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An Improved Parametrization Method for Li-ion Linear Static Equivalent Circuit Battery Models Based on Direct Current Resistance Measurement

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***Abstract*—During many years, battery models have been proposed with different levels of accuracy and complexity. In some cases, simple low-order aggregated battery pack models may be more appropriate and feasible than complex physic-chemical or high-order multi-cell battery pack models. For example: in early stages of the system design process, in non-focused battery applications, or whenever low configuration effort or low computational complexity is a requirement. The latter may be the case of Electrical Equivalent Circuit Models (EECM) suitable for energy optimization purposes at a system level in the context of energy management or sizing problem of energy storage systems. In this paper, an improved parametrization method for Li-ion linear static EECMs based on the so called concept of direct current resistance (DCR) is presented. By drawing on a DCR-based parametrization, the influence of both diffusion polarization effects and changing of Open-Circuit Voltage (OCV) are virtually excluded on the estimation of the battery's inner resistance. This results in a parametrization that only accounts for pure ohmic and charge transfer effects, which may be beneficial, since these effects dominate the battery dynamic power response in the range of interest of many applications, including electro-mobility. Model validation and performance evaluation is achieved in simulations by comparison with other low and high order EECM battery models over a dynamic driving profile. Significant improvements in terms of terminal voltage and power losses estimation may be achieved by a DCR-based parametrization, which in its simplest form may only require one short pulse characterization test within a relatively wide range of SoCs and currents. Experimental data from a 53 Ah Li-ion pouch cell produced by Kokam (Type SLPB 120216216) with Nickel Manganese Cobalt oxide (NMC) cathode material is used.**

I. Introduction

Electrochemical batteries are strongly non-linear electrochemical systems, consisting of a complex mixture of laws of thermodynamics, electrode kinetics and mass transport phenomena [1]. Hence, accurate modelling is not a simple task. During many years, battery models have been proposed with the basic aim at providing either an evaluation of preliminary physic-chemical designs or a performance estimation of already manufactured batteries [2]–[8].

In order to simplify the analysis, battery models have been classified in accordance with their implementation method [3]–[8]. For example, in [3] and [4] models have been classified in four different approaches: physical, empirical, abstract and mixed. On the other hand, the authors of [5] have focused on modelling approaches most suitable for electro-mobility related simulations, identifying next implementation methods: physic-chemical (or physical), empirical, impedance-based and energy-based. However, since impedance-based models are one kind of the so called abstract models and energy-flow based one kind of the so called empirical models, these two categories have already been included in the more broad classification given in [3] and [4]. A more specific overview of impedance-based models, so-called Electrical Equivalent Circuit Models (EECMs), is given in [6] and [7], the latter including as well a comparative study.

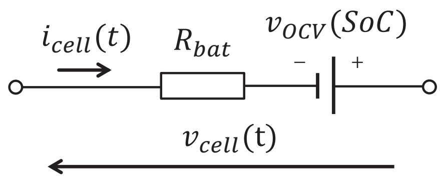


Fig. 1: Linear static EECM of a single cell of a Li-ion battery.

Table I [8] gives an overview of the battery modelling approaches according to the classification given in [3] and [4] considering the following factors: accuracy, computational complexity, configuration effort, analytical insight and purpose. As a general rule, it may be stated that more complex models provide more accurate results, but involve higher computational complexity and configuration effort, defined proportionally to the number and sensitivity of their parameters. Furthermore, advanced characterization tests require specialized methods and testing equipment [2]–[8].

In some cases, simple aggregated battery pack models may be more appropriate and feasible than complex multi-cell battery pack models, e.g. in early stages of the system design process, in non-focused battery applications or whenever low

TABLE I: Overview of Battery Modelling Approaches and Applications

Model Approach	Accuracy	Computational Complexity	Computational Effort	Analytical Insight	Purpose
Physical	Very high	High	Very high	Low	Battery design and model validation
Empirical	Low-Medium	Low	Low	Low	Battery performance estimation
Abstract	Low-High	Low-Medium	Low-High	Medium	Battery performance estimation
Mixed	High	Medium	Low-Medium	High	Battery performance estimation

configuration effort or low computational complexity is a requirement. The latter may be the case of battery pack models suitable for energy optimization purposes at a system level in the context of energy management or sizing problem of energy storage systems. This issue is frequently addressed in the literature, e.g. in hybrid electro-mobility [9]–[16]. Nevertheless, it should be noted that simplifications required by optimization methodologies make accurate modelling of battery performance more challenging, as discussed in [11].

Nowadays, besides lossless and constant efficiency models, a modelling approach broadly followed in the context of energy optimization at a system level in hybrid electro-mobility is to use an aggregated linear static battery pack EECM [9]–[16], over a restricted operating window, without taking into account cell-to-cell differences. Thus, a battery pack model made up of n cells is built from the sum of n-identical single cell models in a certain series-parallel arrangement.

Typically, the single cell EECM considered consists as well on a constant resistor R_{bat}, which represents the battery's inner resistance, in series with a variable DC voltage source $v_{OCV}(SoC)$, which models the relationship between Open Circuit Voltage (OCV) and State-of-Charge (SoC) (Fig. 1).

