33[nd] Electric Vehicle Symposium (EVS33)
Portland, Oregon, June 14 - 17, 2020

Reduced Order Electro-thermal Battery Model Ready for Software-in-the-loop and Hardware-in-the-loop BMS Evaluation for Electric Vehicle

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Summary

The software-in-the-loop and hardware-in-the-loop tests of battery management system require to have a real-time compatible electro-thermal battery pack model. In our study, a numerically complex electrochemical-thermal model has been characterized from experimental data of a nickel-rich, silicon-graphite 18650-type lithium-ion cell. While it represents accurately the electro-thermal battery behavior, it's hardly suitable for real-time application due to its intensively numerical solving effort and related calculation time if no huge numerical efforts are applied to reduce the model. The objective of this paper is to present a simple method to derive a reduced order electro-thermal cell model from the complex electrochemical-thermal cell model and build a real-time compatible battery pack model with the reduced order cell model.

Keywords: battery model, Battery Management System, simulation, hardware-in-the-loop (HiL), BEV (battery electric vehicle)

1 Introduction

Battery management system (BMS) is a critical component for electric vehicles. During the development of BMS, several types of test can be done in order to evaluate its performance: (1) Software-in-the-Loop (SiL) test to evaluate the BMS control algorithm; (2) Hardware-in-the-Loop (HiL) test to evaluate the real time performance of the BMS; (3) test with real battery pack to finally validate the BMS performance. For the SiL and HiL tests, a battery pack model is needed to represent the electro-thermal behavior of the cells in the pack. The battery pack model consists of individual cell models which can be either characterized with experimental measurements or with simulated data from a complex model (e.g., electrochemical-thermal model). The battery pack model must have a good compromise of accuracy and simplicity to be real-time compatible for the SiL and HiL tests. In our study, the numerically intensive pseudo-two dimensional, electrochemical-thermal model for a lithium-ion battery [1] is considered and was parameterized and validated in a wide operating range in our previous work [2]. The problem to solve is to get a reduced order electro-thermal cell model from the electrochemical-thermal model and build a battery pack model which is real-time compatible and ready for the SiL and HiL tests of BMS. The objective of this paper is to present a simple method to get a reduced order electro-thermal cell model from a complex electrochemical cell model and then build a battery pack model with the reduced order cell model. The remaining part of this paper is organized as follows. Section 2 presents the electrochemical model. Section 3 describes the method to get the reduced order electro-thermal model. It also presents the validation of the method by comparing the simulation results between the two models. Section 4 presents the battery pack model build from the reduced order cell model in the simulation software Siemens Simcenter Amesim. Section 5 concludes the paper.

2 Electrochemical model

In our study, the well-known pseudo-two dimensional (p2D) electrochemical-thermal model [1] has been used which is parameterized and validated at various temperatures and current loads for an 18650 nickel-rich, silicon-graphite lithium-ion cell of 3.35 Ah as presented in the work of Sturm et al. [2]. The p2D model used here simulates potentials and concentrations in the active materials and the electrolyte based on porous electrode theory and concentrated solution theory combined via electrode kinetics throughout the thickness of a single electrochemical cell unit containing anode, separator and cathode [1]. Model reduction and implementation into MATLAB 2018a were applied to the p2D model used in this work according to previous works [3]. The Parabolic Profile approximation [4] for the approximation of the particle domain was used together with finite difference method (FDM) for the remaining spatial discretization of the differential algebraic equation system. Crank Nicolson [5] formulation was used for the time discretization and an iterative Newton-Raphson scheme [6] for the overall solving process. No side reactions or multiple particle sizes were included in this p2D model.

While the complete electrochemical model presents many advantages such as giving detailed insight into the electrochemical process inside the battery cell, it is not suitable for real-time simulation due to its high computational cost. To simulate the electro-thermal behavior of a battery pack including many cells connected in series and parallel, a simplified cell model must be used and at the same time it must be able to represent accurately the electro-thermal behavior of the cell.

3 Reduced-order electro-thermal model

Several types of simplified models, which are real-time compatible, are available to represent the electro-thermal behavior of the battery (e.g., equivalent circuit model [7][8][9][10], black box model [11]). In our study, an equivalent circuit model is chosen because it is simple, with a good compromise of accuracy/simplicity and has already been implemented in Simcenter Amesim [12], which is a multi-physical simulation software of Siemens.

3.1 Proposed model

Figure 1 shows the reduced-order electro-thermal model used in our study. The electrical behavior of the cell is represented with an equivalent circuit model incorporating: (1) a voltage source to represent the open circuit voltage (OCV); (2) a resistance R_{ohm} to represent the ohmic resistance responsible for the instantaneous voltage drop when the cell current changes; and (3) several RC circuits $R_{dff}[i]/C_{diff}[i]$ to represent the dynamic behavior of the cell mainly related to the diffusion of Lithium-ion inside the battery cell. Different numbers of RC circuits were used in the literature, e.g., 1 in [7][10], 2 in [9] and 5 in [8]. Having more RC circuits helps to improve the model accuracy at the cost of complexity in parameter identification and higher calculation time [8][9]. The OCV is a function of the SoC and the temperature. Other elements in Figure 1 are functions of the SoC, the temperature and the current.

