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A methodology to model and validate electro-thermal-aging dynamics of electric vehicle battery packs

Lisa Calearo a, Andreas Thingvad b, Charalampos Ziras a, Mattia Marinelli a,∗

a Department of Wind and Energy Systems, Technical University of Denmark, Denmark
b Hybrid Greentech ApS, Roskilde, Denmark

Abstract

It is becoming increasingly important for power system engineers to have accurate yet simple-to-realize models that simulate electric vehicle (EV) battery pack behaviour. This paper proposes a methodology to model and validate the main dynamics – electrical, thermal and aging – that characterize Li-ion batteries without disassembling them from the vehicle. The methodology consists of three steps. The first is the model implementation of the battery pack, considering the mentioned dynamics and their interdependencies. Next, the electrical and thermal parameters are experimentally derived from a Nissan LEAF 40 kWh battery pack. Third, the overall model is validated through real tests. Only electrical power and ambient temperature are provided as model inputs, and the output is compared with the collected measurements from the battery pack. Results show that the model predicts the electro-thermal battery pack behaviour with errors below 5%. The estimated capacity decrease deviates from the measurements and battery management system (BMS) readings up to one percentage point. We conclude our paper by discussing the uncertainty regarding this estimation and the limitations introduced by working with EV battery packs, both on model implementation and field validation.

Keywords:
Electric vehicles
Experimental validation
Li-ion battery pack
Electro-thermal-aging model

1. Introduction

1.1. Motivation

Batteries are key to the electrification of the transport sector. In contrast to the rapid improvement of battery technology, very detailed modelling would need years of work, especially when considering lengthy battery degradation measurements. This is often inconvenient because of the significant required effort, and because the model would be likely obsolete at the completion of the measurements. Due to the rapid growth of EV adoption, it is becoming increasingly important for power engineering studies to have a simple and accurate characterization of battery pack behaviour. The literature offers large number of Li-ion battery models which focus on three main physical aspects: electrical, thermal, and aging [1]. The first reproduces the behaviour of the electric quantities such as voltage and current. The second characterizes the behaviour and distribution of battery pack temperature and individual cells. The third models battery degradation.

There are various proposed models for each of the aforementioned battery dynamics, with varying levels of complexity. For the electrical part many models follow a circuit representation, which has a simple and intuitive implementation, and has been used to reflect the dynamic electrical characteristics of Li-ion batteries [2–4]. Thermal models have also been widely investigated, considering both uniform and non-uniform temperature distributions. Physical implementation can be very specific, complex, and time-consuming [1]. For this reason, the circuit model implementation, which consists of the description of the thermal behaviour by using lumped elements, is often more convenient. Regarding battery aging, degradation is a physico-chemical activity that is uncertain, non-linear, and depends on the chemistry of the cells [5]. In the literature, lifetime estimation of Li-ion batteries is performed in the laboratory, often with accelerated tests, where battery stress factors and levels are chosen to accelerate the desired aging phenomenon [6]. From these measurements semi-empirical models have been derived [7]: the most discussed ones are based on lithium nickel cobalt aluminium (NCA), lithium iron phosphate (LFP) chemistries [8] and lithium manganese oxide-nickel manganese cobalt chemistry (LMO-NMC) [9,10].

Apart from varying levels of complexity, another important aspect is that for typical power system applications, a simplified model on a battery pack level is preferred to models relying on cell modelling. Multiple papers have focused on single cell modelling and validation.

∗ Correspondence to: Technical University of Denmark, Risø Campus, Frederiksborgvej 399, 4000 Roskilde, Denmark.
E-mail address: matm@elektro.dtu.dk (M. Marinelli).

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In [19] the electro-aging model developed for a single cell is used to model was presented, but omitting battery life and cell degradation. In [18] the SOC estimation of an EV battery pack during charging and discharging, without considering the temperature the authors target the dynamic characteristics of the battery pack fundamental battery dynamics: electrical, thermal, and aging. In [17] focus was given on the dependence of the electro-thermal parameters that considers all three dynamics – electrical, thermal and aging – is developed (and implemented in Matlab-Simulink). It is worth noting that the equations used to model the dynamics are valid for both single cells and battery packs, if the appropriate electro-thermal parameters are considered. Limitations of EV battery packs modelling and parameters simplifications/derivations are provided in the manuscript. Second, model parameters are identified through laboratory tests on a single cells and battery packs, if the appropriate electro-thermal parameters are considered. Limitations of EV battery packs modelling and parameters simplifications/derivations are provided in the manuscript.

