Chapter

Parameter Identification, Modeling and Testing of Li-Ion Batteries Used in Electric Vehicles

Mircea Ruba, Raul Nemeș, Sorina Ciornei and Claudia Marțiș

Abstract

The chapter focuses on presenting a detailed step-by-step workflow for theoretical and practical approach of Li-ion battery electric parameter identification. Correct and precise information about the electric parameters of the batteries allows defining several types of simulation approaches. Increasing the complexity of these approaches requires more and more identified parameters and by this more complicated hardware to fulfill the identification process itself. However, the level of complexity must be justified by the need of accuracy as well as the compromise of labor, simulation power and time. In this chapter, several simulation complexity levels are presented via theory and then tested via simulations compared with actual measurements. A proper and well-done analysis of these models helps the future reader to decide whether he will use a complex model, function of the need of accuracy, simulation power and time. The compromise will be highlighted by comparing the error of different approaches compared to actual laboratory measurements. Over all, the chapter will be a gathered guideline for identification, modeling and testing of batteries, ready to be implemented both in simulation and in practical experiments.

Keywords: battery, parameter identification, simulation and modeling, model complexity benchmark

1. Introduction

Nowadays, the interest of research in the field of batteries, both from the electrical and chemical perspectives, gained a lot of field. Many R&Ds from both industry and academia are engaged in developing design, simulation, hardware testing and performance analysis solutions to better the existing batteries. Electrification of transport, both in the area of heavy-duty and light solutions, requires higher and higher performances of the batteries. This influences directly the autonomy of the vehicle reflecting directly the owner's comfort and trust in investing in such new vehicles. The research invested in batteries for increasing more power density into each cell comes with a lot of effort, it is time consuming and returns in higher costs. Nevertheless, thermal stability of the batteries is a very delicate issue, knowing unfortunate events that occurred when batteries caused fires and human injury as well.

The evolution of technology both in engineering and software, reduced the time to market and proper evolution of the batteries, increasing performances whilst diminishing the development costs. Solutions to study batteries are included in a large variety of software; models are already preprogramed into hardware power emulators, ready for use. However, those are often closed-source tools with access only to replace the battery parameters, many times with linear ones. It was proven in many studies that the main electrical parameters of the batteries are far from being linear. Even more, it is known that aging, cell temperature and ambient temperature are extremely aggressive in changing the battery parameters.

Hence, many times custom-made battery electric models are more than a good solution to run studies where the designer can add or dismiss many factors and parameters that are varying with several external influences. In the same time, designing such models simplifies the transition from off-line analysis to real-time applications. The latter tool is not always at the disposal of the designer due to platforms that are dedicated exclusively to computer-based simulators.

On the other hand, performing proper parameter identification of existing cell, to validate their theoretical design, can be quite challenging. There are many published papers that reflect these methods that some are quite simple and lucrative solutions, while others are complex and require expensive setup and a lot of data post-processing.

The present chapter will engage this issue of parameter identification for Li-ion battery cells and present the main used simulation models, and benchmarking of these models will give the reader a certain definition of the advantages and drawbacks of some models versus others. The chapter does not include information regarding the battery control strategies or battery management topics, remaining focused only on the above-mentioned subjects to be presented in detail. Also parameter variations due to large temperature variations or other stress factors were not taken into discussion as these variations can be recorded using the presented methods while imposing such external factors to the subjected battery cells.

In the authors' opinion, there are two main directions of judging the complexity of a model. If considering industrial work, engaging models with lower complexity and good accuracy, is a lucrative solution to reach the desired target not forgetting to decrease the time to market. On the other hand, in academia-based research, more complex models with very high accuracy is the key to prove the designer's skill, to prove the model's benefit and to push to reach a used solution on the large scale. The latter comes with the drawback of high complexity that demands large time consumption and a lot of involved labor.

In the present chapter, such a comparison will prove the above-mentioned aspects while comparing two types of different simulation models for the same type of battery.

2. Battery analysis models

As the batteries are electrochemical entities, there are several directions when approaching and building a simulation model to perform its behavioral analysis. The model can be designed from the chemical or electrical point of view or can be a hybrid mixture between them. Moreover, the battery temperature, as critical parameter, is often analyzed using a thermal model as add-on to the above-mentioned ones.

In the literature, an electrochemical approach is the pseudo-two-dimensional model developed by Doyle [1], which proved to be able to predict quite well the dynamics of Li-ion batteries. The main disadvantage of such a model is the high computational required time.

The authors will approach only the electrical simulation models for batteries due to their electrical engineering education. However, research on batteries should always be considered as a multidisciplinary domain, gathering researchers educated in chemical, electrical and thermal sciences in order to be able to perform a complete and realistic battery cell model.

In the literature, there are several approaches for the electrical simulation of battery cells [2–6]; mainly all are based on electric circuit models (ECM). Function of the battery chemistry, of the required model accuracy and of the designer, there are available simple circuits such as the Thevenin approach [7], complex ones, such as the impedance based spectroscopy approach [8] and middle range circuits such as the first and second order electric circuits [9–12]. The above-mentioned categories range their accuracy from satisfactory to highly precise.

The present chapter will approach the first- and second-order electric circuit-based modeling, detailing aspects such as model design, parameter identification and accuracy testing.

When using the expression that classifies these models into first and second order, these are referred to the number of parallel resistance-capacitance groups used to describe the battery.

In **Figure 1** (left and right), the generic electric circuits for the first- and second-order models, respectively, are depicted. Both have the first resistance in common

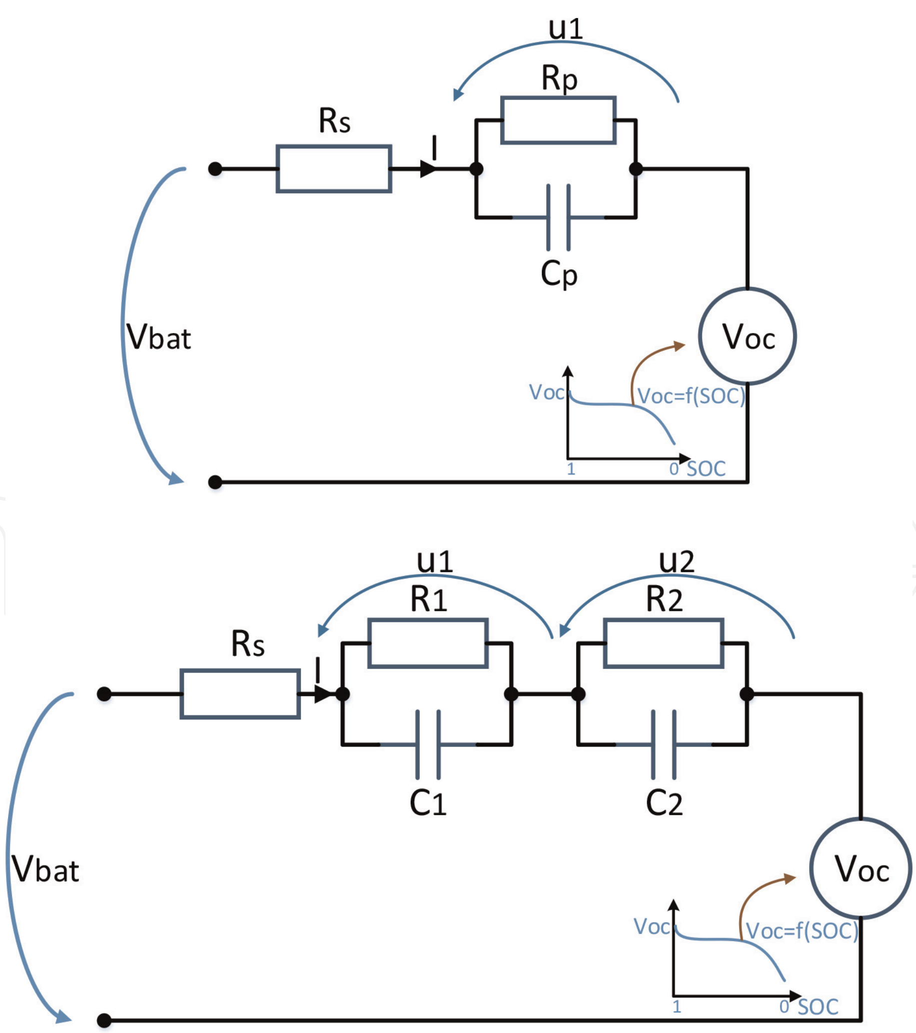


Figure 1.
The ECM for the first-order (top) and second-order (bottom) approaches.