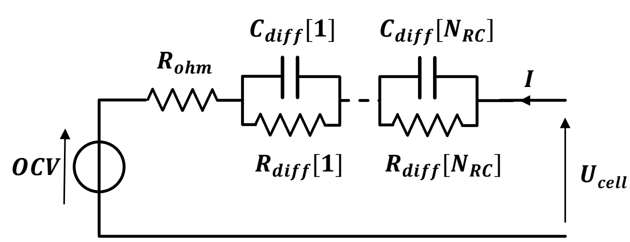


Figure 1: Equivalent circuit model

The SoC is determined by the coulomb counting as follow:

$$SoC = SoC_{init} - \frac{1}{Q_{cell}} \int \frac{\eta_{cell} \cdot I}{3600} dt \tag{1}$$

Where SoC_{init} is the initial SoC; I is the current; Q_{cell} is the cell capacity; η_{cell} is the faradic efficiency which is set to 1 in our study since the faradic efficiency of lithium-ion cells is very close to 1. However, for example the faradic efficiency for NiMH cells should not be neglected. The voltage of the cell is calculated by equation as follow:

$$U_{cell} = OCV - \Delta U_{ohm} - \sum_{i=1}^{N_{RC}} \Delta U_{diff\_i} \tag{2}$$

Where:

- The OCV is calculated with equation as follow to consider the hysteresis behavior of the OCV in battery:

$$OCV = OCV_d + F_{hys} \cdot (OCV_c - OCV_d) + \frac{dU}{dT} \cdot (T_{cell} - T_{ref}) \tag{3}$$

  where OCV_c and OCV_d are open circuit voltages measured in charge and in discharge at the reference temperature T_{ref}; $\frac{dU}{dT}$ is the entropic coefficient; F_{hys} is the hysteresis factor with value varying between 0 and 1 and is calculated by equations:

$$\begin{cases} \frac{dF_{hys}}{dt} = \frac{3 \cdot \frac{dSoC}{dt}}{\Delta SoC_{hys}} (1 - F_{hys}), & during\ charge \\ \frac{dF_{hys}}{dt} = \frac{3 \cdot \frac{dSoC}{dt}}{\Delta SoC_{hys}} \cdot F_{hys}, & during\ discharge \end{cases} \tag{4}$$

  With ΔSoC_{hys} the state of charge variation necessary for full charge/discharge open circuit voltage transition. An example of the open circuit voltage transition is shown in Figure 2: the initial open circuit voltage starts from point (1); during a charge, the open circuit voltage approximates its high boundary defined by OCV_c; during a discharge, the open circuit voltage joins progressively the low boundary defined by OCV_d.

- The ohmic voltage drop ΔU_{ohm} is calculated with equation:

$$\Delta U_{ohm} = I \cdot R_{ohm} \tag{5}$$

- The voltage drop ΔU_{diff_i} for each of the RC circuits (i = 1, 2, ..., N_{RC}) is calculated with equation:

$$\frac{d(\Delta U_{diff\_i})}{dt} = -\frac{\Delta U_{diff\_i}}{R_{diff\_i} \cdot C_{diff\_i}} + \frac{I}{C_{diff\_i}} \tag{6}$$

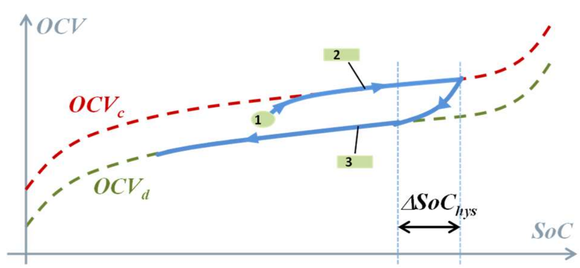


Figure 2: OCV transition between its high and low boundaries

The heat generated by the cell (H_{gen}) during its operation includes the heat related to the entropic coefficient ($\emptyset_{\frac{dU}{dT}}$), the hysteresis loss ($\emptyset_{hys}$), the ohmic loss ($\emptyset_{ohm}$) and the diffusion loss ($\emptyset_{diff}$). The heat generated is calculated with equations as follow:

$$
\begin{aligned}
H_{gen} &= \emptyset_{\frac{dU}{dT}} + \emptyset_{hys} + \emptyset_{ohm} + \emptyset_{diff} \\
\emptyset_{\frac{dU}{dT}} &= I \cdot \frac{dU}{dT} \cdot (T_{cell} + 273.15) \\
\emptyset_{hys} &= -I \cdot \left(\frac{OCV_c + OCV_d}{2} - OCV\right) \\
\emptyset_{ohm} &= -I^2 \cdot R_{ohm} \\
\emptyset_{diff} &= -I \cdot \sum_{i=1}^{N_{RC}} \Delta U_{diff\_i}
\end{aligned} \tag{7}
$$

