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Second Life Batteries in a Mobile Charging Station: Model Based Performance Assessment

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Abstract
Lithium-ion batteries are seen as key elements to reduce global greenhouse gas emissions of transports and energy sectors. Nevertheless, efforts still have to be made to minimize their environmental impact. This article presents a pathway towards circular economy and more sustainable batteries, thanks to their reuse in mobile charging stations for electric vehicles. This work provides the characterization tests results and the modelization of second life batteries in a mobile charging station. Characterization test and electric models presented may be used as references to assess aged batteries performances after their first life. Detailed tests procedures and data results are shared in an open access datapaper.
Keywords:
Battery, Reuse, Charging, Sustainability, Modeling, Equivalent Circuit Model, Open Science

1 Introduction

Mitigating the climate change is seen as the major challenge for 21st century. According to the last Intergovernmental Panel on Climate Change report, transport and electricity production account respectively for 18% and 36% of the global greenhouse gas emissions [1]. To reduce this pollution, electrified vehicles and renewable energies are presented as interesting options. For these usages, lithium-ion batteries are key energy storage elements [1, 2].

Nevertheless, to date there are no sustainable batteries. That is to say that none lithium-ion batteries technologies can be manufactured without depleting natural resources while ensuring that it remain available and affordable for many generations to come [3]. To approach this ideal goal, it is paramount to develop solutions to reduce the detrimental impacts of both the batteries already on the market and the future generations.

The waste management hierarchy presented in figure 1 establishes an order of preference for action to reduce and manage waste [4]. Reduction, reuse, recycling, recovery and disposal are the actions that should be set up to reduce the environmental impact of a product.

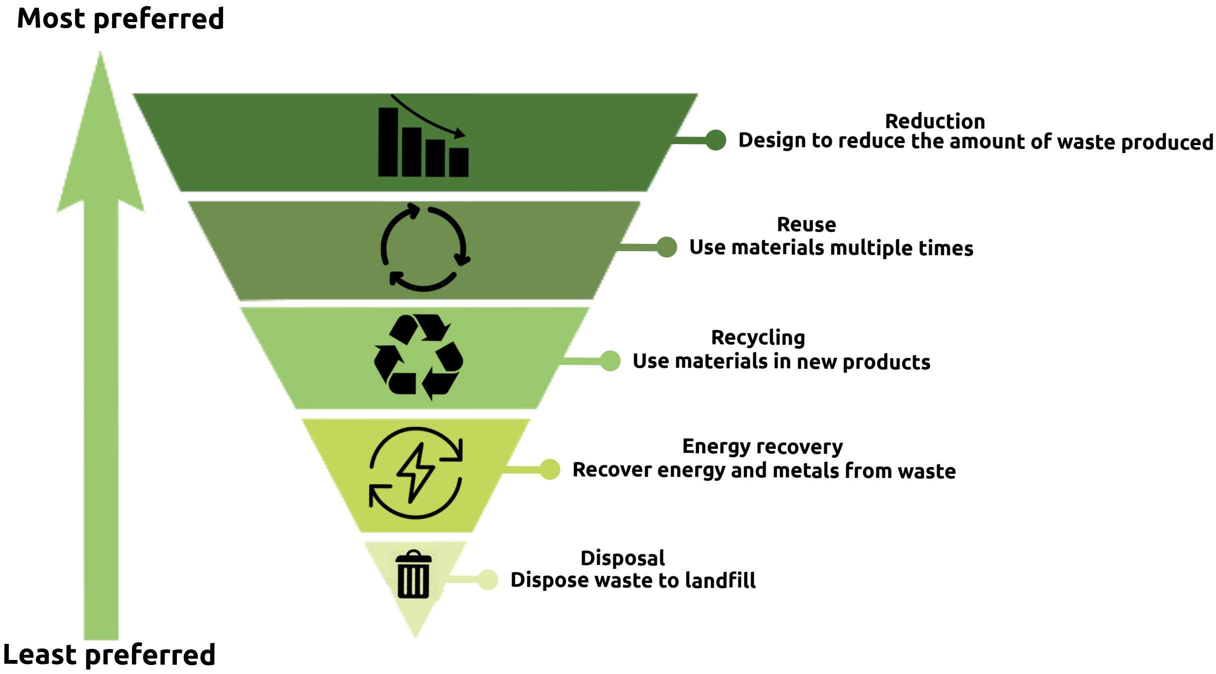

Figure 1: Waste Management Hierarchy. Adapted from [5]

Reduction is the most preferable action, it consists in designing the product in order to limit the waste it will generate at its end-of-life. In the context of batteries, reduction consists in minimizing the quantity of materials used in a battery in others words in reducing the battery size. Electric vehicle powered by smaller batteries would be more economic and more environmentally-friendly [6, 7]. However, such vehicles would have shorter driving ranges and would be more dependent on charging infrastructure.