The instantaneous cell voltage $v_{cell}(t)$ can be obtained as the sum of the DC voltage $v_{OCV}(SoC)$ and the product of the instantaneous cell current $i_{cell}(t)$ by the inner resistance R_{bat} as

$$v_{cell}(t) = v_{OCV}(SoC) + i_{cell}(t)R_{bat} \tag{1}$$

where $v_{OCV}(SoC)$ [V] is the Open-Circuit Voltage (OCV) of the cell, SoC [%] is the cell state-of-charge, $i_{cell}(t)$ [A] is the instantaneous cell current, R_{bat} [Ω] is the inner cell resistance and t [s] is the simulation time.

The SoC may be defined in different ways, taking into account different dependencies [2], [6]–[8]. In the aforementioned context the simplest form is commonly used [9]–[16], which is an estimation based on coulomb counting given by

$$SoC = SoC_0 + \frac{100}{3600Q}\int_0^t i_{cell}(\tau)d\tau \tag{2}$$

where SoC_0 [%] is the initial cell state-of-charge and Q [Ah] the rated cell capacity.

Regarding the variable DC voltage $v_{OCV}(SoC)$, the common approach [9]–[16] to simplify the non-linear OCV vs. SoC characteristic is to use a linear function, which may provide a good fit within a wide range of SoC, as could be deduced e.g. from Fig. 6. The linear function is given by

$$v_{OCV}(SoC) = a + b \cdot SoC \tag{3}$$

where a and b are two constant coefficients calculated in a linear fitting.

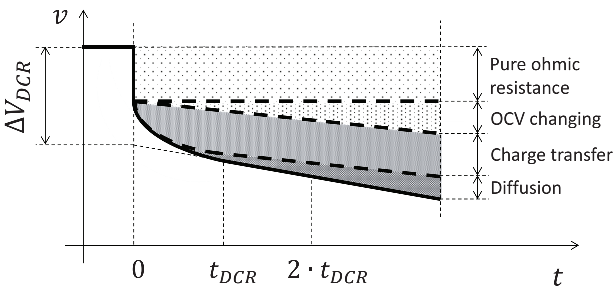


Fig. 2: Schematic representation of the voltage changes of a battery during a discharge current pulse[1].

The instantaneous cell power losses $P_{loss}(t)$ are usually assumed [9]–[16] as the result of Joule heating as

$$P_{loss}(t) = i_{cell}^2(t)R_{bat} \tag{4}$$

In this paper, an improved approach to parametrize the single cell linear static EECM described above is proposed, based on the so called DCR concept. In the following, it is shown that a DCR-based approach may offer a significant accuracy improvement over conventional methods, both in terms of cell terminal voltage and power losses estimation.

DCR has already been proposed in the literature to describe the power or current capability of a cell in high order impedance-based models [17]–[19], but to the best of our knowledge, it has not been proposed as a parametrization method for low order impedance-models itself. As aforementioned, an electrochemical battery is a highly non-linear system. However, Electrochemical Impedance Spectroscopy (EIS) analysis could be performed if quasi-linear conditions are observed. Therefore, by using small AC excitation amplitude the current-voltage linearity may be preserved. But this means that only small-signal impedance can be obtained from EIS. Nevertheless, large-signal impedance is required for highly accurate time-domain simulations. DCR measurements are one of the existing methods used to calculate large-signal impedance from small-signal impedance measurements [17]–[19].

Conventional methods based on off-line current pulse characterization techniques may either take into account too many or too few electrochemical kinetic effects on the parametrization of the inner cell resistance, R_{bat}. This may lead, re-

[1] It should be noted that charge transfer and diffusion polarization are sometimes referred in the literature as activation polarization and concentration polarization, respectively. Moreover, concentration polarization is also often referred as mass transport. The concept mass transport usually refers to three simultaneous phenomena: migration, diffusion and convection. However the mass transport phenomenon is usually simplified as diffusion, since it usually plays a dominant role in electrochemical kinetics.

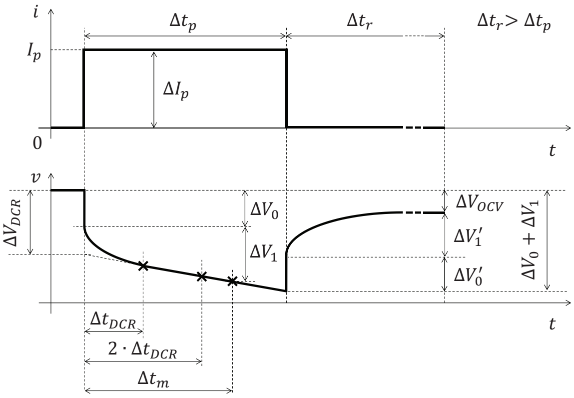


Fig. 3: Schematic representation of the voltage changes used to calculate the DCR, the pure ohmic resistance and the polarization resistance.