(R_s), this being referred to as the internal series resistor that is responsible with the ohmic considered resistance of the battery cell. In **Figure 1** (left), in the first-order approach, the RC parallel group has the role of replicating the dynamic transient of the voltage inside the cell. Its components stand for the polarization resistance (R_p) and the polarization capacitance (C_p). The internal voltage source, denoted with (V_{oc}), represents the open circuit voltage of the Li-ion cell function of its state of charge (SOC).

Now in order to model the first-order ECM, first one has to apply Kirchhoff's law on the circuit, composed of tree voltage drops: the open circuit one, the RC parallel group and the series resistance one, explained in Eq. (1).

$$V_{bat} = V_{oc} - u_1 - R_s \cdot I_{bat} \tag{1}$$

In Eq. (1), the current drained from the battery (or supplied to it, in case of charging) is denoted with (I_{bat}). The voltage drop of the parallel RC connection is simple to be expressed like a derivative:

$$\frac{du_1}{dt} = -\frac{1}{R_p \cdot C_p} u_1 + \frac{1}{C_p} \cdot I_{bat} \tag{2}$$

The open circuit voltage (V_{oc}) represented function of the SOC of the cell is in fact a recorder data from actual cells; however, details about that will be explained later on in the following pages.

Comparing the two circuits depicted in **Figure 1**, one can conclude that in fact, the second-order model includes the first-order one having in addition a second RC parallel group. However, the concept is not straightforward. In the first-order model, the entire polarization dynamics are handled using one RC group. For the second-order model, this dynamical process is replicated using two such RC groups as it can be seen in **Figure 1**. The series resistance and the open circuit voltage components are the same as for the first-order model, while the (R_1C_1) and (R_2C_2) groups denote the activation polarization and the concentration polarization, respectively.

Hence, based on this circuit, the second-order model based again on Kirchhoff's law can be described using Eq. (3).

$$\begin{aligned} V_{bat} &= V_{oc} - u_1 - u_2 - R_s \cdot I_{bat} \\ \frac{du_1}{dt} &= -\frac{1}{R_1 \cdot C_1} u_1 + \frac{1}{C_1} \cdot I_{bat} \\ \frac{du_2}{dt} &= -\frac{1}{R_2 \cdot C_2} u_1 + \frac{1}{C_2} \cdot I_{bat} \end{aligned} \tag{3}$$

The analytical approach for the first- and second-order models described in Eqs. (1)–(3) are exposed as pure electric equations. However, it is known that the parameters used in this model, such as resistance, capacitances, open circuit voltage, or state of charge, must be identified from actual battery cells. Hence, in order to create a link between the analytical battery models and the identification process, both for the first- and second-order models, another approach can be engaged. This drives more forward the mathematical perspective of modeling dynamic signal variations. Using the exponential mathematical function, the models from the above-mentioned equations can be reorganized as follows:

- For the first-order model,

$$V_{bat} = k_0 - k_1 \cdot \exp(-a \cdot t) \tag{4}$$

where the terms (k_0), (k_1) and (a) can be identified from the above equations as coefficients

$$
\begin{aligned}
&k_0 = V_{oc} - R_s \cdot I_{bat} \\
&k_1 = \frac{R_1}{I_{bat}} \qquad a = \frac{1}{R_1 \cdot C_1}
\end{aligned}
\tag{5}
$$

- For the second-order model

$$V_{bat} = k_0 - k_1 \cdot \exp(-a \cdot t) - k_2 \cdot \exp(-b \cdot t) \tag{6}$$

where again by the same identification result the coefficients

$$
\begin{aligned}
&k_0 = V_{oc} - R_s \cdot I_{bat} \\
&k_1 = \frac{R_1}{I_{bat}} \qquad k_2 = \frac{R_2}{I_{bat}} \\
&a = \frac{1}{R_1 \cdot C_1} \qquad b = \frac{1}{R_2 \cdot C_2}
\end{aligned}
\tag{7}
$$

It is important to understand that using this second approach for both the models, one can simply link the battery characteristics to its parameters in order to be able to describe the complete model judging the correct interpretation of the measured values during the parameter identification process.

3. Battery parameter identification

The process of identifying the parameters that are then able to cope with the analytical model to describe the cell's behavior requires a preliminary hardware setup dedicated for such applications. There are several possibilities to build such a test bench. For the present study, the authors built a test bench based on a programmable electronic load and a programmable electronic supply, as depicted in **Figure 2**.

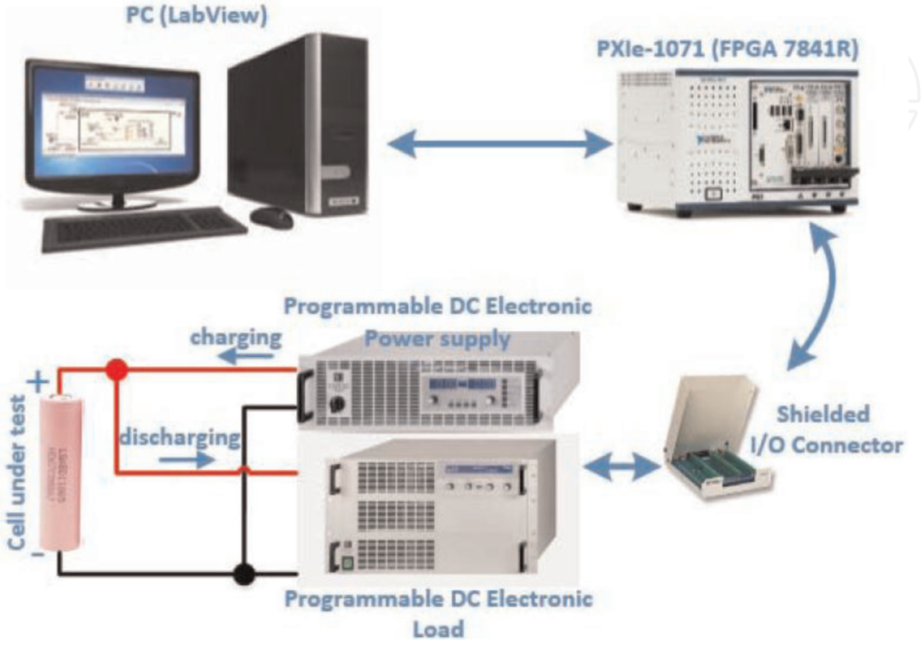


Figure 2.
The test bench for battery parameter identification process and testing.

The used battery to model is a LG (LGABD11865) battery with a rated capacity of 3000 mAh, 3.75 V rated, 4.2 V maximum over charge voltage, 2.7 V minimum discharge voltage, 0.5–1 A charging current and 0.2–0.5 A discharging current.

For the identification process, the battery was connected to a programmable load (EA-EL 9400–150 0–400 V 0–150A 7200 W). From a host computer, the battery was discharged at 1C from 100% state of charge (SOC) till it reached the cut-off voltage. The flowchart of the identification process is depicted in **Figure 3**. Preliminarily, the battery is charged to 100% SOC using a commercial charger. It is left then to relax for 24 h. Afterwards, it is connected to the programmable electronic load that is controlled by the host computer, used also to stream the V_{bat} and I_{bat} to data files, all versus the elapsed time.

The process starts by applying a 1C negative current pulse for a period of 60 s, by this starting the decay of the battery voltage as it is discharged. After the 60 s pulse, the cell is left in relaxation for 180 s. Before performing a new current pulse of 60 s, the battery voltage is compared to the lowest threshold (V_{trs}) of 2.7 V. If the voltage is larger than 2.7 V, the pulse is applied for another 60 s followed by 180 s relaxation period. If the voltage is less than 2.7 V, the process stops as the battery is considered fully discharged.