To enable this shift, developing a reliable charging network is necessary to reduce ”range anxiety”. Mobile chargers are a solution to strengthen the existing infrastructure system. A mobile charging station can be defined as a charger capable of delivering energy autonomously to vehicles, that is to say without support from a human and with no need of an external energy supply. This technology has the advantage of maximizing the utilization rate of the charging station as these chargers are capable of moving from one vehicle to another. They also provide a more flexible charging solution as they are designed for being deployed quickly at any location and with the possibility to adapt the energy embedded and the duration of the stay to the drivers needs [8, 9]. The figure 2 presents two mobile charging stations.

Figure 2: Mobile charging stations from Mob-Energy [10] and Volkswagen [11]

As the energy stored by these robot-like chargers is limited, they should be considered as a complementary technology to the existing ones. To date, the existing mobile charging stations can deliver up 30kWh at a maximal charging speed of 50kW [8]. Powering these mobile charging stations by reused batteries is possible and would be a step further towards circular economy. Reuse can be defined as the complete or partial re-use of the battery for the original purpose the battery was designed for [12]. Reused batteries are commonly named ”second life batteries” in the literature.

This article investigates the deployment of reused batteries in power mobile charging stations. It presents an electric characterization test and two electric models that may be used as reference to assess and emulate reused batteries performances over time. This experimental and modeling work contributes to the existing literature regarding second life batteries as it is the first to assess and model the performance of a high-capacity prismatic cell extracted from real second life electric vehicles battery modules and used in a dynamic application: a mobile charging station. It is also the first one to share experimental data on second life batteries and provides the software used to analyze these data [13, 14].

2 Methodology

This section presents the equivalent circuit models used in the study and the experiments conducted to calibrate them. The work presented can be divided into three parts. First, two equivalent circuit models capable to emulate the voltage response of a lithium-ion cell are introduced. Then, the experimental tests used to identify the models parameters are presented. Finally, the accuracy of each model is validated thanks to cycles which are representative of a real mobile charging station usage. An extensive description of the cells and setup characteristics as well as the tests procedures and quality check are shared in a datapaper [14].

2.1 Equivalent Circuit Models

Estimating accurately the voltage response of a lithium-ion cell over time is paramount in most applications. Indeed, thermal management, energy management and balancing strategies efficiencies strongly depend on the estimation accuracy [15, 16, 17].
In a large number of industrial applications where real-time control is needed, electric models are preferred over electrochemical [18]. Their capability to emulate accurately the voltage with limited computational load make them suitable for embedded applications. Additionally, it is possible to characterize them with non-destructive methods which is indispensable to limit the amount of wasted batteries.

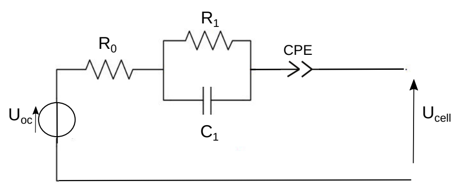

Figure 3: CPE model

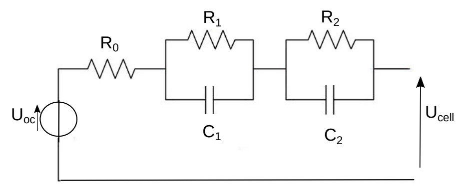

Figure 4: RC model

In this article, two equivalent circuit models have been chosen. The first one is presented in figure 3 and will be named ”CPE model”. It consists of an open circuit voltage (OCV) source in series with three elements: a resistance R_0 which models the ohmic behaviour, a RC circuit for modeling the charge transfer and double layer processes and a Constant Phase Element (CPE) associated to the diffusion behavior [19].