The thermal behavior of the battery cell is represented with a simple thermal model consisted of different elements as shown in Figure 3: (1) a heat source to represent the heat generated by the cell; (2) a thermal capacity of the cell; (3) a thermal convection resistance; and (4) a temperature source to represent the ambient temperature T_{amb}. The cell temperature T_{cell} is calculated with equation:

$$
\frac{dT_{cell}}{dt} = -\frac{A \cdot h_{cov}}{m_{cell} \cdot C_p} \cdot (T_{cell} - T_{amb}) + \frac{H_{gen}}{m_{cell} \cdot C_p} \tag{8}
$$

Where m_{cell} is the cell mass and C_p is the cell specific heat.

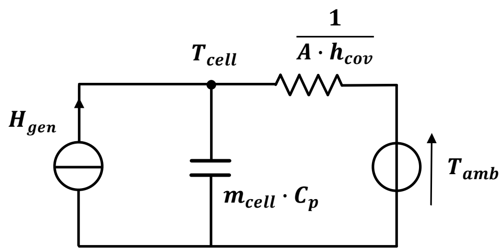


Figure 3: Thermal model of the cell

Table 1 summarizes the parameters needed for the model. The battery model in Simcenter Amesim also includes other features such as aging and thermal runaway modeling, which are not used in our study. Detailed information of the model can be found in the help documentation of Simcenter Amesim [12].

Table 1: Parameters for the reduced order circuit model

Parameter	Description	Unit
Q_{cell}	Cell capacity	Ah
OCV_c	OCV in charge at the reference temperature	V
OCV_d	OCV in discharge at the reference temperature	V
ΔSoC_{hys}	SoC variation for full charge and discharge open circuit voltage transition	%
dU/dT	Entropic coefficient	V/K
R_{ohm}	Ohmic resistance	Ohm
R_{diff}[i]	Diffusion resistance	Ohm
C_{diff}[i]	Diffusion capacitance	F
C_p	Specific heat of the cell	J/kg/K
h_{cov}	Convective heat exchange coefficient	W/m^2/K
S_{conv}	Convective heat exchange area	m^2
m_{cell}	mass of the cell	kg

3.2 Model calibration

The reduced order circuit model is calibrated with simulated data from the electrochemical model. 2 types of test profile are used to generate the simulated data:

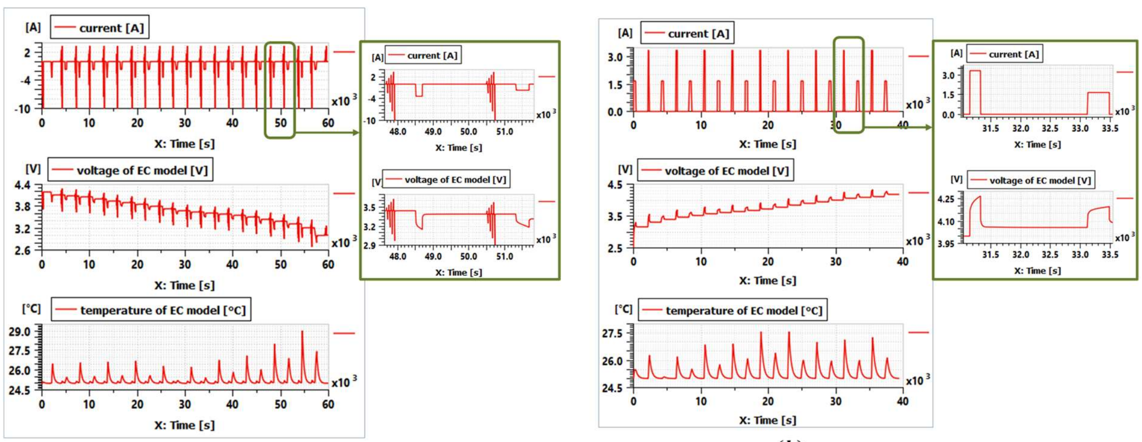
- Test 1: Pulses test. As shown in Figure 4 (a), this profile discharges the cell from 100% to 0% SoC. It includes several groups of short-duration (< 2 s) charge and discharge pulses at different current levels.

Between two groups of pulses, a long-duration discharge with a constant current is used to decrease 5% SoC of the cell. 2 level of currents are used alternatively for the long-duration discharge (1C and 0.5C). Each long-duration discharge is followed by a long rest period (1800 s) to stabilize the cell voltage and temperature.

- Test 2: Charge test. As shown in Figure 4 (b), this profile is consisted of long-duration charges with 2 levels of current alternatively (1C and 0.5C) to charge the cell from 0% to 95% SoC. Each long-duration charge increases 5% SoC of the cell and is followed by a long rest period (1800 s).