3. Methodology

The proposed methodology can be divided into three main steps, and an overview is provided in Fig. 1. First, a battery-pack level model that considers all three dynamics – electrical, thermal and aging – is developed (and implemented in Matlab-Simulink). It is worth noting that the equations used to model the dynamics are valid for both single cells and battery packs, if the appropriate electro-thermal parameters are considered. Limitations of EV battery packs modelling and parameters simplifications/derivations are provided in the manuscript. Second, model parameters are identified through laboratory tests on a Nissan LEAF 40 kWh battery pack. The derived parameters are then included in the Matlab-Simulink model. In the last step, the model is finally validated. The validation consists of comparing the model output with the measured values from real experiments and battery degradation measurements. Electrical tests are used to validate the electrical characterization of the model, comparing voltage, current and SOC measured at the battery pack with the ones derived from the simulation model. Thermal tests are used to validate the thermal characterization of the model, comparing the temperature measured at the EV battery pack with the one derived from the simulation model. Finally, multiple tests are conducted over 3.5 years to measure battery pack capacity degradation.

3. Model implementation

3.1. Electrical dynamics

3.1.1. Equivalent electrical circuit

The electrical dynamics of a battery can be described using a circuit based on the equivalent Thévenin model [4], as shown in Fig. 2. An
3.1.2. State-of-charge (SOC)

The SOC describes the relative charge of the battery at a specific point in time and takes values from 0 (empty) to 100 (full). The evolution of SOC relative to a point in time $t_i$ is given by:

$$SOC(t) = SOC(t_i) + \int_{t_i}^{t} \frac{I(t)}{Q(t)} dt,$$

where $Q(t)$ is the time-dependent battery capacity in Ah. The time-induced degradation is further explained in Section 3.3.

3.2. Thermal dynamics

Thermal dynamics describe battery temperature as a result of Joule loss and heat dissipation. When the cabin and outside temperatures are in equilibrium, the lumped thermal equivalent model of the battery pack is described as in [22]:

$$C_{th} \frac{dT(t)}{dt} = \frac{1}{R_{th}}(T_{out}(t) - T(t)) + P_j(t),$$

where $C_{th}$ is the thermal capacitance and $R_{th}$ the thermal resistance of the battery pack, $T_{out}$ is the outside temperature and $T$ is the battery temperature, assumed to be homogeneous in the pack. $P_j$ are the joule losses of the battery pack, corresponding to the sum of losses on $R_0$ and $R_1$, as given by

$$P_j(t) = R_0 I(t)^2 + \frac{V_{oc}(t)^2}{R_1}.$$

Note that solar irradiance or active heating/cooling are not taken into account because the model is validated in a closed laboratory environment.

3.2.1. Thermal capacitance

$C_{th}$ reflects the ability of the battery to store thermal energy and is equal to the mass $m$ times the specific heat at constant pressure ($c_p$). $c_p$ is derived from the density, volume, and heat capacity of each cell component [23,24]. In a battery pack, cells are grouped into modules including cells materials, casing, etc. Each has a specific heat capacity, and the final battery pack should be an average of the various components specific heat capacities. Since casing and other materials are usually minimized in a battery pack, $c_p$ used for a single cell can be considered representative for the pack. $C_{th}$ is determined as:

$$C_{th} = m \cdot c_p.$$

3.2.2. Thermal resistance

Among the heat transfer methods only conduction is considered due to the limited temperature difference between the battery pack and the environment, which makes radiation transfer negligible. The absence of active cooling results in insignificant convection. In pouch batteries, used in many EVs, conduction is usually considered only in the depth direction because in the length and height directions batteries dissipate significantly less [25]. Differently from the single cell, the thermal resistance of a battery pack is a function of the cells connection, disposition of modules and battery pack in the vehicle. In an EV, the battery pack is placed at the bottom of the car by forming with the modules a parallelepiped [25]. The thermal resistance can be derived by considering the battery pack as a large homogeneous cell, where width, length, and height of the simplified parallelepiped are determined from the characteristics of the modules [25]. $R_{th}$ for the battery pack is derived as follows:

$$R_{th} = \frac{D}{2Sk}.$$

3.3. Aging dynamics

The initial capacity of a battery pack ($Q_i$) is a function of cell capacity $Q_{cell}$, given in Ah, and the number of cells in parallel $N_{cellp}$, such that:

$$Q_i = Q_{cell} \times N_{cellp}.$$

For an EV battery pack, two capacities can be defined: nominal (or total) and usable. The former is the amount of energy the pack...
can theoretically hold (see (9)). The latter is smaller than the nominal capacity and describes the amount of energy that can be used. EV manufacturers can limit the available battery capacity by including a buffer that is not available in the beginning of the vehicle life. This buffer is then released over time, changing the usable capacity during the vehicle lifetime [26,27].

Battery capacity degradation occurs due to irreversible electrochemical side-reactions [5], and can be divided into calendar and cycle degradation. The first is a function of time, temperature, and SOC, and occurs even when the battery is not being used. The second is due to degradation. The first is a function of time, temperature, and the C-rate of the current. Even though in reality only the usable capacity can be exploited, degradation affects the entire capacity. Battery capacity at time \( t \) is expressed as:

\[
Q(t) = Q_i - (q_{cal}(t) + q_{cycle}(t)),
\]

where \( q_{cal} \) and \( q_{cycle} \) are the accumulated calendar and cycle degradation, respectively, expressed as a percentage of \( Q_i \). The equations and parameters for calendar aging are from the Arrhenius equation based model in [22] and from the cycle aging tests in [9]. While the Nissan Leaf cells are not tested in [9] or [22], both publications test NMC cells with similar properties. The formulation is here implemented for the battery pack level, by considering the relevant parameters.

### 3.3.1. Calendar aging

Calendar aging, when battery temperature and SOC are constant, is denoted by \( dq_{cal}^* \) and is estimated by using the Arrhenius equation [22]:

\[
dq_{cal}^* = f \exp\left(-\frac{E_a}{R T_K}\right) \frac{1}{86400^{0.5}},
\]

where \( f \) is the pre-exponential factor, \( E_a \) is the activation energy equal to 24.5 kJmol\(^{-1}\), \( R \) is the gas constant equal to 8.314 Jmol\(^{-1}\)K\(^{-1}\), \( T_K \) is the absolute battery pack temperature in K and \( i \) is the time in seconds. Pre-exponential factor \( f \) is a function of both SOC and temperature. Temperature dependency is neglected here and a constant value of 25 °C is considered, since this was the most typical temperature during our measurement campaign, but it is straightforward to include. In this work, \( f \) takes the following form [25]:

\[
f(SOC) = \begin{cases} 
1.04 \cdot SOC^2(t) + 89.72 \cdot SOC(t) + 1224.6 & \text{if } SOC(t) \leq 50, \\
10.35 \cdot SOC^2(t) - 1083.6 \cdot SOC(t) + 11447 & \text{if } 50 \leq SOC(t) < 70, \\
2.64 \cdot SOC^2(t) - 409.55 \cdot SOC(t) + 22035 & \text{if } 70 \leq SOC(t).
\end{cases}
\]

By replacing \( T_K \) by \( T_K(t) \), \( dq_{cal}(t) \) is obtained for varying SOC and temperature:

\[
dq_{cal}(t, SOC) = f(SOC) \exp\left(-\frac{E_a}{R T_K(t)}\right) \frac{1}{86400^{0.5}}.
\]

Thus, the accumulated calendar aging is derived as:

\[
q_{cal}(t) = \int_0^t dq_{cal}(t, SOC) \, dt.
\]

### 3.3.2. Cycle degradation

It is proportional to the number of full charge-discharge cycles and battery temperature [22]. In this article we consider the Wang model [9] as it provides a compromise between accuracy and simplicity, and it is based on the NMC, a commonly used chemistry in vehicle applications. Incremental cycle degradation is provided by:

\[
\frac{dq_{cycle}(t)}{dt} = B_1(T_K) \exp(B_2(T_K)C-rate(t)) \cdot n \cdot eqCycles(t),
\]

\[
B_1(T_K) = aT_K^b(t) + bT_K(t) + c,
\]

\[
B_2(T_K) = dT_K^e(t) + e.
\]