Through the entire process, while V_{bat} is larger than V_{trs}, the data is recorded and streamed to external files, with a sampling of 10 sample/s.

The resulted variation of the voltage function of the discharge current is depicted in **Figure 4**, where the 60 s length pulses of −3 A were followed by a relaxation period of 180 s. With such recorded data, one can proceed with the identification process for both first- and second-order model parameters.

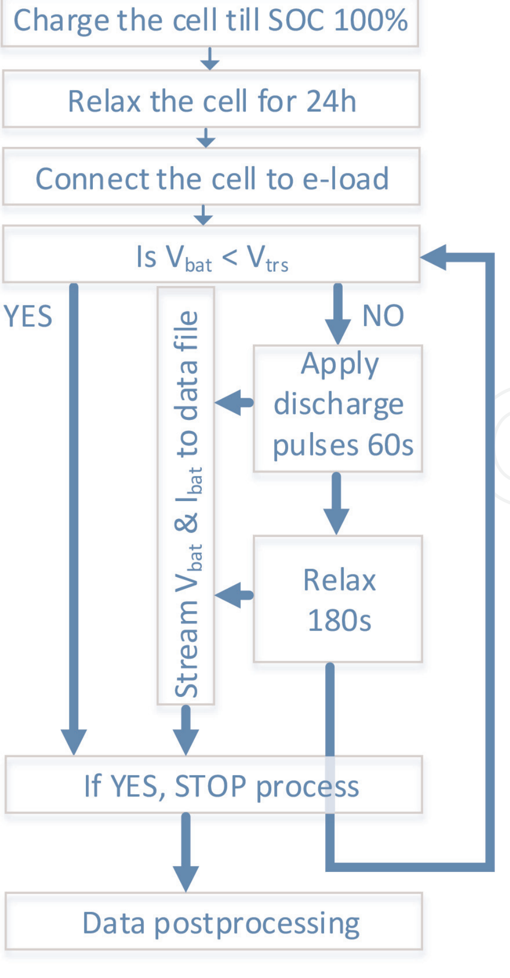


Figure 3.
The flowchart for the battery identification process data recording.

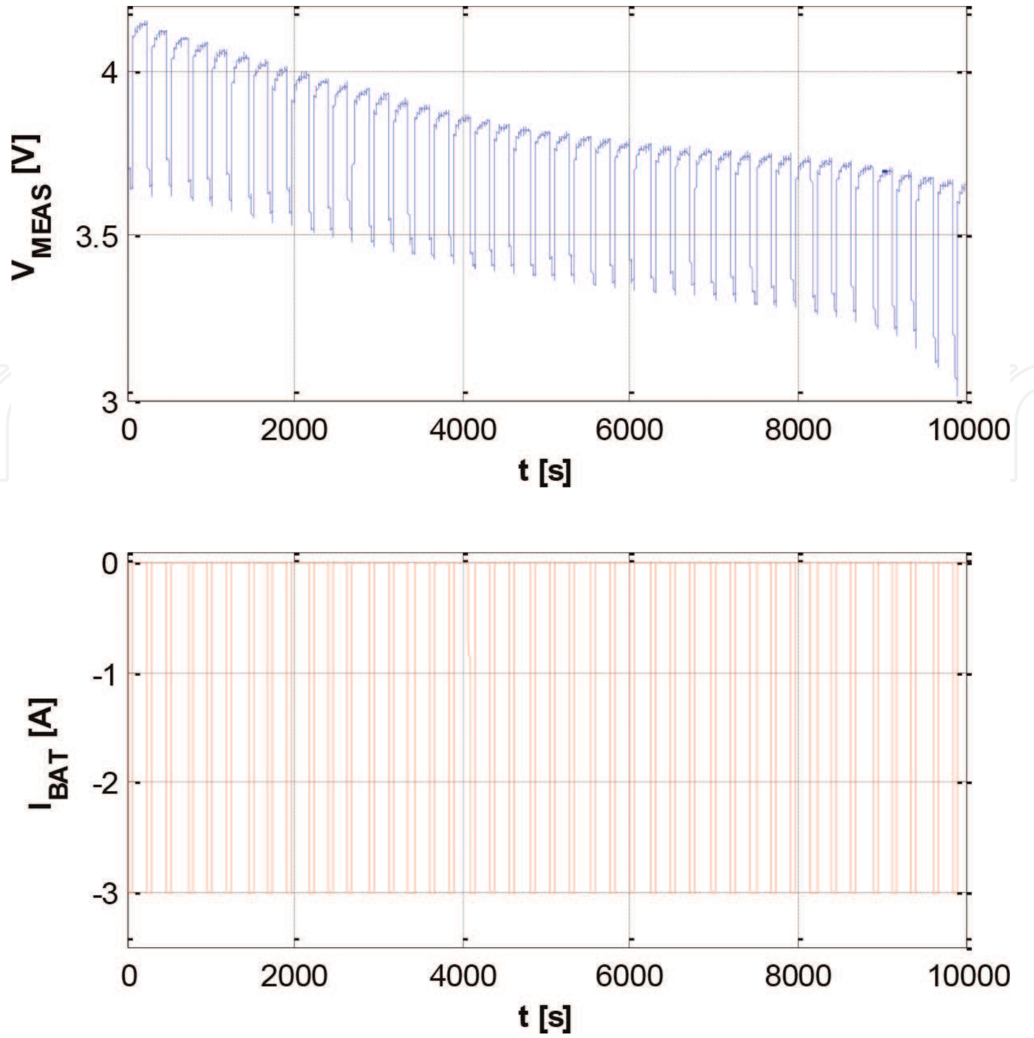


Figure 4.
The battery voltage (top) and the discharge current (bottom).

The data recorded into the external files is afterwards processed for the actual parameter identification of the Li-ion cell. Section 3.1 details all the necessary information for a clear hands-on methodology of data post-processing for parameter identification.

3.1 Open circuit voltage and series resistance identification

Independent for what type of circuit the designer wishes to build, first or second order, there are some parameters that are mandatory to be identified for both approaches. These parameters are the open circuit voltage (V_{oc}) and the series resistance (R_s). To understand their identification and role in the battery behavior, from **Figure 4**, the period according to one discharge current and one relaxation time is zoomed in **Figure 4**. All the identification steps will be explained with regard to this figure.

In **Figure 4** it can be seen that (V_{oc}), corresponding to each pulse, is in fact the open circuit voltage measured just prior to the current pulse that will discharge the battery. This value is measured from SOC 100% till 10% and recorded as V_{oc} = f (SOC), as depicted in **Figure 6**.

The second parameter, the series resistance (R_s) that creates the large visible voltage drop when applying the discharge current, can be quite easily computed. Knowing the V_{oc} at the start of each discharge pulse and measuring the (V_2) voltage

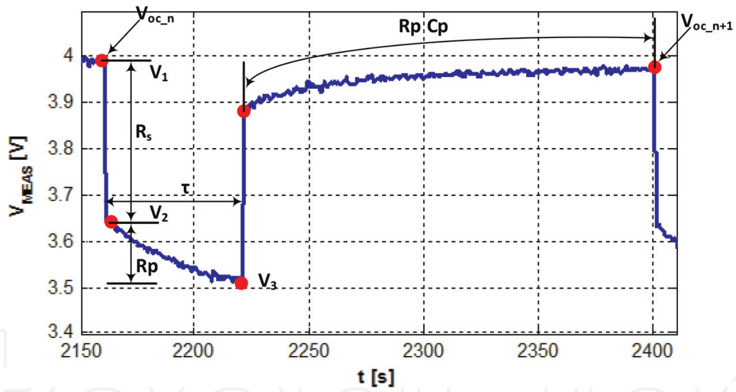


Figure 5.
The detailed voltage variation for the battery parameter identification (first-order model).