These test profiles are designed on the one hand to facilitate the parameter identification with the Battery Identification Assistant tool in Simcenter Amesim [12]. On the other hand, the duration for the pulses and the current levels for the long-duration discharges or charges are chosen to minimize the temperature variation of the cell during the test. These profiles can be easily adapted to test other battery cells.

In our study, the test profiles were applied to the electrochemical model at 3 ambient temperatures (5, 25 and 45 °C). Figure 4 shows the examples of the simulated data from the electrochemical model at 25 °C for the 2 test profiles respectively.



(*a*) (*b*)

Figure 4: (a) Test 1: pulses test (b) Test 2: charge test

The parameters in Table 1 are identified with the Battery Identification Assistant tool in Simcenter Amesim as explained in the following paragraphs.

3.2.1 OCV_d and OCV_c

The OCV_d and OCV_c are identified with the relaxation phase after each long-duration discharge or charge. The value at the end of each relaxation after the long-duration discharge (Figure 4 (a)) is considered as the OCV value in discharge. Figure 5 shows an example of the OCV_d identified at the 3 temperatures. The same process allows to get the OCV_c at the 3 temperatures by using the charge profile in Figure 4 (b). 25 °C is chosen as the reference temperature in our study to calculate the open circuit voltage with equation (3).

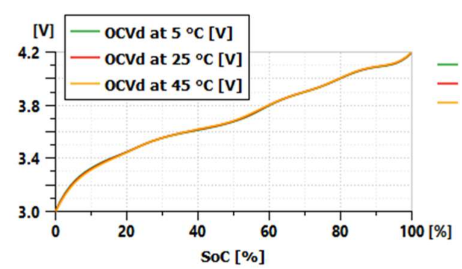


Figure 5: OCV_d identified at different temperatures

3.2.2 ΔSoC_{hys}

Figure 6 shows the hysteresis between the OCV_d and OCV_c at 25 °C. The experimental test results of a Li-ion cell in [13] show that the state of charge variation (ΔSoC_{hys}) necessary for full charge/discharge OCV transition is from 15% to 25% in most of the case. In the absence of tests to identify ΔSoC_{hys}, its value is set arbitrarily to 15% in our study.

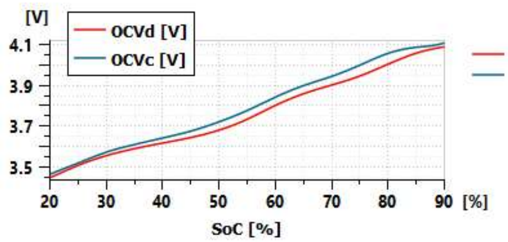


Figure 6: Hysteresis between OCV_d and OCV_c at 25 °C

3.2.3 dU/dT

The entropic coefficient curve can be calculated by using the OCV curves identified previously as follow:

$$\left.\frac{dU}{dT}\right|_{x}^{T_1,T_2} = \frac{OCV_x(T_1)-OCV_x(T_2)}{T_1-T_2} \tag{9}$$

Where T_1 and T_2 are 2 different temperatures; OCV_x can be OCV_d or OCV_c. In our case, the OCV is identified at 3 temperatures in discharge and in charge. There are therefore 6 possible combinations to calculate 6 curves of entropic coefficient as illustrated in Table 2. The average curve of the 6 entropic coefficient curves is the one to be used in the reduced order circuit model. The average curve is shown in Figure 7.

Table 2: 6 combinations to calculate entropic coefficient

$\boldsymbol{OCVx}$	OCV_d	OCV_d	OCV_d	OCV_c	OCV_c	OCV_c
T_1 (°C)	5	25	45	5	25	45
T_2 (°C)	25	45	5	25	45	5
$\boldsymbol{\left.\frac{dU}{dT}\right\|_{x}^{T_1,T_2}}$	$\left.\frac{dU}{dT}\right\|_{d}^{5,25}$	$\left.\frac{dU}{dT}\right\|_{d}^{25,45}$	$\left.\frac{dU}{dT}\right\|_{d}^{45,5}$	$\left.\frac{dU}{dT}\right\|_{c}^{5,25}$	$\left.\frac{dU}{dT}\right\|_{c}^{25,45}$	$\left.\frac{dU}{dT}\right\|_{c}^{45,5}$

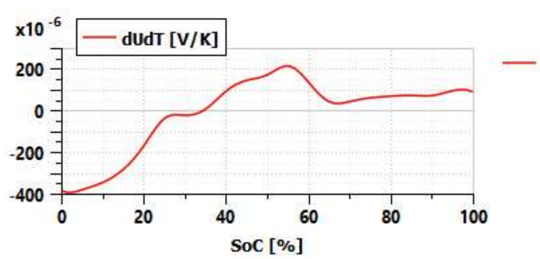


Figure 7: dU/dT used in the reduced order circuit model

3.2.4 R_{ohm_d} and R_{ohm_c}

The instantaneous ohmic resistances are identified with the groups of short-duration pulses (Figure 4 (a)). These pulses allow to get the ohmic resistance value at different SoCs, currents and temperatures. Figure 8 shows the result of the ohmic resistance identified at 25 °C.