C-rate\((t) = \frac{|I(t)|}{Q(t)}, \quad eqCycles(t) = \frac{C-rate(t)}{2 \cdot 3600}.
\]

The values of \( a, b, c, d \) and \( e \) are 8.58 \times 10^{-6} \text{ Ah}^{-1}\text{K}^{-2}, -0.0051 \text{ Ah}^{-1}\text{K}^{-1}, 0.759 \text{ Ah}^{-1}, -0.0067 \text{ K}^{-1} - (\text{C-rate}) \) and 2.35 (\text{C-rate})^{-1}, respectively. eqCycles is the equivalent number of full charge and discharge cycles, which is divided by 3600 because a time step of 1 s is used. \( n \), equal to 1.5 Ah is used to normalize the formulation per Ah/cycle [22,28]. The total cycle degradation is:

\[
q_{cycle}(t) = \int_0^t \frac{dq_{cycle}(t)}{dt} \, dt.
\]

### 4. Experiment setup and tests

#### 4.1. Battery electric setup and tests

In this work, a Nissan LEAF with a nameplate capacity of 40 kWh and NMC prismatic/pouch cells is considered. The battery pack has 96 cells in series and 2 in parallel, for a total of 192 cells. More information regarding the cells and modules are provided in [25]. The battery pack nominal voltage is 350 V [29], whereas the nominal capacity in Ah is an unknown value, as it is not provided by the manufacturer. In [30], a nominal battery capacity of 112.6 Ah is referred to as the usable capacity. Via the onboard diagnostics port (OBD-II), the initial nominal capacity is read to be equal to 115.44 Ah, which could correspond to the total capacity. The first value results in an energy capacity of 39.5 kWh, whereas the second in 40.4 kWh. The presented model is implemented considering a nominal capacity of 115.44 Ah. Despite the difference between the two values being small, an impact will be observed during the aging investigations.

#### 4.2. Tests setup

Fig. 3 provides an overview of the setup for the performed tests: the main components are the DC charger and the EV. The power from the DC charger is directly flowing into the 400 V bus [31]. When connected to the charger, the vehicle is turned off and parked in the laboratory, hence the DC/AC converter is not consuming power. DC power coming from the DC charger and going to the 400 V bus is split between the Li-ion EV battery and the auxiliaries connected to the 12 V bus. To isolate the DC power entering the battery, the power to the DC/DC converter and auxiliaries is measured in point B and subtracted from the power measured at the DC charger side in point A. The current is measured in point A with a current clamp (Prosys CP30) with accuracy of ±1%, whereas the battery voltage is measured with a voltage differential probe (Hioki P9000-01) with accuracy of ±0.5%. The voltage of the auxiliary battery is directly measured in point B, whereas the current flowing into the 12 V battery (from the main battery) is measured with a current clamp (Prosys CP1005) with accuracy of ±1%. A Hioki LR8431 datalogger with an accuracy of ±0.1% full scale is used to log and record the measurements with a 1-second resolution step. The power in point A is the product of voltage and current, resulting in an accuracy of 2%. Whereas the energy flowing into the 12 V bus has a final accuracy of 1.3%. Therefore, the total accuracy of the measurements is 2.3% (further details can be found in [31]). In the remaining sections, when referring to battery power we will consider the power measured in A minus the power in B. The battery is charged via the external ±10 kW DC charger with the CHAdeMO connector. The charger can be controlled both in charging and discharging modes. Nevertheless, due to internal charger constraints, it is not possible to control the discharging process when SOC is below 20% [32]. Internal battery measurements are read from the BMS and CAN-bus of the internal EV computer through a Bluetooth reader connected to the OBDII-port. The Bluetooth OBDII-reader sends the data to a mobile phone with the Leaf Spy Pro app [33]. The available measurements are:
4.3. Performed tests