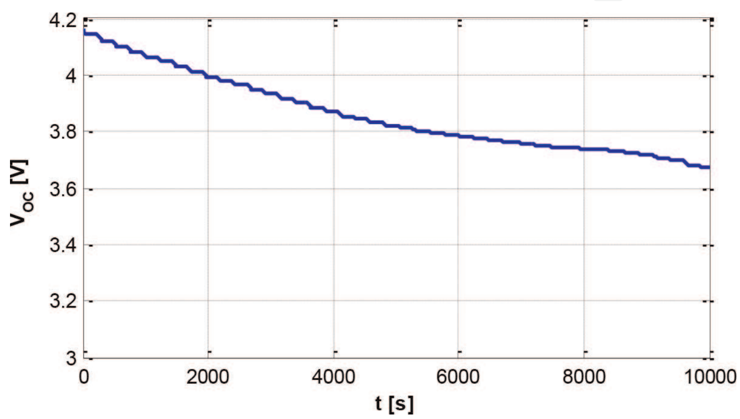


Figure 6.
The open circuit voltage for the entire discharge cycle.

(from **Figure 5**) and knowing the value as well of the pulsed current applied make it easy to compute the (R_s) resistance based on Ohm's law (see Eq. (8)):

$$R_s = \frac{V_{oc} - V_1}{I_{bat}} \tag{8}$$

From this point on, the post-processing of the acquired data to identify the parameters for the first- and second-order models will by slightly different. To be able to clearly understand each process, these will be treated separately with both equations and explanations, coped with the represented parameters from **Figure 5**.

3.1.1 First-order parameter identification

Going back to Eqs. (1) and (2), one can see that the open circuit voltage together with the series resistances was already identified as a general parameter for all battery models. What remains to be calculated are the polarization resistance (R_p) and polarization capacitance (C_p). In **Figure 5**, it can be seen that for each discharge current pulse, the lowest value of the voltage is marked with (V_3). Based on Ohm's law, coped with the discharge current, one can simply compute the value of the polarization resistance as in Eq. (9).

$$R_p = \frac{V_2 - V_3}{I_{bat}} \tag{9}$$

On the other hand, the value of the (V_3) voltage function of time is influenced by the polarization capacitance of the battery (C_p). Therefore, knowing the value of the polarization resistance and the time length of the current pulse (τ), it is straightforward to compute the capacitance as in Eq. (10).

$$\tau = R_p \cdot C_p \tag{10}$$

Generally, these computations are done during the discharging periods; however, these are valid to be computed for the relaxation time as well. Normally, the voltage variation gradient both in discharge and relaxation periods should be the same, and this justifies the previous explanation. As the entire data recorder when proceeding with the battery identification process is a function of the SOC, the calculated parameters will be as well a plotted function of the SOC. In **Figure 6**, for the first-order model, the open circuit voltage, the series and polarization resistances and the polarization capacitance for the entire range of battery discharge are plotted. It can be observed that the series resistance has a generally constant value over the entire period, while the polarization one increases when the SOC is over 90%. In the same manner, the polarization capacitance as 3 regions, one between 0 and 40% SOC where is it quite constant, then between 40% and 80%, a region with larger values and decreases a lot when the cell's SOC goes for the fully charged value.

3.1.2 Second-order parameter identification

In order to quantify the parameters for the second order, the same zoomed plot from **Figure 5** is used again, but this time, the approach is slightly different. In **Figure 7**, the parameters to be identified are detailed in the voltage variation. The open circuit voltage and the series resistance quantification remains the same as detailed in the first paragraphs of Section 3.1. The remaining parameters to be calculated are linked to the model expressed in Eqs. (6) and (7). The reason of using exponential expressions instead of derivative ones is justified by the fact that the two RC groups of the second-order ECM are difficult to be separated. Hence, the shape of the voltage during the relaxation time (or the discharge time) is directly described by these two RC groups connected in series.

Actually, in the exponential voltage variation, one can observe that visually there is a period of fast variation and then a second one, of slow variation. It is impossible to define clearly these periods and to admit that one group is responsible for one period and the other one for the second period. Hence, the identification process includes both groups altogether. The reason of describing the battery model with exponential variations is justified in fact by the method of calculating these four parameters (R_1, R_2, C_1 and C_2). This method is handled using a curve fitting procedure, based on the measured voltage shape. Using the *fit* function programmed in MATLAB Coder and applied for each relaxation period over the entire discharge cycle of the battery will return preliminary values for the four parameters, corresponding to each period. In order to give the reader a clear step-by-step procedure of handling this identification process, the authors considered that it is more lucrative to detail this post-processing phase of the identification:

- First, record all the transient regimes for each relaxation time into a matrix.
- Apply the curve fitting procedure for each of the recorded variations based on Eq. (6).
- Save the resulting constants (k0, k1, k2, a, b) into another matrix.
- Compute for each set of constants the values for R_1, R_2, C_1 and C_2.

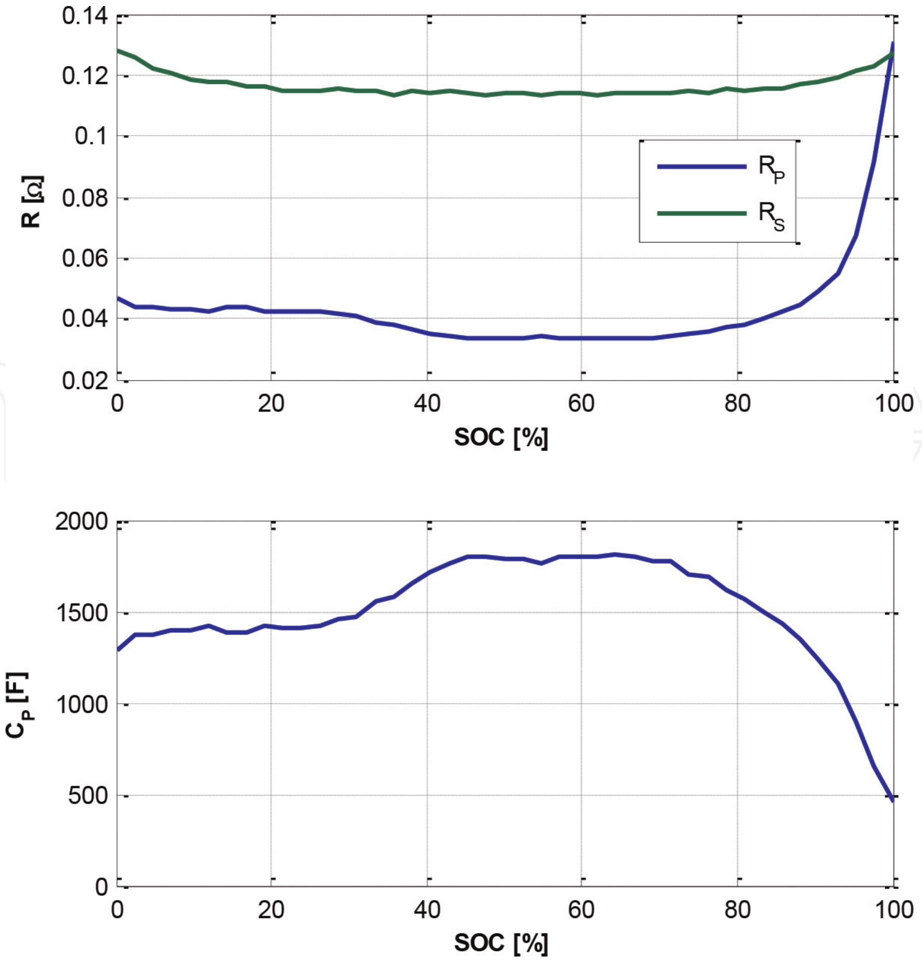


Figure 7.
The detailed voltage variation for the battery parameter identification (second-order model).

As general settings for the *fit* function, the best approach is to use nonlinear least squares, bounded by upper and lower values that are mandatory to be positive and realistic. The results of the fitting process will return the battery parameters that fit quite well with the measured voltage variation when reconstructing it based on the computed data. However, higher accuracy can be reached if one applies an optimization procedure of the fitted parameters to the actual measured voltage shape.

In **Figure 8** (top), the actual measured voltage (V_{MEAS}) with blue and the voltage variation obtained using Eq. (6) with the fitted parameters (V_{FITT}) with black are depicted. It is noticeable that there is some difference between the two characteristics, as well as in **Figure 8** (bottom), with black; the difference between the two is highlighted in black, following the variation of (err_{FITT}).