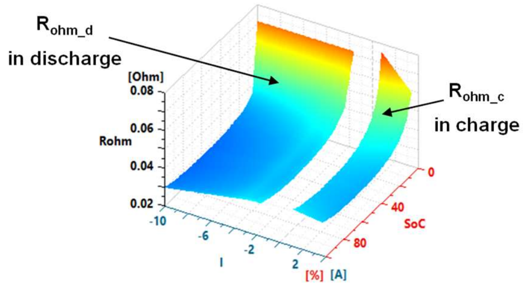


Figure 8: Ohmic resistances at 25 °C

3.2.5 RC circuits

By using the long-duration discharges and charges in Figure 4, the RC circuits $R_{dff}[i]/C_{diff}[i]$ are identified with the Battery Identification Assistant tool of Simcenter Amesim. Instead of identifying directly several RC circuits, the tool identifies a Warburg impedance represented by 2 parameters (a diffusion resistance R_{ss} and a time coefficient T_c). The identification process of the Warburg impedance is similar to the ones in [14][15]. Once the Warburg impedance is identified, it can be easily approximated by different number of RC circuits in the Simcenter Amesim battery model with the help of the RC transformation tool[12]. Figure 9 shows the R_{ss} and T_c identified at 25 °C.

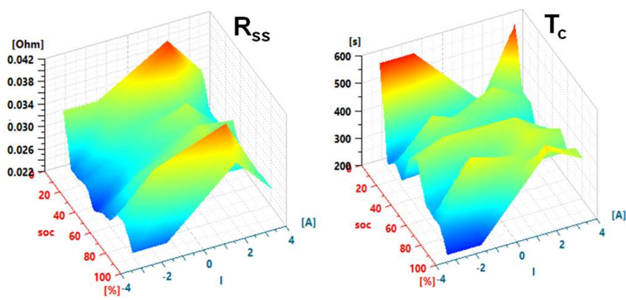


Figure 9: Warburg impedance at 25 °C

3.2.6 Thermal parameters

The parameter values of the thermal model are the same as the ones used in the electrochemical model as shown in Table 3.

Table 3: Values of parameters for the thermal model

Parameter	Value	Unit
C_p	791.86	J/kg/K
h_{cov}	27.5087	W/m^2/K
S_{conv}	0.00421525	m^2
m_{cell}	0.04622	kg

3.3 Model validation

Figure 10 shows the simulation sketch in Simcenter Amesim to evaluate the performance of the reduced-order circuit model. The sketch includes several elements such as (A) the battery model which represents the electrical model in Figure 1; (B) a convective heat exchange component and a thermal mass to represent the thermal model in Figure 3; (C) a resistance to represent the connector resistance in the electrochemical model; (D) a virtual test bench to deliver current to the battery model and measure the voltage; (E) 3 tables which import the current, voltage and temperature data generated by the electrochemical model (EC model). This sketch allows to compare the estimation of the two models on the battery voltage and temperature for the same current profile.

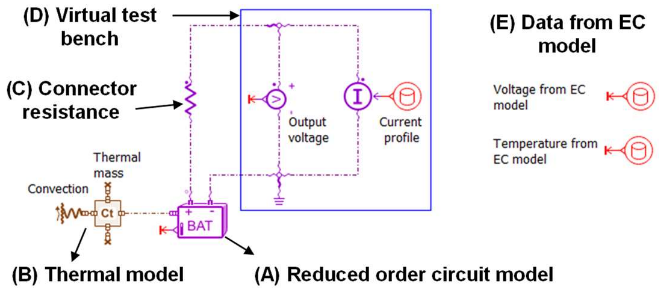


Figure 10: Simulation sketch for model validation in Simcenter Amesim

To evaluate the performance of the reduced order circuit model, a validation test profile in Figure 11 (a) has been applied to the reduced order circuit model and the electrochemical model. The profile includes a constant current charge phase to represent fast charge situation; several long-duration discharges to set the cell at different SoCs; and several dynamic cycles at different SoCs to represent the situation during driving. As explained in paragraph 3.2.5, the number of the RC circuit can be easily set in the reduced order model with the help of the RC transformation tool in Simcenter Amesim. Simulations with 5 different number of RC circuits (N_{RC} = 1 to 5) have therefore been done. Figure 11 (b), (c) and (d) show the comparison of the two models on the estimation of battery voltage and temperature at respectively 5, 25 and 45 °C, with N_{RC} = 1 in the reduced order circuit model. These figures show that the reduced order circuit model (ROC model) can reproduce correctly the voltage and temperature behavior of the electrochemical model (EC model).