4.3.1. Electrical tests

This test is used to characterize the electrical dynamics: parameters $R_0$, $R_1$, $C$, and $V_{oc}$ are derived from the conventional current interruption method [21]. The battery pack is step-wise charged from 20 to 100% SOC, with a relaxation time of 10 min at every step. Below 20% it is not possible to control the charging, due to limitations caused by EV-charging equipment. The SOC is read from the BMS, which provides the value for the entire battery pack. As shown in Fig. 4, the cell voltage is deviating more for lower SOC values, whereas for high SOC values voltage is more balanced between the cells. Similar to the voltage, the SOC of the single cell would also deviate. However, above 5% SOC the difference is negligible and the SOC provided by the BMS is expected to be the average value. During the electrical test the charging current is equal to 24 A, whereas during the relaxation time the charging current is zero. Ambient temperature during the electrical tests is 23 ± 1 °C. Two tests are performed, one with battery temperature during the test equal to 32 ± 2 °C and one with 25 ± 2 °C.

4.3.2. Thermal test

This test is used to characterize the thermal parameters: $R_{th}$ and $C_{th}$. To ensure that the entire battery pack temperature is stabilized to $T_{out}$, the EV is parked in the laboratory for 5 days with a constant ambient temperature of 23 °C and SOC equal to 60%. The test consists of continuous charging and discharging cycles of the battery pack, between 55 and 65% SOC, and a constant current magnitude. This procedure is cycled until battery temperature reaches a stable value. The current during the test is approx. ±24 A, with a positive value when discharging and negative when charging.

4.3.3. Driving test

This test is used to validate the electrical dynamics of the battery. The vehicle cannot be driven outside the laboratory, and measurements are collected as described in Section 4.2. Thus, a simulated cycle is performed by considering the ±10 kW charger available in the laboratory. The vehicle was discharged from 100 to 20% SOC considering a driving cycle scaled to the available charging/discharged power, keeping power variations limited to ±10 kW.

4.3.4. Charging test

This test is used to validate the thermal dynamics of the battery. The vehicle is charged with a 20 kW charging power from 5% to 97% SOC. The charging consists of two phases, a constant current phase and a constant voltage phase [31].

4.3.5. Capacity tests

They were performed six times since the battery was purchased in summer 2018: on 14/11/18, 8/11/19, 9/10/20, 4/6/21, 3/9/2021, 4/4/2022. They consist of an entire charge of the battery pack. Before the charge, the EV battery is fully discharged through the auxiliary loads of the vehicle to measure the entire capacity [31]. Due to the temperature and C-rate dependency of battery capacity [35], charging sessions are performed in the working condition of EV batteries: with C-rate of 0.2 and battery temperature between 20 and 30 °C. During the first four hours of the test the current is constant and equal to 24 A, while battery pack voltage increases from 280 to 403 V. During the last 30 min the voltage is constant and the current gradually decreases from 24 to 0 A. Battery capacity is calculated through the integral of the difference between the current at the battery pack (point A) and the current at the 12 V auxiliary battery (point B) (see Fig. 3).

5. Parameters derivation

The electrical and thermal parameters of the battery model presented in Section 3 were derived through the respective tests described in Sections 4.3.1 and 4.3.2, respectively. In this section, the methodology of parameter deviation is detailed, and the calculated values are presented.
5.1. Electrical parameters

The current interruption method [21] is applied at different SOC values to determine the electrical parameters of the battery. The method can be analysed in three stages. The first when the EV is being charged, and the current is flowing in the battery pack \( (t < t_0) \). The second happens almost instantaneously at \( t = t_0 \) when the current is stopped and the voltage drops suddenly. Let the subscripts \((\cdot)_0\) and \((\cdot)_1\) denote the time immediately before and after a time instance, respectively. The third happens when voltage decreases until it reaches a steady state at \( t = t_1 \). \( R_0 \), \( R_1 \), \( V_{oc} \) and \( C \) are determined at a certain SOC and temperature by using the measurements of \( V \) and \( I \) as follows:

\[
\begin{align*}
R_0 &= \frac{\Delta V(t)}{\Delta I(t)} = \frac{V(t_0) - V(t_{0+})}{I(t_0) - I(t_{0+})} \quad \text{(20)} \\
V_{oc} &= V(t_1) \\
V_{oc} &= \text{equal to } V(t_1).
\end{align*}
\]