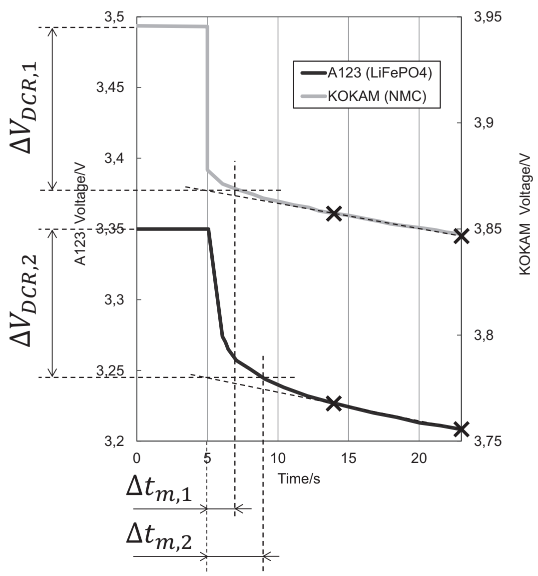


Fig. 4: Voltage in time for two different Li-ion cells and schematic representation of the calculation of the DCR voltages $\Delta V_{DCR,1}$ and $\Delta V_{DCR,2}$ and their equivalent measurement times $\Delta t_{m,1}$ and $\Delta t_{m,2}$.

spectively, to overestimation or underestimation of the battery power response when the model is subjected to dynamic charging or discharging profiles. By drawing on a DCR-based methodology, the influence of both diffusion polarization effects and changing of OCV are virtually excluded on the estimation of R_{bat}, resulting in an improved parametrization which accounts practically for pure ohmic and charge transfer effects on R_{bat} (Fig. 2). This may be beneficial, since pure ohmic and charge transfer effects dominate the battery dynamic power response in the range of interest in most applications, including hybrid and battery electric vehicles [18]–[21].

The paper is organized as follows. In Section II the techniques used for experimental characterization and the methods applied for model parametrization are discussed. In Section III experimental data and parametrization results are shown for commercial Li-ion batteries. In Section IV model validation is presented based on a detailed comparison of different modelling approaches. Finally, Section V gives the conclusions.

II. Linear Static Battery Model Parametrization Methods

DCR measurement is proposed in this paper as an improved approach to parametrize linear static battery models of Li-ion batteries (Fig. 1), e.g. in the context of battery modelling in energy optimization problems. A schematic representation of the voltage changes used to calculate the DCR and the other conventional current pulse characterization techniques is given in Fig. 3.

Conventional current pulse characterization techniques consist of applying a constant current pulse of certain amplitude ΔI_p to the battery and measuring the resulting change in the terminal voltage, either during the pulse ΔV_j or after the pulse $\Delta V_j'$. Notice than j represents the sub-indexes employed in Fig. 3. Then, the resistance is just obtained by applying Ohm's law, i.e. by dividing the change of voltage by the change of current.

The characterization technique is so-called current injection method if the voltage change is measured during the current pulse Δt_p. Alternatively, if the voltage change is measured after the current pulse, i.e. during the relaxation time Δt_r , the technique is so-called current interruption method.

Typically, the values of the voltage changes measured with the current injection method are slightly higher in comparison to the values measured with the current interruption method. Influence of the diffusion polarization is one of the causes of the divergence of results, which could be mitigated if the relaxation time Δt_r of current interruption method is increased until quasi-equilibrium state is achieved [22], [23]. The other cause of this divergence is the change of OCV ΔV_{OCV} caused by SoC variation when a current injection method is applied. Nevertheless, the magnitude of the OCV change depends on the specific OCV vs SoC characteristic, as well as on the current pulse amplitude ΔI_p and length Δt_p.

While on the subject of conventional approaches, two parametrization methods are commonly proposed in the literature to estimate the value of the battery inner resistance R_{bat} based on aforementioned current pulse characterization techniques [9]–[16]. The first one consists of using the value of the pure ohmic resistance R_0, which corresponds to ratio of the change of voltage and the amplitude of the current pulse, measured either immediately after the beginning or the end of a pulse, $\Delta V_0 \,/\, \Delta I_p$ or $\Delta V_0' \,/\, \Delta I_p$ respectively. The second one consists of using the value of the pure ohmic resistance plus the polarization resistance, which corresponds either to the change of voltage during certain measurement time Δt_m divided by the amplitude of the current pulse, $(R_0 + R_1) = (\Delta V_0 + \Delta V_1) \,/\, \Delta I_p$, or to the change of voltage during the relaxation time divided by the amplitude of the current pulse, $(R_0' + R_1') = (\Delta V_0' + \Delta V_1') \,/\, \Delta I_p$. These methodologies have been proposed in existing standards to determine the battery power capability of electric vehicles, considering both current injection and current interruption, and using different pulse lengths or relaxation times [24].

However, as discussed earlier, conventional methods either take into account too many or too few effects on the parametrization of R_{bat}. In general, if the value of the pure ohmic resistance may be used, R_0 or R'_0, the battery dynamic power response is underestimated, since charge transfer effects are not considered. Inversely, if the value of pure ohmic resistance plus the polarization resistance is used, $(R_0 + R_1)$ or $(R'_0 + R'_1)$, the battery dynamic power response may be overestimated, since in every case not only the charge transfer, but also the diffusion effects are considered.

The DCR measurement technique consists of applying a constant current pulse of certain amplitude ΔI_p and certain duration Δt_p to the battery and measuring the resulting change in the terminal voltage during the pulse. Then, the voltage curve between Δt_{DCR} and $2\Delta t_{DCR}$ it is linearised and the resulting line is continued up to the start of the current pulse as shown in Fig. 2, Fig. 3 and Fig. 4. In this way the voltage drop ΔV_{DCR} is defined. Finally, the value of DCR is calculated as the aforementioned change of voltage divided by the amplitude of the current pulse, $DCR = V_{DCR} \,/\, \Delta I_p$ [17]–[19].

It should be noted that Δt_{DCR} may be selected differently depending on the battery or its conditions, e.g. temperature or ageing state. Of course, always considering for the duration of the current pulse that $\Delta t_p \geq 2\Delta t_{DCR}$. However, a rule of thumb is to choose a value for Δt_{DCR} that ensures that the battery terminal voltage is almost linear between Δt_{DCR} and $2\Delta t_{DCR}$ [18], [19].