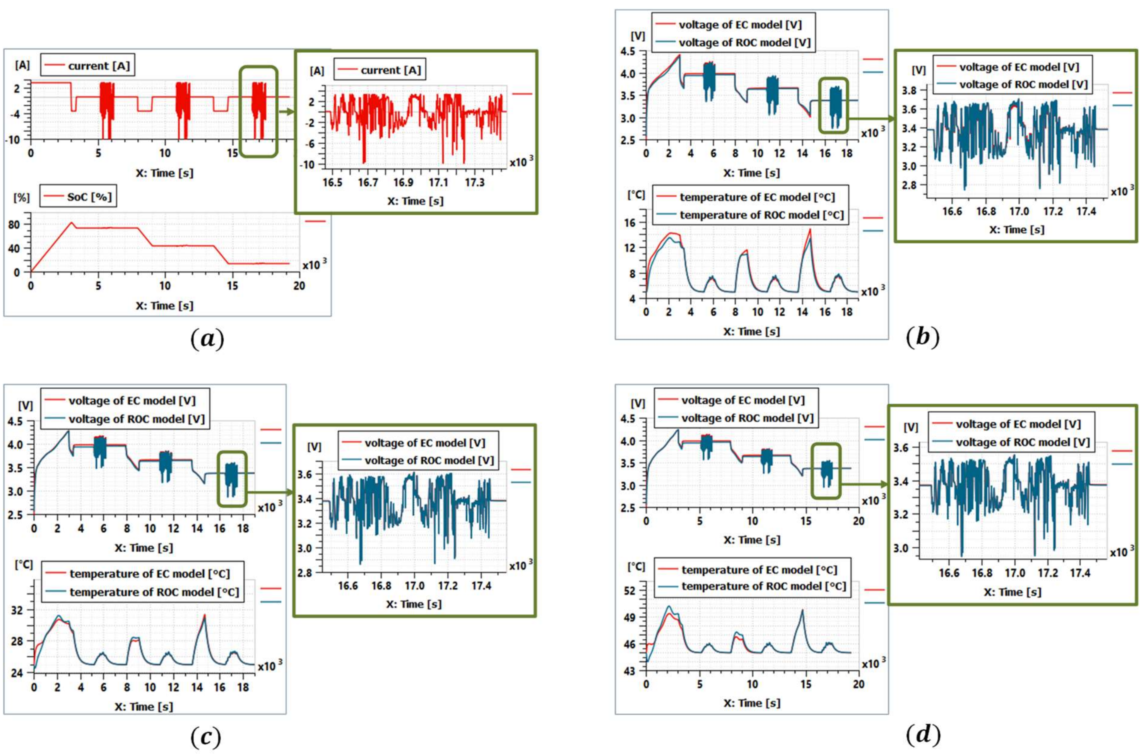


Figure 11: (a) Validation current and SoC profiles (b) Validation test at 5 °C (c) Validation test at 25 °C (d) Validation test at 45 °C

To evaluate quantitatively the performance of the reduced order circuit model, the RMS (root mean squared) errors for the voltage and temperature estimation are calculated by the equation as follow:

$$e_{RMS} = \sqrt{\frac{\sum_{k=1}^{N_s}\left(V_{ECM,k}-V_{ROM,k}\right)^2}{N_s}} \tag{10}$$

Where $V_{ECM,k}$ is the voltage or temperature of the electrochemical model; $V_{ROM,k}$ is the voltage or temperature of the reduced order circuit model; N_s is the number of the voltage or temperature data sample. Table 4 and Table 5 present the RMS errors of the voltage and temperature estimation according to the number of RC circuits used. The results show that the reduced order circuit model with 1 RC circuit is sufficient to simulate correctly the electrochemical model. Adding additional RC circuits doesn't improve significantly the estimation precision. The RMS errors of the reduced order circuit model are similar to the ones reported in other works in the literature [7][9].

Table 4: RMS Error for voltage estimation

RMS error of voltage	**1 RC (mV)**	**2 RC (mV)**	**3 RC (mV)**	**4 RC (mV)**	**5 RC (mV)**
5 °C	36	36	35	35	36
25 °C	29	29	29	29	29
45 °C	29	28	28	28	28

Table 5: RMS Error for temperature estimation

RMS error of temperature	**1 RC (°C)**	**2 RC (°C)**	**3 RC (°C)**	**4 RC (°C)**	**5 RC (°C)**
5 °C	0.55	0.55	0.54	0.54	0.54
25 °C	0.32	0.32	0.32	0.32	0.31
45 °C	0.34	0.34	0.34	0.34	0.34

4 Battery pack model

4.1 Battery pack model in a virtual test bench

In our study, the battery pack model is composed of 16 modules in series; each module is composed of 12 groups in series and each group is composed of 20 cells in parallel (20P12S). There are 3840 cells in total. The battery pack, together with a BMS developed by another partner, will be implemented in an electric vehicle (Voltia eVan) in the future stage of our project. To evaluate the performance of the BMS before hardware implementation in the eVan, a real-time compatible battery pack model is needed for the SiL and HiL tests.