On the other hand, if one applies an optimizer to fit more accurately with the battery parameters, the results reveal a highly precise characteristic that superimposes quite well on the measured one. In **Figure 8** (top), with red, the voltage variation using optimized parameters is plotted (V_{OPT}), while in **Figure 8** (bottom), the (err_{OPT}) is much smaller than the one obtained without optimization.

For the optimization process, the authors used a tool offered by MATLAB Simulink, called *Control and Estimation Tool Manager*. The benefit of using the tool provided by MATLAB Simulink is that the user does not have to have mathematical skills to implement optimization algorithms, investing his time and effort directly in using those existing for optimizing his model in development. This tool uses the model of the battery designed in MATLAB Simulink with the fitted parameters and varies them until the smallest error between the measured voltage variation and the model output is reached. This optimization is carried out for each relaxation time, as it was done for the preliminary fitting process. The resulted data are recorded into a matrix and will result in the battery parameter function of the SOC of the battery.

In **Figure 9** (top left), the main window of the Control and Estimation Tool Manager is depicted. There are several already implemented optimization algorithms that can be chosen, setting the number of iterations, the tolerance and the search method for each of them. One example is highlighted in **Figure 9** (top right) that shows the variations of the parameters carried out by the optimizer to reach the

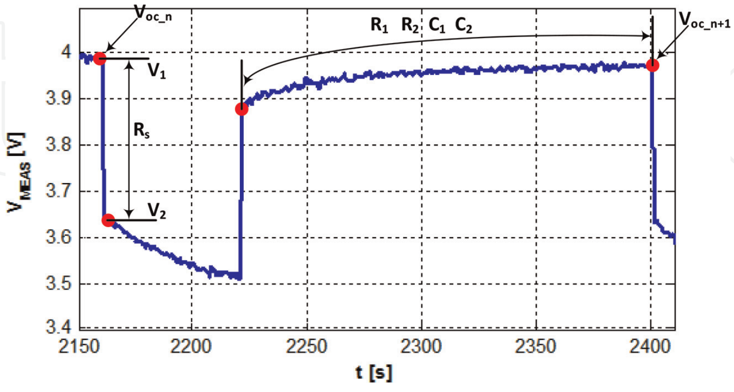


Figure 8.
Comparison of the fitted and optimized parameters influence (second-order model).

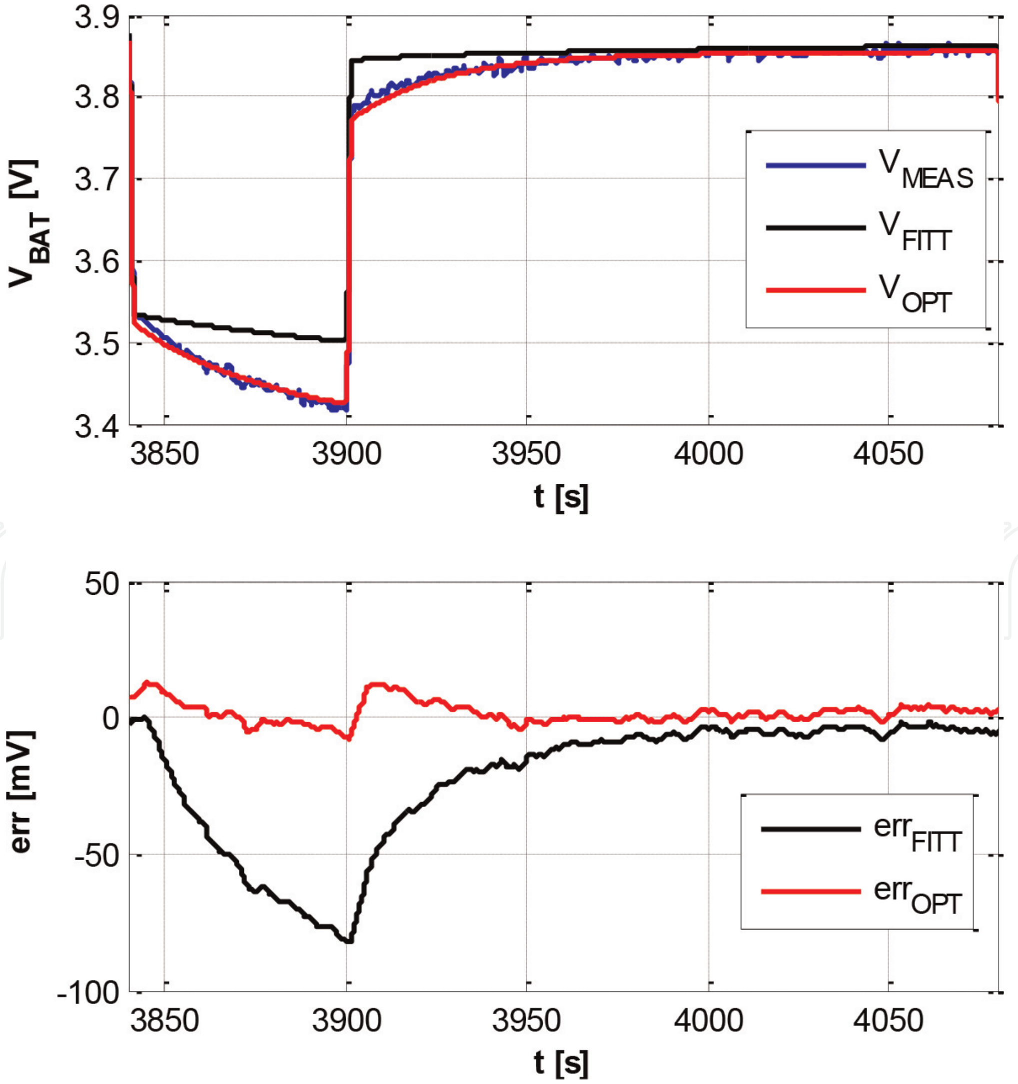


Figure 9.
The MATLAB Simulink Control and Estimation Tool Manager.

closest battery model output voltage variation compared to the measured one. The final comparative result is depicted in **Figure 9** (bottom), proving a closely complete overlap between the measured and the simulated curves, obtained for the new optimized battery parameters.

In **Figure 8**-bottom, comparing the results of the fitted and optimized models it is clear that in case of the latter, only 10 mV of error is reached while the fitted one yells for maximum of 70 mV error. Indeed, the labor and computation time for obtaining the optimized parameters is larger; however, if one requires high precision, it is the compromise that needs to be considered.

4. Battery model benchmarking

In the previous chapters, first- and second-order battery models with their equivalent circuits, parameter identification process and post-processing computations were presented. It is logical that the first-order battery model is the simplest one, yelling for simple parameter identification, simple modeling and simple data post-processing. However, undoubtable the accuracy of the first-order model is comparatively lower than the accuracy of the second-order model, especially by its nature that lacks components to describe the exponential transient of the battery voltage. It's been proved however [10] that such first-order models can be used to create fast, reliable and realistic simulation programs. In order to increase the level of scientific impact of the proposed chapter, the discussion of benchmarking battery models will continue focusing only on second-order models. However, in the literature, the main differences of the first- and second-order battery models were already detailed up to an extent. The added value of this chapter to the actual status of research is a different approach that focuses on the second-order battery model complexity and compromises when building the simulation programs.

It is known that nowadays, the simulators designed to emphasize phenomena especially in electrical engineering are more and more constructed using real-time platforms. By this, simulation sampling and accuracy of the results compared to those measured are mitigated seriously.

However, considering the large amount of data that needs to be recorded into matrixes for all the battery parameters becomes challenging when creating real-time simulation programs. Generally, such data becomes core in lookup tables (LUT). Loading LUT on a real-time processor becomes difficult as it requires space and decreases the sampling speed of the processor. For example, using field-programmable gate arrays (FPGAs) becomes even more complicated in this approach, as those require add-on external flash memory, and by this the system becomes quite complicated as the interaction of the memory and the FPGA needs also to be additionally programmed.

Normally, a battery model architecture for the second-order model would require 6 LUTs as follows: one for the (V_{oc}), one for the ohmic resistance (R_s) and four others for (R_1, R_2, C_1 and C_2).