By using a DCR-based methodology, the influence of both diffusion polarization effects and OCV changing are virtually neglected (Fig. 2) [17]–[19]. Although, it should be noted that the values of R_{bat} parametrized using a conventional method and a DCR-based may overlap for a particular case (Fig. 11). However, in a broad sense, DCR-based parametrization may represent a more robust and consistent assessment tool. Particularly, if a current injection method is used, it may be possible to find for a certain cell a measurement time Δt_m for calculation of ΔV_1 that may result in parametrization values for R_{bat} similar to the ones obtained using a DCR approach, as shown in Fig. 11). However, if the same measurement time Δt_m is used to characterize a different cell, e.g. from a different chemistry, it may result that the parametrization values for R_{bat} may differ from the ones obtained using a DCR approach.

This concept is illustrated in Fig. 4, which shows the voltage in time for two cells from different manufacturers, formats and cathode chemistries, when an 18 s current pulse is conducted at 80 % SoC. The first one is an uncycled 53 Ah Li-ion pouch cell produced by Kokam with a Nickel Manganese Cobalt oxide (NMC) cathode. The second one is an uncycled 2.5 Ah Li-ion cylindrical cell produced by A123 systems with a Nanophosphate LiFePO4 cathode. Experimental data for the latter comes from [23]. The pulse current is 1 C (53 A) and 4 C (10 A) respectively. For this example $\Delta t_{DCR} = 9$ s is considered. It can be observed that the measurement time for calculation of change in the terminal voltage during a conventional current injection test that may result in parametrization values for R_{bat} similar to the ones obtained using a DCR approach, i.e. $\Delta V_0 + \Delta V_1 \approx \Delta V_{DCR}$, is different for each cell. For the NMC cathode cell $\Delta t_{m,1} \approx 2$ s, while for the LiFePO4 cathode cell $\Delta t_{m,1} \approx 4$ s.

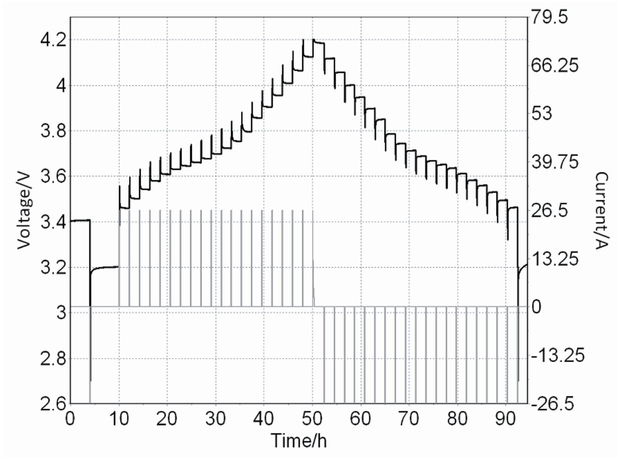


Fig. 5: Exemplary OCV test at 25 °C and 0.5 C.

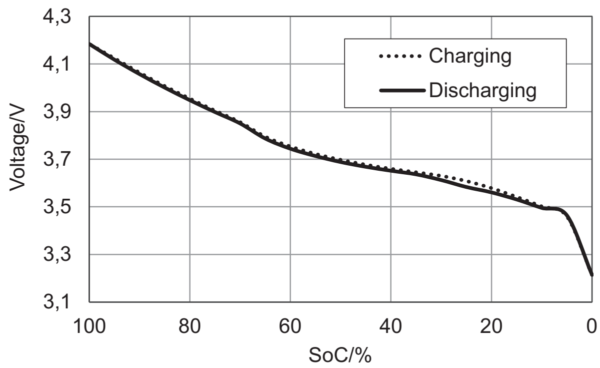


Fig. 6: Exemplary OCV vs. SoC characteristic estimated from OCV test at 25 °C and 0.5 C.

III. Experimental Characterization Data and Parametrization Results

It should be noted that the values of the battery inner resistance measured by current pulse characterization technique are not only sensitive to the specifications of the methodology applied, i.e. DCR measurement, current injection or current interruption, pulse length (Δt_p), pulse amplitude (ΔI_p), relaxation time (Δt_r) or DCR measurement time (Δt_{DCR}), but also to factors like temperature, SoC or SoH. These dependencies and their effects on the parametrization results are investigated in this paper, based on experimental data from a commercial Li-ion battery, with the exception of the influence of SoH: calendar and cycling studies are beyond the scope of this paper and will be considered in a future extension.

For illustrative purposes, exemplary experimental data from current pulse characterization test conducted on an uncycled Kokam 53 Ah SPLB 120216216 Li-ion NMC pouch cell are displayed in Fig. 6 [11] and Fig. 7.