Considering 3\( r \) as the relaxation time, i.e., the necessary time for voltage to get inside the band \( V_{oc} \pm 0.05|V_{oc} - V(t_{0+})| \), \( R_1 \) and \( C \) are derived from:

\[
\begin{align*}
3r &= 3R_1 C \\
V(t_{0+}) - V_{oc} &= \frac{V_{oc} - V(t_0)}{I(t_0)} = R_1 . \quad \text{(21)}
\end{align*}
\]

Fig. 5 shows the measured voltage, current, and SOC during the current interruption method when the SOC is equal to 23.5% and average battery temperature equal to 32°C. When the current of 24 A is interrupted at \( t_0 \), there is an instantaneous voltage drop caused by \( R_0 \), and thus:

\[
R_0 = \frac{347.90 - 346.15}{24.16 - 0.00} = 72.43 \text{ mΩ .}
\]

For \( r > t_0 \) the presence of \( R_1 \) and \( C \) causes a voltage drop with an exponential dependency from \( t_0 \) to \( t_1 \), when the capacitor is completely discharged and the voltage reaches the steady-state value. \( V(t_1) \) corresponds to the open-circuit voltage \( V_{oc} \). The time period required for the voltage to enter the band \( V_{oc} \pm 0.05|V_{oc} - V(t_{0+})| \) is 3\( r \), see Fig. 5. The first subplot also shows the fitted curve (in red), which verifies that the investigated battery can be characterized by a single RC block, as described in Section 3.1.1. For other batteries additional RC blocks may be needed and their values can be similarly derived by dividing the voltage decrease into multiple steps. 3\( r \), \( R_1 \) and \( C \) for SOC = 23.5% are determined by:

\[
\begin{align*}
3r &= t_2 - t_0 = 4384 - 3980 = 404 \text{ s} \\
R_1 &= \frac{V_{oc} - V_{oc}}{I_{oc}} = \frac{346.15 - 343.90}{24.16} = 93.13 \text{ mΩ} \\
C &= \frac{3r}{3R_1} = \frac{404}{3 \cdot 93.13 \cdot 10^{-3}} = 1446 \text{ F}.
\end{align*}
\]

Furthermore, the plot shows that the measured voltage \( (V) \) reaches a constant value before \( t_1 \) and thus the 10 min relaxation time is long enough to calculate \( V_{oc} \). The electrical parameters are determined with the same procedure for the SOC values listed in Table 1 between 20 and 90% SOC, whereas intermediate values can be derived via linear interpolation. The table provides the results for two average battery temperatures of 25 and 32°C. For the missing measurements, below 20% SOC the values are extended from experimental results and voltage-capacity characteristics of the Nissan cells [36], and by linear extrapolation for SOC larger than 90%. Fig. 6 shows the \( V_{oc} \)-SOC relationship.

Considering 96 cells in series and 2 in parallel of the battery pack, the average cell resistance ranges between 3 and 6 mΩ, which is comparable with the similar Kokam 53 Ah SPLB 120216216 Li-ion NMC pouch cell [37] with values between 2.5 and 4 mΩ. Similarly, the average capacitance per cell can be derived from the battery pack values. This ranges between 35 and 96 kF, comparable with the values measured for similar NMC cells with 36–60 Ah capacity [18].

5.2. Thermal parameters

The battery pack temperature sensors are positioned on critical points to ensure safe operation. Fig. 7 shows \( T_{out} \) and the three battery temperatures measured by the sensors of the RMS (\( T_1 \), \( T_2 \), \( T_3 \)) during the thermal test. All temperatures show a first-order time response over the 34 h testing period. They reach the following steady-state values: \( T_{in} = 38.5 \°C \), \( T_{2in} = 36.5 \°C \) and \( T_{3in} = 33.5 \°C \). In this model, the intermediate temperature \( T_2 \) is taken as the most representative temperature.