The second model is presented in figure 4 and will be named ”RC model”. It consists of a voltage source OCV in series with a resistance R_0 which models the ohmic behavior, a RC circuit for modeling the charge transfer and double layer processes and a second RC circuit associated to the diffusion behavior [20]. To maximize the model accuracy during relaxation, adding more RC circuits would be necessary [21]. Nevertheless it would also drastically increase the computational time for more advanced simulation using this model [22].

2.2 Experimental Setup

In this study, a second life SAMSUNG SDI 94Ah cell with NMC positive electrode have been tested at 0, 25 and 40°C. This cell have been extracted from a BMW I3 module bought on the second life battery market. Experimental setup was made of a Bitrode Battery Testing System and two climatic chambers (Vötsch VT 3050 and Friocell 707).

Table 1 presents the characterization test protocol at a single temperature and figure 5 is the voltage profile of the test.

Table 1: Reference characterization test

Step	Test	Estimated duration (h)
1	Capacity test	18
2	Impedance test	8
3	Pseudo OCV test	42
4	Mobile charging station cycles	12

Step 1 is a capacity test, it consists of a serie of three full charge/discharge cycle. The mean value of the three measurement is considered for the capacity measurement. Step 2 is an impedance measurement thanks to a serie of current pulses at different state of charge (20, 30, 40, 50, 60, 70, 80 and 90%) and current levels (0.3C, 0.5C, 0.8C, 1C and 1.3C).

Step 3 is a pseudo-open circuit voltage measurement thanks to a full discharge/charge at C/25. Finally, step 4 is the validation cycles used to assess the models accuracy in a mobile charging station usages. The validation profile and result are precisely described in the section 3

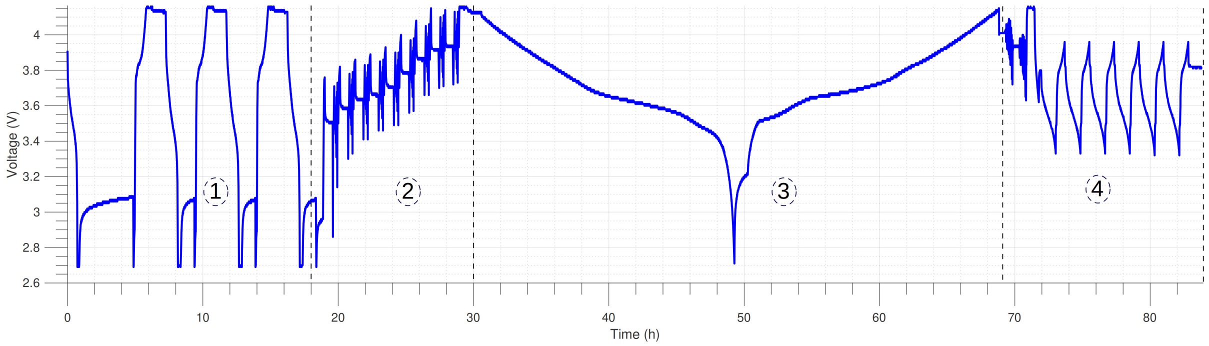

Figure 5: Voltage profile of the test

2.3 Model identification

For each temperature, the models RC and CPE parameters are identified in four steps.

First, the capacity is calculated according to the equation 1. The mean value of the three measurement in step 1 is considered.

$$Q(t) = \frac{1}{3600} \int_{t_0}^{t} i(t)dt \tag{1}$$

$Q(t)$ is the capacity (Ah), t is the time of a cycle charge/discharge (s) and i is the current in the cell (A).

Second, the state of charge is computed according to the equation 2.

$$SoC = 100 * [SoC_{t0} + \frac{1}{3600 * Q_{nominal}} \int_{t_0}^{t} i(t)dt] \tag{2}$$

SoC is the state of charge of the cell (SoC=100% if the cell is fully charged and SoC=0% if the cell is fully discharged), SoC_{t0} is the initial cell state of charge and $Q_{nominal}$ is the capacity given on the datasheet (Ah).

Then, the open circuit voltage is determined thanks to the step 3 of the test. It is calculated by averaging the low-rate charge and discharge voltage curves, this technique is known as pseudo-open circuit voltage [23].