The current pulse test displayed in Fig. 6 is often referred as OCV test, since it is usually conducted to obtain the OCV

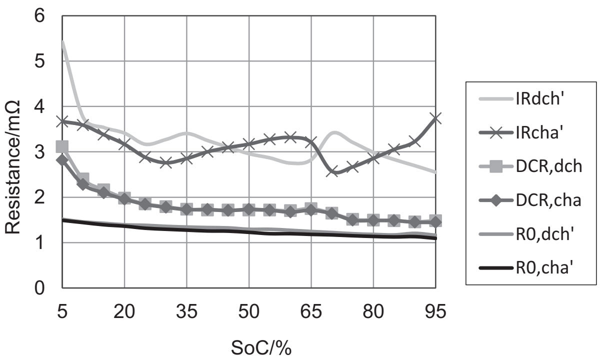


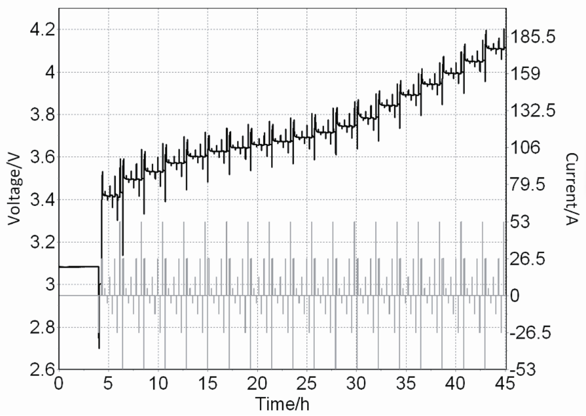
Fig. 7: Exemplary parametrization results of R_{bat} obtained from OCV tests at 25 °C using a current interruption method during charge and discharge current pulses: pure ohmic resistance (R_0') and pure ohmnic plus polarization resistance ($IR' = R_0' + R_1'$). For comparison, DCR results from Fig. 10 at 0.5C are also displayed.

vs. SoC characteristic, shown in Fig. 5. In this case, the test was conducted at 0.5 C (26.5 A) and 25 °C. Before the OCV test begins, a full charge and discharge cycle was conducted in order to calculate the charging and discharging capacity. Then, the battery tester is programmed to fully charge and discharge the cell in sequential steps of 5 % SoC, considering a 2h relaxation time between consecutive pulses. From these experimental data, besides the OCV vs SoC characteristic (Fig. 5), it may be calculated the battery's inner resistance R_{bat}, according to the parametrization techniques described in previous section (Fig. 7).

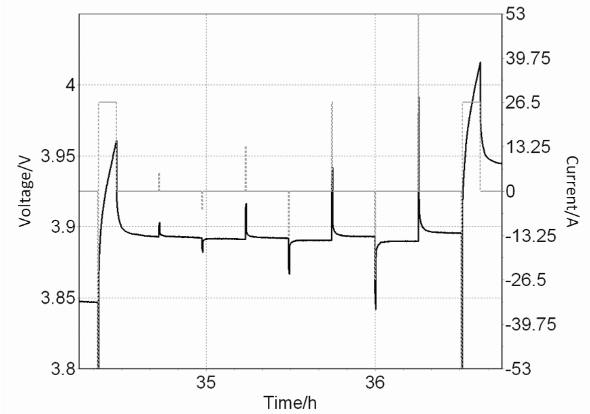
On the other hand, the current pulse tests displayed in Fig. 8 are often referred as pulse power characterization tests, since they are conventionally used to characterize the power capability of a cell. Pulse power characterization tests are intended to determine the internal resistance over the cells usable voltage range using a current test profile that includes both discharge and charge pulses at different SoC levels. In the exemplary case shown in Fig. 8 consecutive steps of 5 % SOC are considered, with a pulse length of 20 s and a relaxation time after each pulse of 15 min, and current levels of 0.1 C, 0.25 C, 0.5 C and 1 C.

In Fig. 9 exemplary parametrization results from pulse power characterization tests at 25 °C and 0.1 C are presented, comparing a DCR approach with conventional current injection techniques, using 10 s and 20 s as measuring times for ΔV_1 and 10 s for Δt_{DCR}. Furthermore, in Fig. 10 DCR parametrization results from pulse power characterization test at 25 °C are shown for the whole range of discharge and charge currents studied in Fig. 8. For the range of currents studied, it can be observed in Fig. 10 a relatively small variation of the value of DCR for a large SoC window, from 20 % to 80 % SoC, which means that a constant average value of DCR may be used in dynamic discharge simulations over a wide SoC range without large accumulative errors in cell voltage or power losses estimation, as shown in next section.

In order to show the effect of the temperature on the DCR



(a) Overall view



(b) Detailed view

Fig. 8: Exemplary pulse power characterization test at 25 °C.

parametrization results, the same pulse power characterization tests presented in Fig. 8 for 25 °C, have been conducted at three other temperatures: 15, 35 and 45 °C. Fig. 12 displays the DCR parametrization results for these temperatures, taking into account the average value of the DCR over the same range of discharge and charge currents studied in Fig. 8. As expected, for higher temperatures a lower average DCR is calculated. It should be noted that, similarly to Fig. 10, a relatively small variation of the average value of DCR for a large SoC window, from 20 % to 80 % SoC, is calculated for all the temperatures under study.

This characteristic is becoming more evident at higher temperatures and, conversely, less evident at lower temperatures. These results suggest that further studies at lower temperatures could be conducted to gain more insight. The DCR parameterization results presented in this paper show good agreement with the results presented in [18] for a 40 Ah Li-ion pouch cell produced by Kokam (Type SLPB 100216216H) with Nickel Manganese Cobalt oxide (NMC) cathode material. The interested reader can find in [18] also studies at higher C-rates and lower temperatures, which complement the present work from a qualitative point of view.