By using the reduced order cell model descripted in Section 3, a battery pack model has been built in Simcenter Amesim. Figure 12 shows the simulation sketch of the electric vehicle including the battery pack model. The battery pack model includes 16 modules in series as the real pack. However, not every single cell is represented in each module of the battery pack model. To limit the number of components in the sketch, each module includes only 4 battery models in series. Each battery model is used to represent 3 groups of cells, which means 60 cells (20P3S) in total. All these 60 cells are considered to be identical, so only one battery model is enough to represent all of them by configuring the architecture of the battery model in Simcenter Amesim to be 20 in parallel and 3 in series (20P3S). By doing so, the battery pack is split into 48 battery models, which allows to have access to, for example, 48 temperatures at different places in the battery pack. The battery pack casing is also modeled. The casing is divided into 16 parts and each part is represented by a thermal mass element. The thermal mass of each part of the casing is connected to the nearby module.

The battery pack model is connected to the vehicle model of the Voltia eVan via the electric powertrain. Furthermore, a functional BMS is implemented in the simulation sketch to control the active air cooling of the battery pack via its casing. This functional BMS will be replaced by the real BMS function in the SiL environment and by the real BMS in the HiL environment.

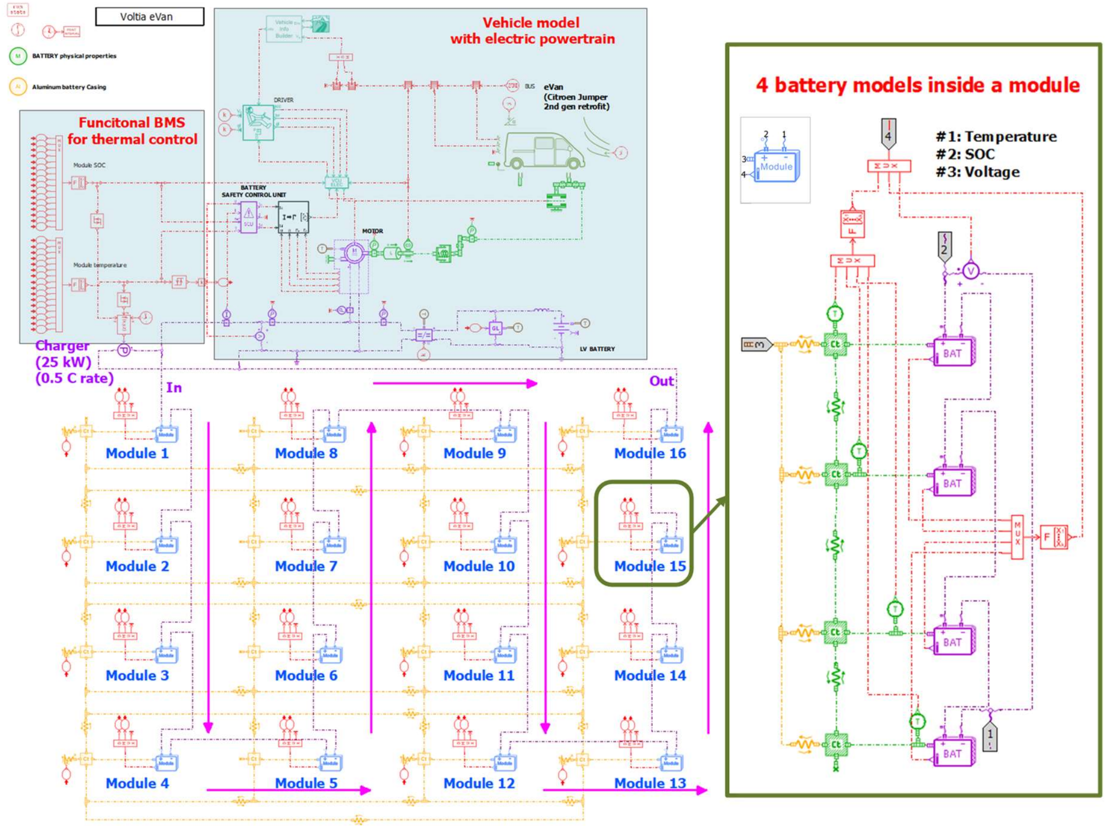


Figure 12: Integration of the battery pack model in a virtual test bench of an electric vehicle in Simcenter Amesim

4.2 Scenarios for battery pack cooling

To illustrate the use of the battery pack model with a BMS, a case study is presented in Figure 13 to compare the electro-thermal behavior of the battery pack under 2 cooling scenarios: with and without the active air cooling. For the scenario with the active air cooling, the functional BMS is used to turn on the air cooling when one of the 48 battery models reaches 35 °C. In this case, the heat exchange of the casing with its environment will change from natural convection (with h_{cov} equal to 20 W/m²/K) to forced convection (with h_{cov} equal to 200 W/m²/K). The active air cooling is turned off when all the 48 temperatures are less than 30 °C. For both scenarios, the battery pack is charged during the first 2 hours. Then the vehicle follows 2 WLTP driving cycles. The comparison of the simulation results for the 2 scenarios shows that the active cooling helps to increase the effective charge time and decrease significantly the battery cell temperatures.