Using an architecture as the one depicted in **Figure 10** leads to high-accuracy, realistic results but also large memory necessity, long simulation time and non-realistic sampling time. Hence, such design models are not at all justified to be implemented into real-time processors.

However, there is another approach that can be used in the case of real-time applications. Analyzing the parameter variations from **Figure 11**, although these are for the first-order circuit, the following statement is valid for the second-order circuit as well. It can be seen that around a SOC of 60%, these parameters are quite constant. Sudden variations are recorded only around 10% and 100% of SOC.

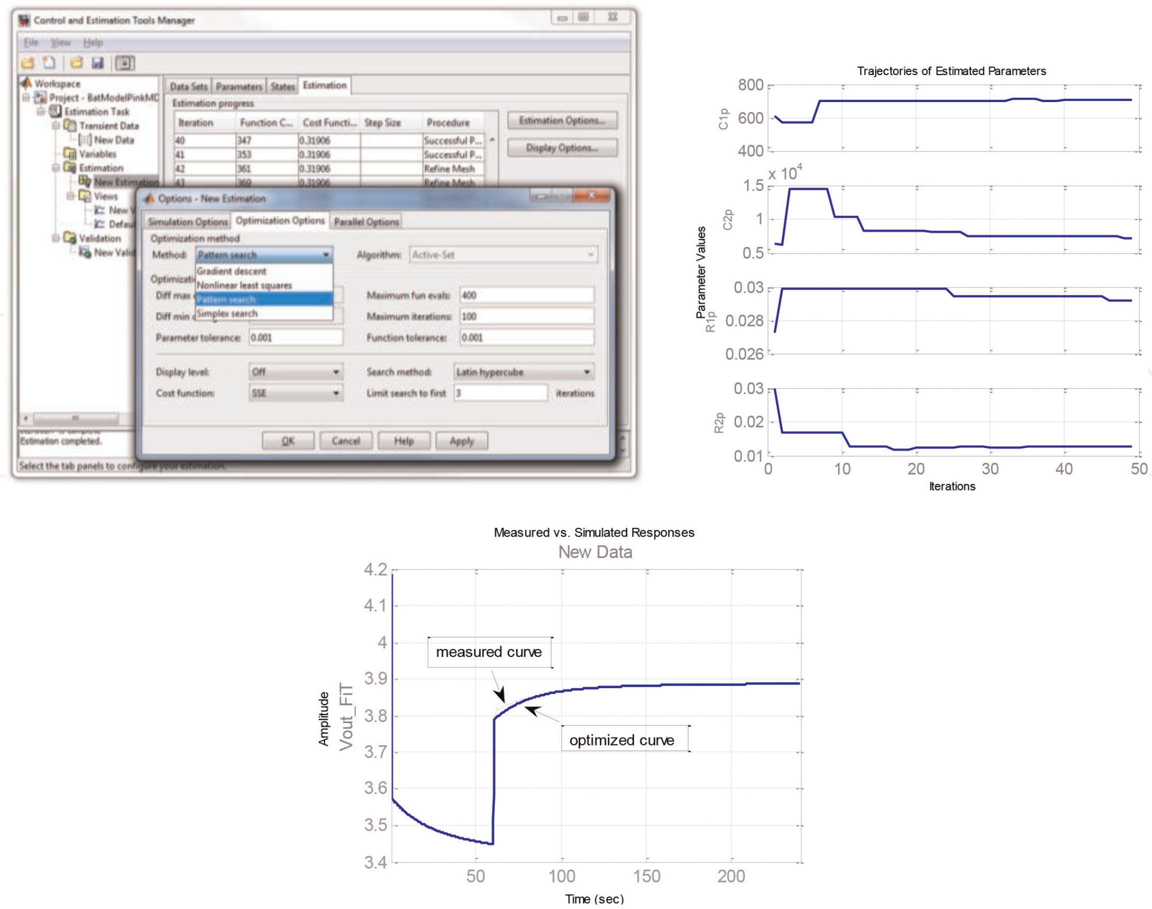


Figure 10.
The second-order battery model based on LUTs.

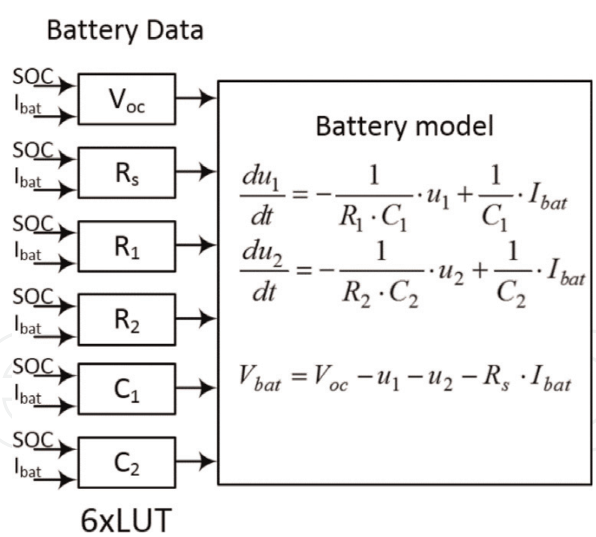
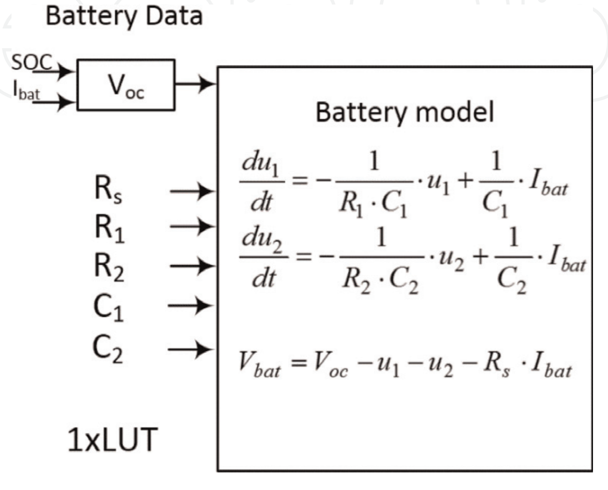


Figure 11.
The R_s, the R_p and the C_p functions of the SOC for the first-order model.

Hence, an approach that can simplify the modeling of a second-order circuit is to use instead of LUTs for each parameter constant values for the parameters recorded at a SOC of 60%.

In **Figure 12**, the reduction of the model complexity of the second-order battery can be observed. Instead of 6 LUTs, only one remains, namely, the (V_{oc}) function of the SOC. The rest of the parameters are constants, as mentioned before.

As it can be seen, the model is highly simple right now, and it contains only one LUT. The variation of the (V_{oc}) depicted in **Figure 6** that is identical for both the first- and the second-order models can be in fact described instead of a LUT with a polynomial function. With this the model, it becomes even more simple, without any LUT. In **Figure 13**, the results for the three different approaches, the fitted one, the optimized one and the one based on constants, all versus the measured one, are plotted. For all, the difference between the measured quantity and the one obtained from the three models is depicted in **Figure 13** (bottom). Still, the largest error is returned by the fitted values, while the smallest error is given by using LUTs with optimized values. However, it is interesting to observe that when using constant values, fetched at a SOC of 60%, the error is more than satisfactory. It has to be mentioned that the constant values were fetched out of the optimized data at the



$$\frac{du_1}{dt} = -\frac{1}{R_1 \cdot C_1} \cdot u_1 + \frac{1}{C_1} \cdot I_{bat}$$
$$\frac{du_2}{dt} = -\frac{1}{R_2 \cdot C_2} \cdot u_2 + \frac{1}{C_2} \cdot I_{bat}$$
$$V_{bat} = V_{oc} - u_1 - u_2 - R_s \cdot I_{bat}$$

Figure 12.
The second-order battery model based on constants.