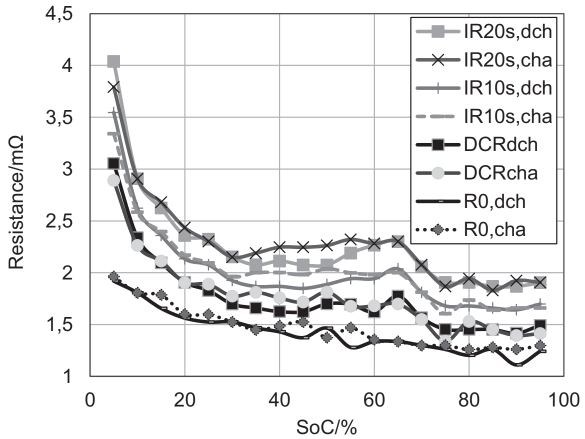


Fig. 9: Exemplary parametrization results of R_{bat} obtained from pulse power characterization tests during charge and discharge pulses: DCR, pure ohmic resistance (R_0) and pure ohmnic plus polarization resistance ($IR = R_0 + R_1$).

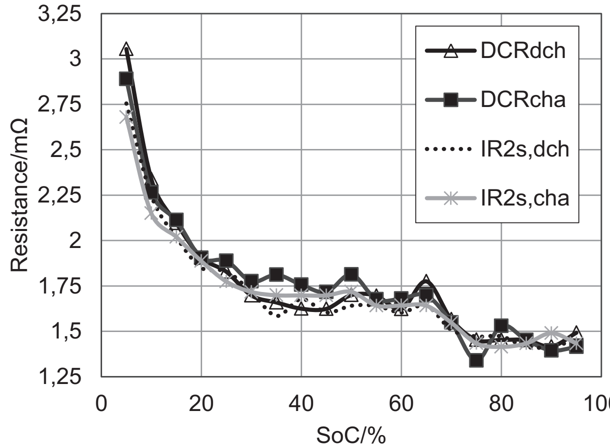


Fig. 11: Exemplary parametrization results of R_{bat} obtained from pulse power characterization test during charge and discharge current pulses: a conventional current injection method, considering 2 s as measuring times for ΔV_1, is compared with a DCR method.

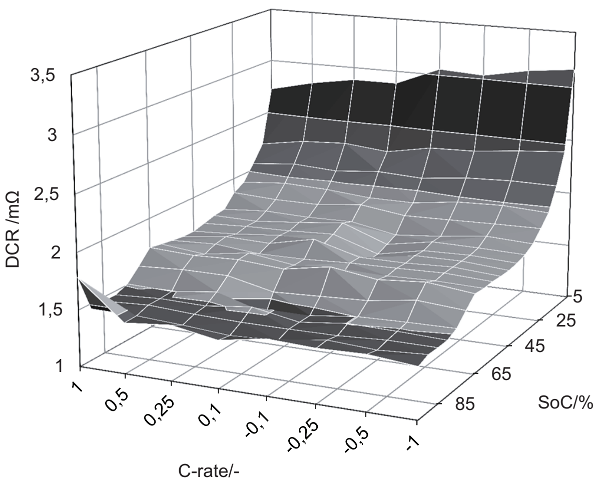


Fig. 10: DCR parametrization results from pulse power characterization test at 25 °C and different C-rates.

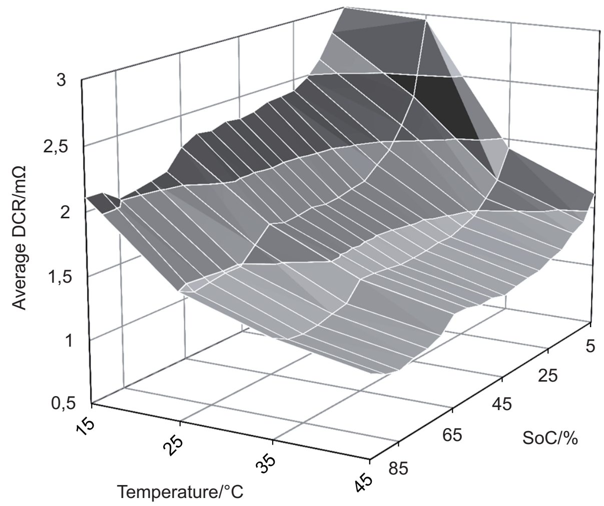


Fig. 12: Average DCR parameterization results for different temperatures.

IV. DCR Model Validation

In this section, the performance of the linear static EECM with DCR-based parametrization is compared with other battery models. Low and high order, linear and non-linear, static and dynamic EECMs are considered, for the purposes of performance evaluation and model validation.

In Fig. 14 the voltage profile of a first order non-linear dynamic EECM (Fig. 13) together with four linear static EECMs (considering R_{bat} as $R'_0 + R'_1$ and R'_0, DCR and an optimal parametrization) is presented, with a dynamic discharging profile obtained from a power demand determined by simulation of a Battery Electric Vehicle, over a standard US06 driving cycle.

With exception to the optimal parametrization, all models are parametrized using aforementioned experimental data from OCV test at 25 °C (Fig. 5 and Fig. 6), estimating the value of the inner resistance R_{bat} as a DCR, a pure ohmic resistance (R'_0) or a pure ohmic plus polarization $(R'_0 + R'_1)$, considering average values of the discharge resistances over an SoC window of 5-80 %, $\Delta t_r = 2$ h and $\Delta t_{DCR} = 10$ s. From the OCV test data, using the same current interruption method, the pure ohmic resistance, the polarization resistance and the capacitive element values are estimated for the first-order non-linear dynamic (NLD) EECM. Moreover, regarding the NLD model, a non-linear OCV vs. SoC characteristic is also considered. Nevertheless, since an insignificant voltage hysteresis effect is observed (Fig. 6) with respect to charge and discharge processes, the average OCV vs SoC characteristic is applied.

