also determined to be of great relevance in the degradation of batteries. While the highway predominant scenario degrades batteries quicker because of the greater C-rate, these batteries have 75.51% more lifetime in the urban driving scenario and 16.00% less lifetime in the highway predominant driving scenario, both considering a 22-kW charger and compared to the mixed driving scenario.

The charging power is the major second influence, but of the same relevance, on the C-rate. Considering the mixed driving scenario, the 7-kW charging power extends battery lifetime by approximately 51.02% and the 43-kW charging power reduces it by approximately 12.25% compared to the 22-kW charging power.

Cycling aging characterization is necessary for improving battery lifetime by developing new optimized strategies for charging and discharging, not only in EVs but also in BESSs. Once the cells have reached their EoL, it becomes necessary to find an application to give them a second life or to develop a recycling system to reduce their environmental impact. Therefore, a degradation model that is as accurate as possible can help in the search for the optimum EoL point as well as in the characterization of their residual economic value. Although the CF is predominantly important in EVs, the characterization of the PF may become important in case the batteries are given a second life and used in BESS applications, as their maximum power is more limited.

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