Co-identification procedure of equivalent circuit model of batteries from short-term experiments

Dino Hrvanovic · Ignacio Peñarrocha-Alós · Emilio Pérez · Carlos Díaz-Sanahuja · Günter Prochart

Abstract In this paper we propose a co-identification iterative procedure aimed at estimating static and dynamic components within an equivalent circuit model for batteries, exploiting a limited amount of data with the aim to shorten the experiments needed to acquire data for identification. The proposed algorithm estimates iteratively the model parameters by segregating the measured terminal voltage into static Open Circuit Voltage (OCV) and dynamic (voltage drop across Rs and Cs) voltage terms. In each iteration, first the OCV-SOC curve model is identified using a virtual OCV measurement derived from the voltage and a previously estimated dynamic voltage. Secondly, the dynamic behavior model is identified using a virtual dynamic voltage measurement derived from the voltage and the recently estimated OCV. This iterative identification process allows to obtain models for both static and dynamic components. The paper validates the effectiveness of this approach in precisely identifying equivalent circuit parameters from limited experimental data.

1 Introduction

Rechargeable Energy Storage Systems (ESS) are considered a clean energy source for most autonomous applications, from low-energy, low-power portable devices to high-energy, high-power applications such as smart-grid and Electric Vehicles (EVs). A high demand in grid renewable ESS and EVs makes the Lithium-Ion Batteries (LIBs) presently one of the most accepted ESS on the market. This is due to the fact that, when compared with other choices of rechargeable batteries [1]- [2], LIBs have several advantages: high energy density, high power density, wide voltage range, long cycle life and environmental friendliness [3]. Furthermore, when referring to LIBs, there is a wide variety of chemistries and packaging formats (each with different characteristics), although the fundamental working principles of these LIBs remain the same [4].

Due to requirements in automotive industries such as long range, fast acceleration and efficiency, LIBs in EVs are targeting high capacity and a large serial-parallel numbers of cells. This may lead to problems such as safety, durability, uniformity and cost [3]. To tackle these challenges in real applications, LIBs need to operate within their safe and reliable operating area, what needs the use of a Battery Management System (BMS). Some of the main BMS functions to keep the cells in safe operation and actuate in case of abuse or malfunctioning are: cell parameters authentication and monitoring, cell balancing, protection and cell state estimation [5]-[6]. In particular, it is highly critic to estimate, among other parameters regarding cells' status, state of charge (SOC) of the battery. Among the most extended techniques to estimate SOC, because of their simplicity, are the Coulomb counting (also known as ampere-hour counting or current integration) and estimation by measuring the open circuit voltage (OCV). However, the former is an open loop estimator very sensitive to different error sources [7] and the latter generally requires a very long rest time, which makes it unpractical to use in real-time applications [8].

In this situation, state observer based estimators and, in particular, Kalman filter based approaches, have been widely proposed in the literature [8–10]. For their adequate functioning, KF-based algorithms require a proper battery model which, very often, is in the form of an equivalent circuit model (ECM) [11]. This concludes that battery modelling

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is a key part of the estimation design process [12]. However, obtaining these models, and especially the SOC-OCV curve, is very time-demanding and requires dedicated equipment [13]. Furthermore, the model defining parameters change with battery aging [14], what would require periodically repeating dedicated experiments for actualizing them for an optimal behaviour of the BMS algorithms.

In this work, we consider the problem of developing a co-identification procedure that is executed offline after gathering short data. The algorithm iteratively estimates the static SOC-OCV curve and the passive ECM elements. This algorithm is capable of obtaining this model with a limited amount of data coming from an experiment of short duration, thus facilitating the inclusion of these experiments in the BMS workflow.

2 Problem statement

The correlation between OCV and SOC is crucial in the initial stages of modelling any battery and is dependant on the battery chemistry [15]-[16]. To experimentally establish the OCV-SOC relationship, extensive and time-consuming experiments to acquire measurements must be undertaken each time a new cell chemistry requires modelling. Two widely recognized methods in literature are commonly employed to establish the correlation among OCV, SOC and the available cell capacity:

- Open-Circuit voltage Technique [17]
- Galvanostatic Intermittent Titration Technique (GITT)[18]

As it can be seen from [17]-[18], conducting these experiments is time-consuming. Besides time, in order to conduct it correctly, special laboratory equipment such as temperature chambers and cell testers are needed.

This study focuses on the challenge of constructing a battery model based on short-term experimental data. The model aims to precisely represent both mid-term behaviour, which encompasses voltage fluctuations due to SOC, and short-term transients arising from dynamic behaviour.

In this work, we consider an equivalent circuit model (ECM) with a series resistance and two RC branches (2RC) as the one shown in Fig. 1. This kind of model is extensively used for modeling of the voltage response of the battery as it offers a good compromise between simplicity and accuracy [11].

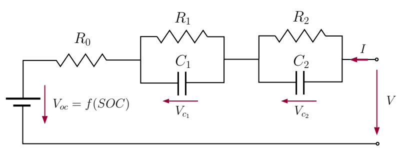

Fig. 1 Equivalent electrical circuit.