Furthermore, from this power profile, an optimal parametrization for the linear static model is obtained. Considering the change of voltage caused by the internal

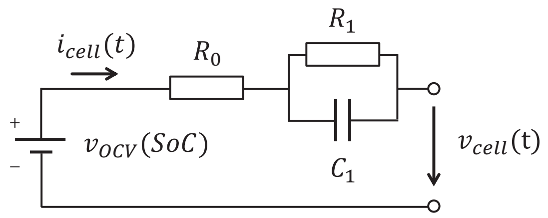


Fig. 13: First order non-linear dynamic EECM of a single cell of a Li-ion battery.

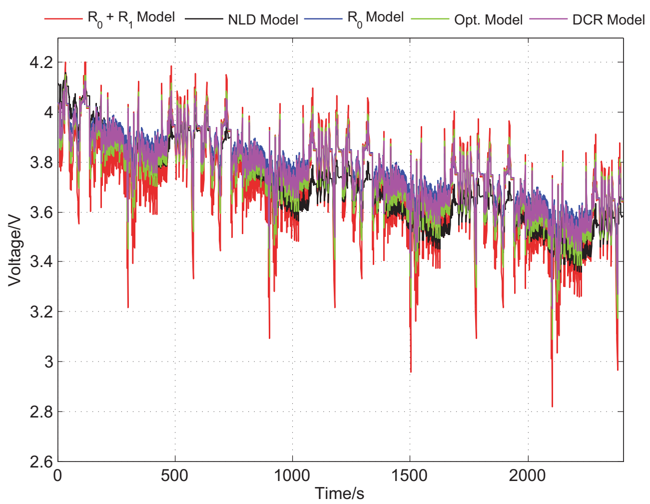


Fig. 14: Exemplary estimation of battery voltage during dynamic discharging profile using different ECCMs.

impedance

$$\Delta V_{R_{bat}}(t) = v_{OCV}(SoC) - v_{cell,NLD}(t) \tag{5}$$

by applying the current demanded by the driving cycle (for the NLD model), a final identification problem can now be posed as a simple linear least-squares problem:

$$R_{OPT} = \underset{R_{bat}}{argmin} \sum_{k=0}^{N} (\Delta V_{R_{bat}}(t_k) - R_{bat} i_{bat}(t_k))^2 \tag{6}$$

where R_{OPT} is the internal impedance that provides a better approximation between the non-linear dynamic and linear static behaviours, in this specific application. N is the size of the training data set. In this case, the parametrization is obtained from a known voltage and current profiles (obtained from the NLD model, the most accurate in this paper) instead of using typical characterization tests. In other words, the optimal R_{OPT} value varies according to the proposed application.

In Fig. 15, the simulation results shown in Fig. 14 are analysed from the point of view of cell voltage mean squared error, max. voltage error and total cell power losses for each of the three linear static EECMs implemented, using the first-order NLD EECM as a reference. It should be noted that an experimental dynamic discharge profile is not used as a reference due to the complexities of measuring the power losses, since a calorimeter may be required. According to these results, a DCR-based approach may offer a significant

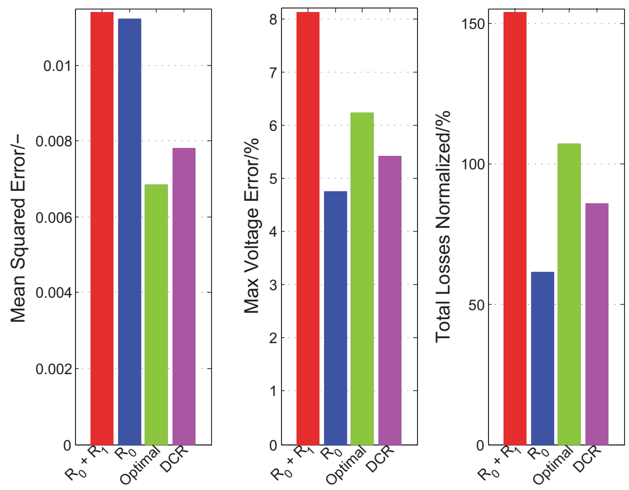


Fig. 15: Cell voltage mean squared error, max. voltage error and normalized total cell power losses for each of the three linear static EECM, using the first-order NLD EECM as a reference.

accuracy improvement over the other conventional methods ($R'_0 + R'_1$ and R'_0), both in terms of cell terminal voltage and power losses estimation. The total power losses estimated with the DCR parametrization are only 14 % less than the losses estimated with the NLD model, while the R'_0 parametrization provides 39 % lower losses and the $(R'_0 + R'_1)$ parametrization 54 % higher losses. Furthermore, the mean squared error of the voltage estimation using DCR parametrization is 31 % and 30 % lower than the $(R'_0 + R'_1)$ and R'_0 parametrizations, respectively. Regarding the maximum voltage error, since the inner resistance obtained with DCR parametrization is higher than R'_0 the maximum voltage error is slightly higher in the DCR case. In other words, in average the voltage estimation results are closer to the NLD model with the DCR parametrization, however some peak currents may provide instantaneous errors slightly higher than the model with the R'_0 parametrization.