Finally, the impedance parameters are identified. The resistance R_0 which models the ohmic behaviour is determined first as it has the shortest dynamic. This impedance is determined from the voltage drop presented in the figure 6 .

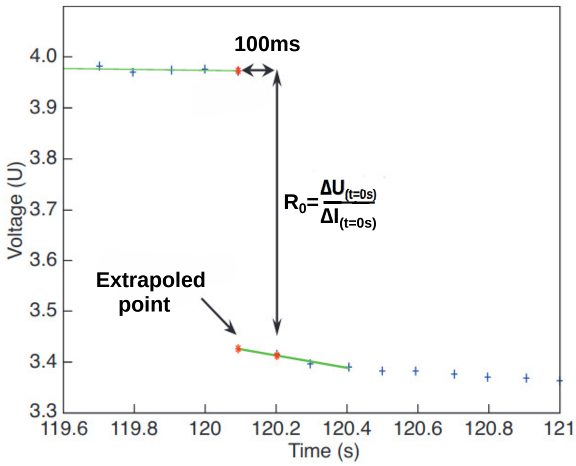

Figure 6: R_0 determination. Inspired from [19]

As the battery cycler sampling frequency may be not high enough to have numerous data points during the front voltage, a linear extrapolation is done for.

The charge transfer and double layer impedances are numerically determined by minimization of the quadratic error between the voltage output of the model and the response of the cell [19]. The equation 3 and 4 respectively present the error function for the RC and the CPE models.

$$error_{RC} = U_{cell} - [OCV - I_{cell}(R_0 + R_1 + R_2) + I_{cell}(exp(\frac{-t}{R_1C_1})exp(\frac{-t}{R_2C_2}))] \quad (3)$$

$error_{RC}$ is the error between the experimental measurement and the model simulation (V), U_{cell} is the cell voltage measurement (V), OCV is the open circuit voltage (V), I_{cell} is the current in the cell (A), R_0 is the resistance which models the ohmic behavior (Ohm) and t is the time (s). $R1$, $C1$, $R2$ and $C1$ are the parameters to calibrate to minimize the error.

$$error_{CPE} = U_{cell} - [OCV - I_{cell}R_0 - I_{cell}\frac{t^{\alpha}}{Q\alpha!}] \quad (4)$$

$error_{CPE}$ is the error between the experimental measurement and the model simulation (V), U_{cell} is the cell voltage measurement (V), OCV is the open circuit voltage (V), I_{cell} is the current in the cell (A), R_0 is the resistance which models the ohmic behavior (Ohm) and t is the time (s). Q and α are the parameters to calibrate to minimize the error [24].

3 Results

In this section, the experimental and simulation results are presented. All the data presented have been processed thanks to the software DATTES [25].

3.1 Experimental results

The figure 7 presents the open circuit voltage measured in step 3 as a function of depth of discharge at 0, 25 and 40°C.