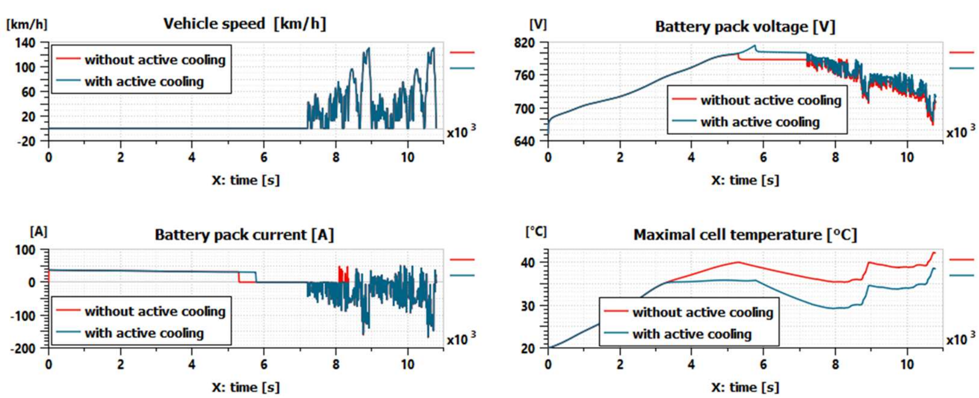


Figure 13: Comparison of results between 2 cooling strategies

4.3 Real time capacibility

To use the battery pack model for the SiL and HiL tests, the simulation time of the battery pack model must be analyzed to confirm its real time capability. Indeed, model in the SiL platform and especially in the HiL platform must be run with fixed step solver and must be faster than real time at each integration step. Figure 14 shows an analysis of the simulation time for the scenario with the active air cooling. The simulation sketch in Figure 12 was run with a fixed step solver by setting the integration time step to 0.002 s. The simulation was carried out on a laptop with Intel i7 2.6 GHz CPU, 16 GB RAM and a 512 GB SSD hard drive. In Figure 14, the cumulative CPU time for the simulation is 801 s at the end of the simulation, which is 13 times faster than the duration of the scenario (10800 s). The mean CPU time used per step (0.0001 s) is 20 times faster than the fixed time step value (0.002 s). The real-time capability of the model in Figure 12 is then validated.

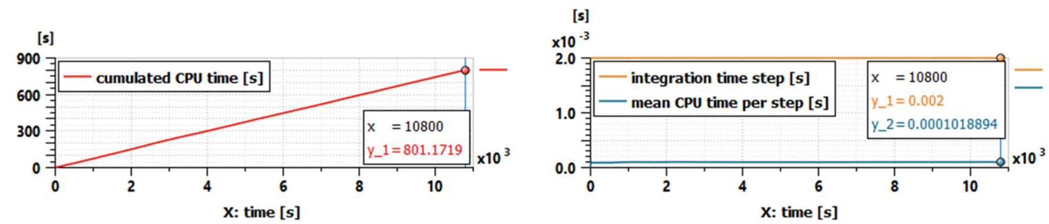


Figure 14: Comparison of results between 2 cooling strategies

5 Conclusion

In this paper, a simple method is proposed to get a reduced order electro-thermal cell model from a complex electrochemical cell model. The method requires only 2 tests per temperature to the electrochemical model to collect the simulated data of voltage and temperature. An equivalent circuit model is then identified from the simulated data. The method has been applied to get the reduced order model from the electrochemical-thermal p2D model calibrated for a nickel-rich, silicon-graphite lithium-ion cell of 3.35 Ah. The reduced order model can reproduce correctly the voltage and temperature behavior of the electrochemical model according to the validation tests. The method is generic so it can be applied with minor modification to any complex electrochemical models calibrated for other battery cells.

With the reduced order model, a battery pack model has been created and integrated in the virtual test bench for an electric vehicle in Simcenter Amesim. The real time capability of the pack model has been analyzed and validated via the simulation of a cooling scenario during vehicle normal operation with charging and driving cycles. The battery pack model is then ready to be used for the SiL and HiL tests of the BMS.

Acknowledgments

This work has received funding from the European Union's Horizon 2020 research program under the grant "Electric Vehicle Enhanced Range, Lifetime And Safety Through INGenious battery management" (EVERLASTING-713771).

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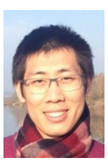

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