In its turn, the optimal approach presents a more accurate result in comparison to the reference parametrization (NLD model), in relation to all the other methods. In terms of mean squared error there, less 14 % of error is obtained in comparison to the DCR model. In terms of total power losses only 7 % of error is obtained relatively to the NLD model. Nevertheless, for the same reason aforementioned to the other models, the DCR model presents a smaller maximum voltage error when compared to the optimal model.

It should be noted, however, that the optimal parametrization is obtained from a known current and voltage profiles. In that sense, for typical profiles, an optimal linear static model can be generated presenting a simple, but relatively accurate model. On the other hand, the DCR method proved, in this case, to be more accurate than typical characterization methods for linear static models without assumptions of the application profile.

For illustrative purposes, a constant current discharge step at 1C, 25 °C and 50 % SoC is shown in Fig. 16. Experimental battery voltage is compared with the estimations from differ-

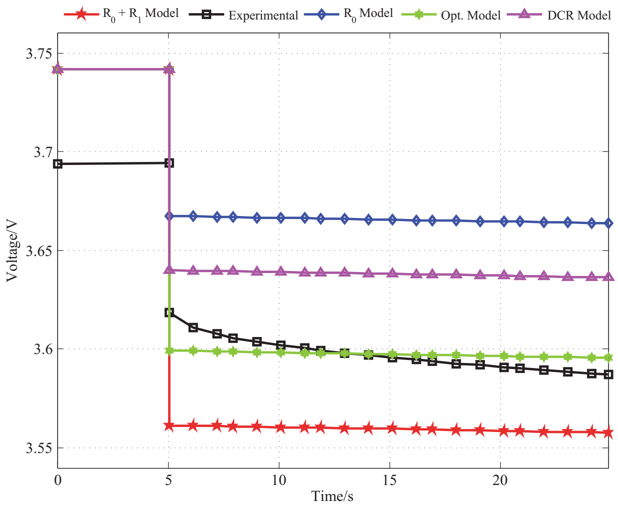


Fig. 16: Exemplary estimation of battery voltage during constant current discharge step at 1C, 25 °C and 50 % of SoC using different linear static models with different parametrizations.

ent linear static models, considering different parametrization methods.

V. Conclusion

By drawing on a DCR-based methodology, the influence of both diffusion polarization effects and changing of OCV are virtually excluded on the estimation of the inner resistance, resulting in an improved parametrization which accounts practically for pure ohmic and charge transfer effects. It was demonstrated that this may be beneficial, since pure ohmic and charge transfer effects dominate the battery dynamic power response in the range of interest in most applications, including hybrid and battery electric vehicles.

Moreover, it has been shown, using experimental data, that the values of the battery inner resistance measured by current pulse characterization technique are sensitive to the specifications of the methodology applied and to factors like temperature, in good agreement with previous results from the literature.

With regard to the influence of the pulse current amplitude, for the range of currents studied (-1 C to 1 C), a relatively small variation of the value of DCR was observed for a large SoC window, from 20 % to 80 % SoC. This means that a constant average value of DCR may be used in dynamic discharge simulations over a wide SoC range without large accumulative errors in cell voltage or power losses estimation.

On the other hand, regarding the temperature effect, DCR increases non-linearly with the reduction of temperature. This suggests that, as expected, temperature is a factor that cannot be neglected, whatever the parametrization method. It should be noted that a relatively small variation of the average value of DCR for a large SoC window, from 20 % to 80 % SoC, is observed for all the temperatures under study (15, 25, 35 and 45 °C). This characteristic is more evident at higher temperatures and, conversely, less evident at lower temperatures, which suggest that special care should be taken when modelling battery dynamic power response at lower temperatures.

Finally, for purposes of performance evaluation and model validation, the performance of the linear static EECM with DCR-based parametrization is compared with other battery models during a dynamic discharge simulation. Low and high order, linear and non-linear, static and dynamic EECMs are considered. Mean squared error, max voltage error and total losses are used as performance metrics, using the NLD model as a reference. The dynamic discharging profile is obtained from a power demand determined by simulation of a Battery Electric Vehicle, over a standard US06 driving cycle.

As anticipated, the DCR model achieved significant improvements in terms of cell terminal voltage and power losses estimation in comparison with other conventional pulse characterization methods, which tend to overestimate or underestimate the battery dynamic power response.

Moreover, for evaluation purposes, an optimal internal resistance is obtained for the linear static model using the NLD model as a reference. An ordinary least-squares estimation technique for linear regression is applied. The sum of square residuals (change of voltage offsets) is minimized over the realistic dynamic discharging profile. The performance of the linear static circuit parametrized with optimal method is slightly better than the DCR method in terms of mean squared error and power losses.

However, it should be noted that a DCR method may not present the limitations, complexity or infeasibility problems of a statistical regression analysis. An optimal parametrization requires a simulation with a complex battery model or a real battery dynamic test in order to obtain the dynamic voltage profile. Furthermore, sometimes the battery current demand may be unknown, e.g. in energy management problems in hybrid systems, since the power allocation is an output. Last but not least, sometimes the current demand may come from certain system-level demand, e.g. a driving cycle in e-mobility, requiring a full-system model or field tests. These issues do not affect the DCR method, which in its simplest form may only require one short pulse characterization test within a relatively wide range of SoCs and currents to provide a solution close to the optimal.

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