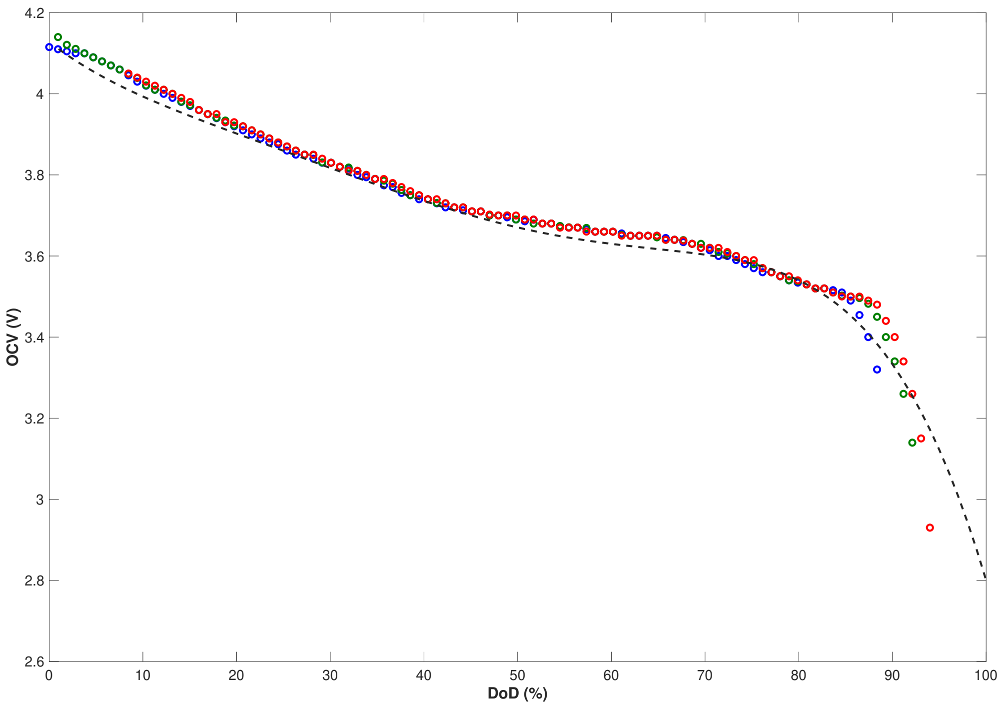

Figure 7: Experimental OCV-DoD relationship curves for second life battery at 0°C (blue dot), 25°C (green dot), 40°C (red dot) and the datasheet OCV-DoD relationship curve at 25°C (dashed line)

In the datasheet, the open circuit voltage is measured thanks to a galvanostatic intermittent titration technique at 1/3C. This methodology is more precise than the pseudo-ocv as it is not subject to current polarization.
The table 2 gathers the capacities measured during the step 1 at 0, 25 and 40°C.

Table 2: Capacity measurements and state of health at 0, 25 and 40°C

Temperature	0°C	25°C	40°C
Second life cell Capacity (Ah)	86	92.1	93.1
Datasheet Capacity (Ah)	No data	95.2	95.7
State of Health Capacity (%)	Unknown	96.7	97.3

The capacities given in the datasheet have been measured in charge with a CC/CV profile and a 1C current. This methodology is very close from the one used in this work. A state of health "capacity" can consequently be calculated thanks to the equation.

$$SoH_Q = 100 * \frac{Q(t)}{Q_{nominal}} \tag{5}$$

SoH_Q is the state of health "capacity" (%), $Q(t)$ is the capacity measured during the test (Ah) and $Q_{nominal}$ is the nominal capacity (Ah).

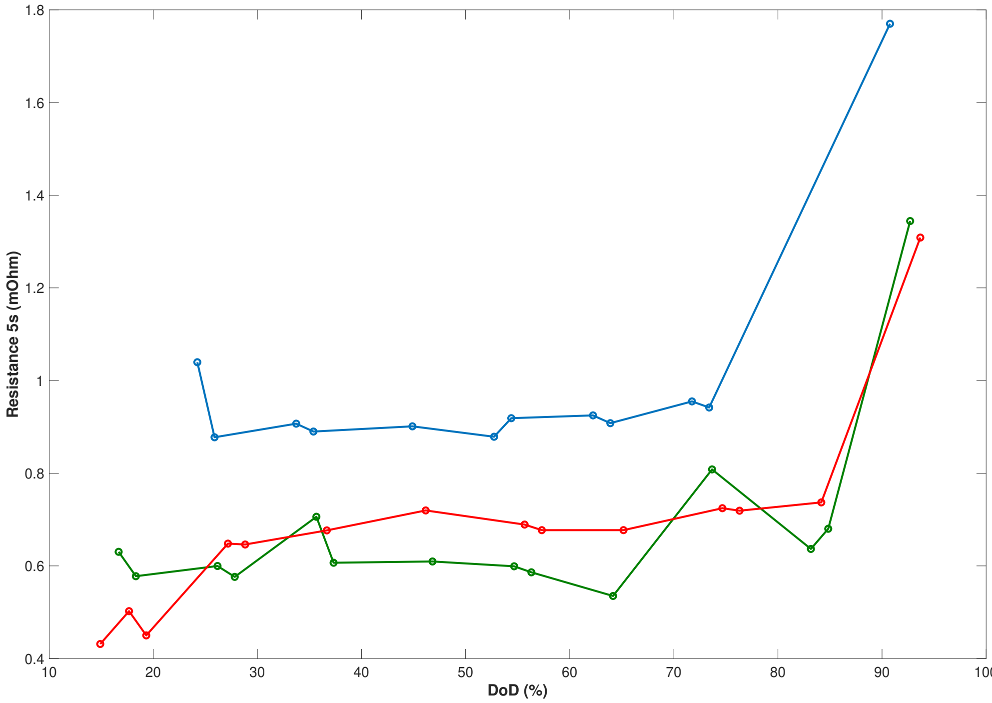

Figure 8: 5 seconds experimental resistance at 1C and 0°C (blue line), 25°C (green line), 40°C (red line)

The resistance given in the datasheet can not be compared to the measurement because they have been measured at 413A and 294A while in the step 2 the maximal current was 122A.