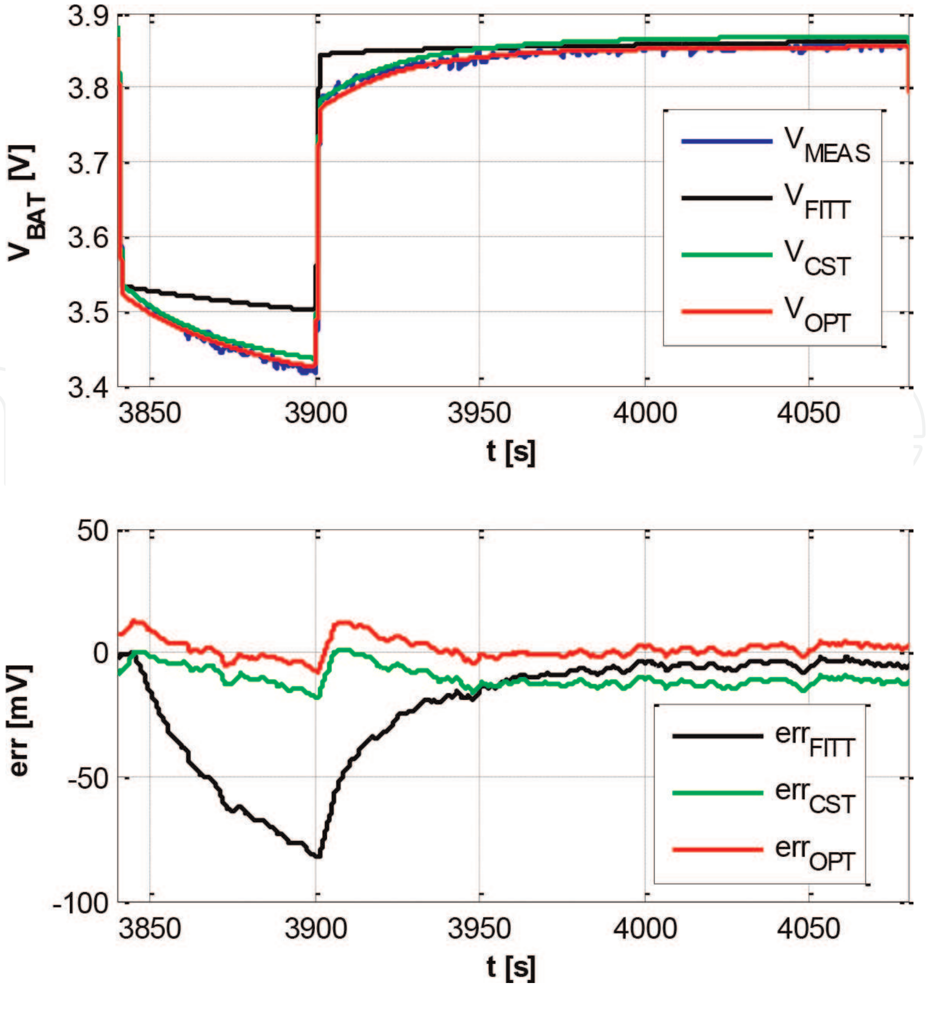


Figure 13.
The comparison of the three different modeling approaches for second-order ECM.

SOC of 60%. The results detailed in **Figure 13** and the explanations regarding this approach prove that one can simply build a second-order battery model that can perform simulations on a real-time processor, even a FPGA.

4.1 Experimental validation of the proposed models

As already stated, the focus of the chapter is around the second-order Li-ion battery modeling; hence, the proof of correct approach will be engaged still on second-order modeling compared to actual measurements.

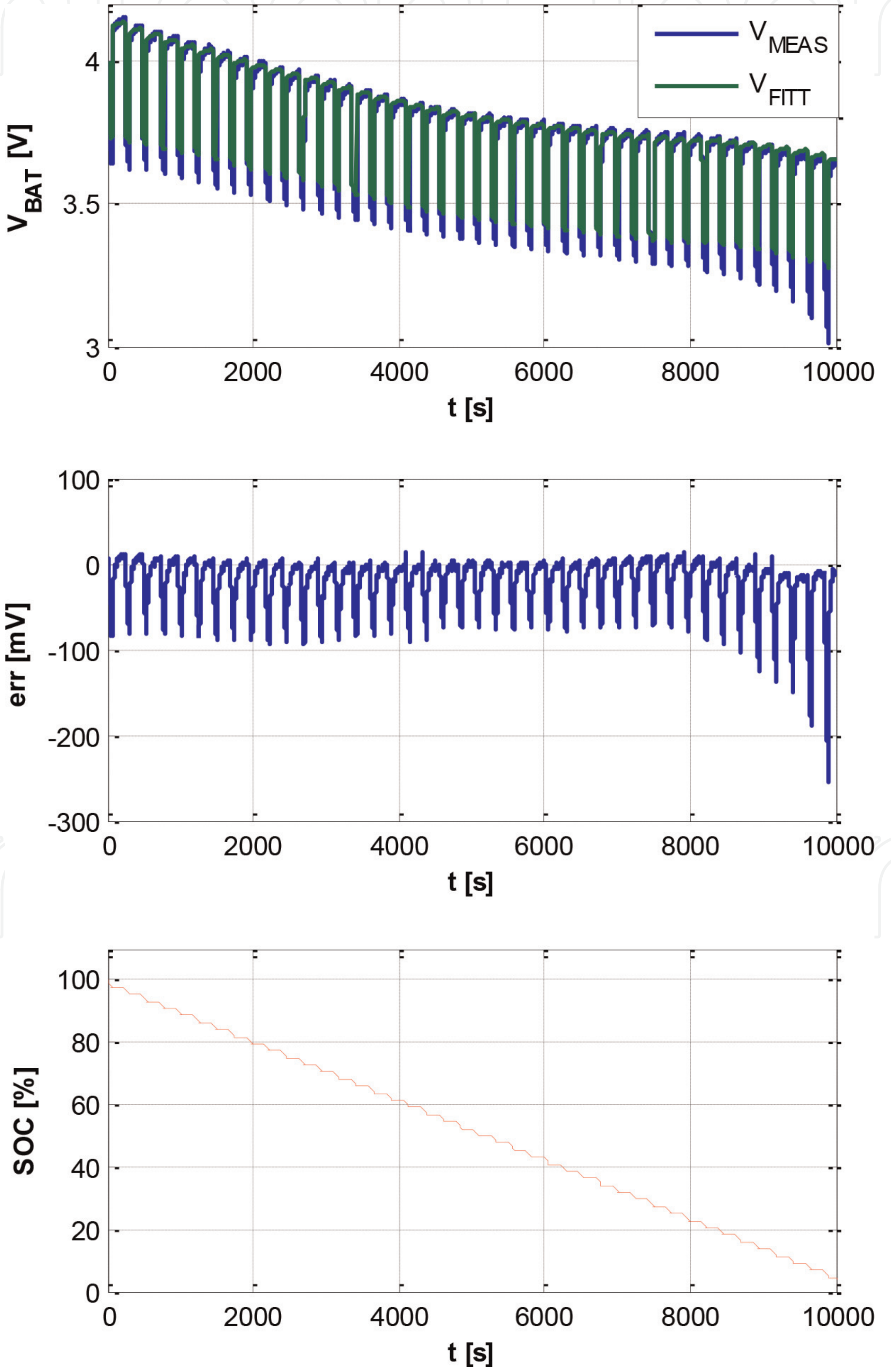


Figure 14.
The measured vs. fitted parameters voltage (top), their difference (middle) and the SOC (bottom).