3\( r \) is the time required to reach 95% of the temperature difference between the initial temperature \( T_0 \) and the steady-state value \( T_{oc} \). As shown in Fig. 7, a \( T_2 \) value of 35.85 \°C is reached after \( 3r = 27 \text{ h} \), thus \( r = 9 \text{ h} \). The thermal resistance is calculated as:

\[
R_{th} = \frac{T_{in} - T_{out}}{T_{in} - T_{out}} = \frac{T_{in} - T_{out}}{(R_0 + R_x^*)T_x^2}.
\]

where \( T \) is the average absolute current value during this test, equal to \( 24 \text{ A} \). \( R_0 \) is the average value of the resistance when the SOC is between 55 and 65%. \( R_x^* \) is derived by fitting the value that minimizes the error between the measured and simulated temperature, eventually leading to \( R_{th} = 0.169 \text{ K/W} \). \( T \) is the mean value of the measured absolute current.

The thermal capacitance is then derived as:

\[
C_{th} = \frac{3r}{3R_{th}} = \frac{27 \cdot 3600}{3 \cdot 0.169} = 191716 \text{ J/K}.
\]
From $R_{th}$ and $C_{th}$ we can derive $k$ and $c_p$. Considering the battery pack as a large homogeneous cell, with a thickness of 136 mm, length of 1188 mm and width of 816 mm [25], $k$ is derived via (24):

$$k = \frac{D}{4S R_{th}} = \frac{0.136}{4 \cdot (1.188 \cdot 0.816) \cdot 0.169} = 0.21 \frac{W}{m \cdot K}.$$ 

Despite the approximations for deriving $k$, the final value is in line with previous studies [23, 38, 39]. Similarly, $c_p$ is derived as:

$$c_p = \frac{C_{th}}{m} = \frac{191716}{208.8} = 918 \frac{J}{kg \cdot K}.$$ 

where $m$ is the sum of the weight of the 24 modules (8.7 kg per module), without considering steel boxes, plates, wire harnesses and electronics. The derived value is following literature values of NMC Li-ion pouch batteries, typically between 700 and 1300 J/(kg K) [23, 38].

6. Model validation

In this section, the results of the presented models are compared with the tests performed in the laboratory. The tests are performed without disassembling the battery from the EV.

6.1. Electrical and thermal testing

6.1.1. Electrical test

The electrical test previously considered to determine the electrical parameters is here used to show the importance of accounting for the aging dynamics considerations in the model. First, the measured values during the electrical test are compared with the model output. The input of the model is battery temperature and electrical power measured during the test. The measured voltage, current, and SOC values during the electrical test are shown in Fig. 8 with black curves. In the same figure the percentage errors of the measured values against the ones obtained by our proposed model are depicted. Remember that the electrical dynamics are influenced by the battery capacity through the SOC formulation. Thus, capacity needs to be adjusted in (4) by using the estimated value from the proposed aging model. For this reason the error values without capacity adjustment are indicated by subscript $Q_w$, and with adjustment by $Q_a$. The original capacity is equal to 115.44 Ah. During the electrical test, the estimated value is equal to 109.5 Ah (1.2 years elapsed) (see Fig. 12). Fig. 8 shows how errors evolve over time. The resulting errors when using the proposed adjustment of the battery capacity are negligible for most of the test. Larger errors are observed during the first hour due to the extrapolation of the electrical parameters for SOC below 20%. Further research is ongoing to determine electrical parameters for lower SOC values by including measurements from the BMS.

6.1.2. Driving test

Fig. 9 shows the results of the driving test, where the battery was discharged from 100 to $\sim$20% SOC while performing a simulated driving test. The figure provides on the left axis the measurements of voltage, current, and SOC, and on the right the percentage error between measurements and model output. For better illustration only the error with adjusted battery capacity (105.2 Ah) is provided. Test results validate the accuracy of the electrical model, leading to voltage, current and SOC estimation errors below 2%.

6.1.3. Thermal test

The measured values during the thermal test are compared with the model output. To validate the accuracy of the thermal model the
measured voltage, current, SOC, and outside temperature during the test are used, instead of the relevant output from the electrical model. In Fig. 10 the simulated vs the measured temperature of the considered sensor are shown. Errors are larger for the thermal model, compared to the electrical, but still below 5%. If the output of the electrical model was used (instead of the measured values), the adjusted battery capacity should be considered.