3.2 Validation profile

The section 2.3 have presented the identification of the models parameters, which consisted in determining each parameter separately thanks to a part of the characterization test. In this section, the different parameters are gathered to form the models RC and CPE and run simulation.

A mobile charging station's usage profile inspired by real ones have been used to compare the models capabilities to emulate the voltage response of the reused batteries. The real usage profiles have been provided by the company Mob-Energy.

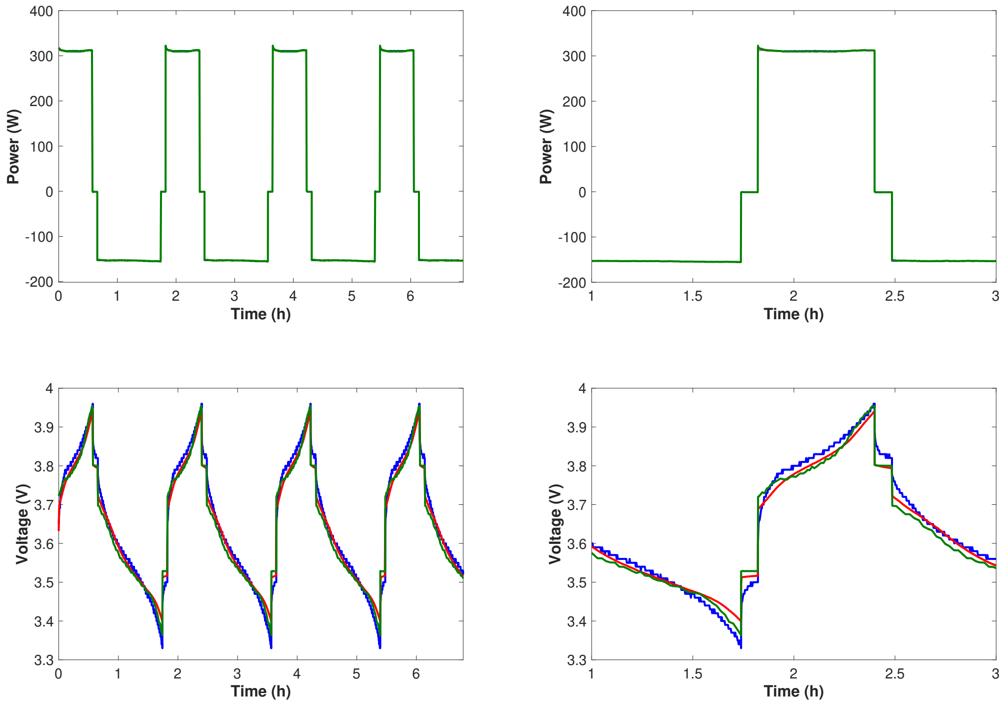

Figure 9: Experimental data (blue line) compared to simulation results for the CPE model (green line) and the RC model (red line) at 25°C

Figure 9 (a) and figure 9 (c) present the mobile charging station usage profile with power levels given for a single lithium-ion cell. The voltage response of a cell is also presented in figure 9 (b) and figure 9 (d) .

The usage profile plotted on figure 9 (c) is a power profile. It is composed of a high power discharge (about -150W) which corresponds to the energy transfer from the charger to the vehicle. Then, the robot-like charger moves to charge on the grid which corresponds to the low power discharge (almost 0W). Finally, the mobile charging station is charged by the grid at approximately 300W. It can now move to the next vehicle to charge. This pattern is repeated 3 times in a 6 hours time slot as presented in figure 9 (a).