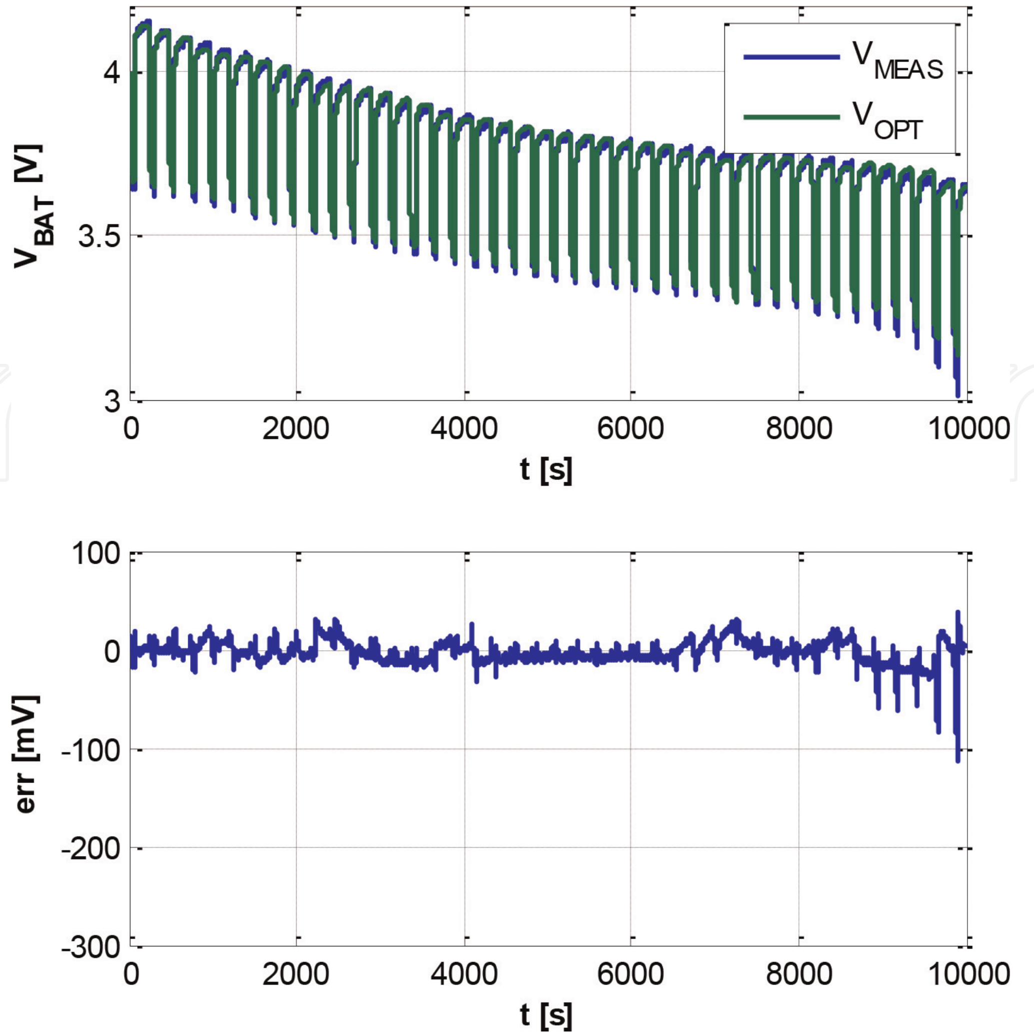


Figure 15.
The measured vs. optimized parameters voltage (top), their difference (bottom).

The simplest method of experimentally validating the analysis is to compare the measured discharge characteristic of the battery for the complete cycle with the results obtained from each modeling method.

In **Figure 14**, the validation of the model with fitted parameters is accomplished versus the actual measured battery voltage. To have a transparent comparison, the instantaneous error over the entire discharge range is computed. Generally the error is less than 100 mV and increases to larger values especially when the SOC is less than 20%. In **Figure 15**, the measured voltage is compared to the one obtained from simulations using the optimized parameters. Here, the error is consistently smaller than in the previous case, reaching 100 mV only when the battery is completely discharged. The SOC depicted in **Figure 14** is valid for **Figures 15** and **16** as well. The last analyzed model is the one where the LUTs are replaced with constant values fetched at a SOC of 60% (**Figure 16**). Analyzing the error one can state that this is larger than for the model with optimized values in LUTs but smaller than for the one with fitted values in LUTs.

The accuracy of the model based on constants is more than satisfactory and proves that designing such model can run both on computer and real-time platform simulators, reaching high accuracy and realistic behavior.

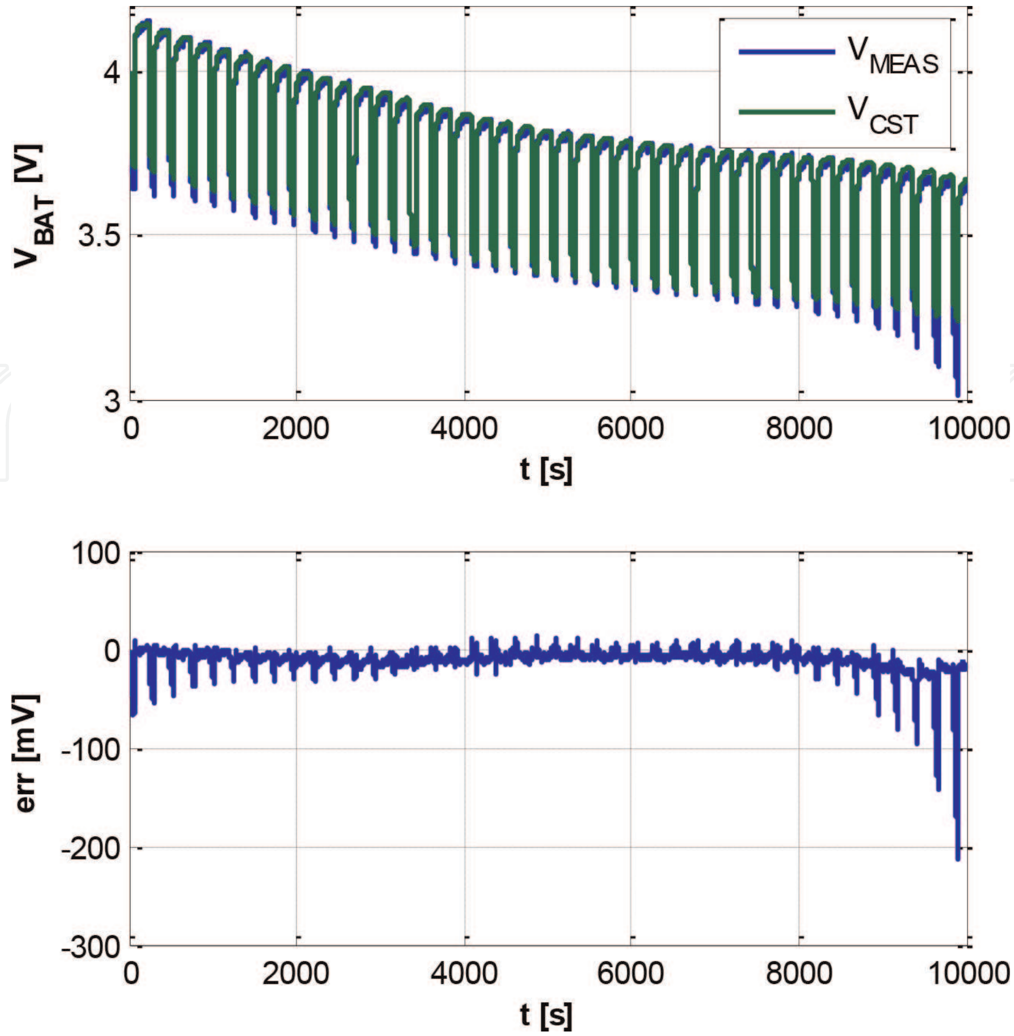


Figure 16.
The measured vs. constant parameters voltage (top), their difference (bottom).

5. Conclusions

The research conducted on battery modeling and simulation that is now a hot topic in many research facilities both in academia and industry sectors requires precision, accuracy and transparency but at the same time demands reaching all these with the assumption of simplicity. There are many publications that reach impressive accuracy when modeling battery cells but with the cost of high complexity and large data manipulation inside the model. When speaking about pure scientific impact, such models are more than beneficial to those involved in their development. However, when coping with industry applications, the precision is as important as is the simplicity. Hence, using the general architecture of high precision models and manipulating their parameters to avoid data overflow and keep the accuracy in satisfactory boundaries become a lucrative solution.

The authors proved in this chapter that one can reach with wise interpretation such solutions that are simple to use, are simple to design and offer the possibility to simulate quite close to the real behavior a Li-ion battery cell.

Author details

Mircea Ruba*, Raul Nemeş, Sorina Ciornei and Claudia Marţiş
Technical University of Cluj Napoca, Romania

*Address all correspondence to: mircea.ruba@emd.utcluj.ro

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