6.1.4. Charging test

Fig. 11 shows the measured temperature of the battery on the left axis and the error difference between measured and modelled temperatures on the right axis. It should be highlighted that thermal dynamics are a function of the joule losses, derived as in (6). These are dependent on the electrical parameters, whose characterization has been developed for an average 25 and 32 °C and linearly extrapolated for the remaining temperatures. Despite the error being limited to 5%, a further characterization of the electrical dynamics at lower temperatures would further improve the thermal model behaviour.

6.2. Capacity testing

The investigated EV is parked in the university laboratory, has only been driven 43 km since 2018, and has been used a few times per year for experiments. Due to limited usage, the battery power is always zero, except during the tests. Fig. 12(a) shows the SOC during the 4 year lifetime and the points in the time where the tests occurred. Ambient temperature in the laboratory is on average 21 °C with small variations. Since the EV is rarely driven, degradation is predominantly caused by calendar aging. Even under frequent charging and usage, calendar aging is expected to be the major degradation factor during the first years [31].

Fig. 12(b) provides the measurements with the fitting curve (Meas), the BMS readings with the fitting curve (BMS read), and the model (Model) results. The capacity decrease from the first measurement (1 year elapsed) to the final (4.4 years elapsed) corresponds to 3.3% for the BMS reading, 2.8% for the measurements and 3.9% for the model. This results in an estimated capacity decrease deviation of up to one percentage point from both measurements. Multiple reasons can explain such differences, and while we may not be able to exactly weigh each, we wish to offer several discussion points:

- The battery construction day is not provided to users. Also, battery SOC during the first months of the vehicle is unknown. In our case, the vehicle was registered in Denmark in Summer 2018 and was previously used as an exhibition car. Since the production of the LEAF 40 kWh began in Japan in October 2017, it is considered that the vehicle was 1 year old during the first measurement in December 2018. It is assumed that SOC during the first year was approximately 70%.

- The initial capacity assumed in the model is 115.4 Ah. This value, not disclosed by the manufacturer, has been derived from the BMS. Furthermore, the capacity of a battery is a function of the temperature and its exact definition is left to the individual manufacturer, as explained in the IEC standard 62660 part 1 [40].

- With the capacity test we measure the usable capacity. Usable and total capacity coincide if the EV manufacturer does not limit the former with buffers, whose presence may not be known to the user and can change over time.

- During the measurements the SOC never reaches 0 or 100%, because it is not possible to completely discharge the EV below 1% and not charge it above 98%. Therefore, the capacity measured during the charging process may have to account for the fact that the charging session cannot include the whole SOC range and that the complete capacity, although not accessible to the user, should include that additional 3%.
Since the only way to measure total capacity would be to disassemble the battery pack from the EV, further research is undergone to understand and quantify the impact of EV manufacturer choices on capacity measurements [27].

7. Conclusion

This article proposes a methodology to model and validate electro-thermal-aging dynamics of EV Li-ion battery packs, without disassembling them from the EV. The methodology consists of three phases. The first is modelling the battery pack as a large homogeneous cell, including three main dynamics—electrical, thermal and aging—and their interdependency. The second is the derivation of electrical and thermal parameters of the EV battery pack by laboratory tests. After the characterization, during the third phase, the model is validated. Here the model is simulated considering as input the battery power and temperature measured during the tests, and the model output is compared with the measured values. Even though the dynamics have a different time constant, fast for electrical and slow for the thermal and aging, results show that it is relevant to consider their interactions.

The primary objective of this work is to attempt the first step towards developing and validating a simple-to-realize EV battery pack model for power system applications. During the model implementation and field measurements, multiple obstacles were encountered, opening new research questions. First, electrical parameters dependency on temperature and aging should be further investigated, also accounting that measurements are performed on EV batteries, where temperature is not constant and homogeneous during the measurements. Second, temperature in different battery locations can deviate up to 5 °C during usage, and this should be accounted in future work possibly by dividing the battery into sections, to determine more precisely if and where the battery degrades faster. Third, the measured battery capacity in this work is only influenced by calendar aging. Our future work will also consider cycle aging, but in that case, disaggregating the effect of each of the two degrading factors is a challenging task. Our next main goal is to validate the performance of the proposed model on other EVs with different battery chemistry, and investigate to what extent such a model can be generalized.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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