3.3 Model accuracy analysis

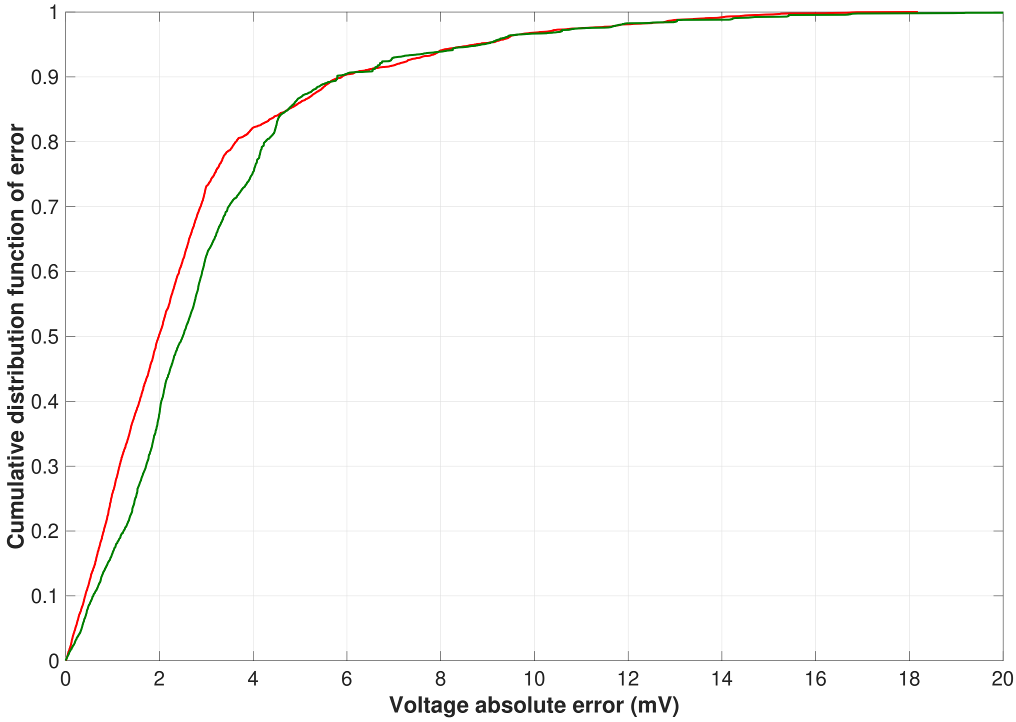

Figure 10: Cumulative distribution function of error probabilities for CPE model simulation (green line) and RC model simulation (red line)

Figure 10 presents the error distribution functions of the models. For both the CPE model and the RC model, the simulation error is lower than ± 6mV, ± 10mV and ± 16mV in respectively 90, 95 and 99% of the profile. These levels of accuracy are in the order of magnitude of other electric models in the literature [19, 20, 26]. To improve the models accuracy, the parameters responsible for the voltage dynamics especially during relaxation, and end of charge and discharge should be optimized.

Table 3 shows that CPE and RC models have comparable absolute average error but simulation time is significantly in favor of the later. To run simulations with limited computation load, the RC model should be favored.

Table 3: Performance comparison of the models

	Simulation time (s)	Average absolute error (mV)
CPE model	91	5.5
RC model	30	4.7

4 Conclusion

This article presents a procedure for characterization and modelization through equivalent circuit models for second life batteries. The main experimental and modelization results are presented in this article. An extensive description of tests procedures and data test results are shared in a datapaper [14]. The software used in this study is called DATTES and is also open source [25].

This experimental and modeling work contributes to the existing literature regarding second life batteries as it is the first to assess and model the performance of prismatic high capacity cell extracted from a real electric vehicle battery pack. It also describes a new dynamic application for reuse: the mobile charging stations. The models presented have shown their capability to emulate accurately the voltage response of a SAMSUNG SDI 94Ah cell. Future works will aim to improve the accuracy of these models and investigate the evolution of the model parameters with ageing.

Acknowledgments

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Presenter Biography

Marwan Hassini was born in Saint-Malo, France, in 1997. He received the Master's Degree in electrical engineering from the University of Technology of Compiègne, France, in 2020. Since October 2020, he is a Ph.D. student in electrical engineering from the University of Lyon, France. His thesis is entitled: "Second life lithium-ion batteries in a charging robot: Aging study". Marwan Hassini's personal website gathers its whole scientific contributions: `https://mhassini.gitlab.io`