In Fig. 1, $I(t)$ is the battery current; $V(t)$ is the terminal voltage; V_{oc} is the OCV, which depends on SOC; R_0 is the series resistance; and the RC branches are used to model the time constants $\tau_1 = R_1 C_1$ and $\tau_2 = R_2 C_2$ that describe the slow and fast transient response caused by charge transfer and diffusion within the LIBs [9].

By applying elemental circuit principles, the behavior of the LIB is modelled by the following differential equations:

$$SOC(t) = SOC(0) + \frac{1}{C_{bat}} \int_0^t I(t)\,dt \tag{1a}$$

$$V_{R_0}(t) = R_0 I(t) \tag{1b}$$

$$\dot{V}_{c,i}(t) = \frac{-1}{\tau_i} V_{c,i}(t) + \frac{R_i}{\tau_i} I(t), \quad i \in \{1,2\} \tag{1c}$$

$$V(t) = \underbrace{f_{OC}(SOC(t))}_{V_{OC}(t)} + \underbrace{V_{R_0}(t) + V_{c1}(t) + V_{c2}(t)}_{V_{DYN}(t)} \tag{1d}$$

where C_{bat} is the LIB capacity; and $V_{c1}(t)$ and $V_{c2}(t)$ are the voltages in both capacitors. The static part of the output voltage. V_{OC} can be expressed as

$$V_{OC} = f_{OC}(SOC), \tag{2}$$

and the dynamic part of the output voltage can be rewritten as an implicit differential equation as

$$f_{DYN}(V_{DYN}(t), I(t)) = 0, \tag{3}$$

For the identification procedure, C_{bat} and all the passive ECM elements are considered constant in time and independent from SOC and temperature, furthermore, the charging and discharging efficiency has been considered unitary.

In the sequel, we show our identification proposal to make use of limited data to obtain at the same time the static equation (2) and the differential equation (3).

3 Proposed approach

The identification procedure proposal that we present in this work is based on the following assumptions w.r.t. the battery behaviour for the acquired data.

A0: We have experimental data that have voltage and current measurements as well as state-of-charge computations. The experiments cover almost the full SOC range.

A1: The measurable voltage $V(t)$ is the addition of open circuit voltage ($V_{OC}(t)$) plus the voltage drop in the RC branch $V_{DYN}(t)$, i.e.,

$$V(t) = V_{OC}(t) + V_{DYN}(t) \tag{4}$$

A2: The voltage level of $V_{OC}(t)$ is one or more orders of magnitude higher than $V_{DYN}(t)$.

With these assumptions we can state the following ones that are the basis of our proposed iterative identification procedure

A3: If we have an initial guess of time values $V_{DYN}(t)$ called $\hat{V}_{DYN}(t)$, we can use $V(t) - \hat{V}_{DYN}(t)$ as our measurement of $V_{OC}(t)$, i.e., $V_{OC}^m(t) = V(t) - \hat{V}_{DYN}(t)$ [1]. With that vir-

[1] superscript m refers to virtual measurement

tual measurement $V_{OC}^m(t)$ and the available data $SOC(t)$ we can infer an estimation of the static curve $OCV - SOC$, i.e., the function $f_{OC}(\cdot)$ in $V_{OC} = f(SOC)$ by fitting $f(SOC)$ to $V_{OC}^m(t)$. The open circuit voltage that can be explained with that estimated function and the available data $SOC(t)$ is called then $\hat{V}_{OC} = \hat{f}_{OC}(SOC)$.

A4: If we have an initial guess of $V_{OC}(t)$ called $\hat{V}_{OC}(t)$, we can use $V(t) - \hat{V}_{OC}(t)$ as our measurement of V_{DYN}, i.e., $V_{DYN}^m(t) = V(t) - \hat{V}_{OC}(t)$. With that $V_{DYN}^m(t)$ and the available data $I(t)$ we can infer an estimation of the parameters of the differential equation (3), i.e., the function $f_{DYN}(\cdot)$ by using $V_{DYN}^m(t)$. With the identified function $\hat{f}_{DYN}(\cdot)$ and the available data $I(t)$ we can then obtain the dynamic voltage that can be explained with that function by solving numerically the differential equation $\hat{f}_{DYN}(\hat{V}_{DYN}(t), I(t)) = 0$.

From the above stated assumptions and hypothesis, we present now the overall procedure to obtain the model of the battery. The steps (**S**) can be summarized as follows:

S0: Obtain the experimental data set.
S1: Define the parameters to be estimated.
S2: Initialization.
S3: Obtain the parameters for the static curve (2).
S4: Obtain the parameters for the dynamic behaviour (3).
S5: Iterate over **S3** and **S4** until convergence.

Now we detail each of the steps:

S0: Set a sampling period T. Acquire a periodically sampled set of data $V(t)$, $I(t)$ and $SOC(t)$ fulfilling the requirements expressed in **A0**, leading to data sets

$$\{V\} = \{V_0, V_1, \ldots, V_N\}, \qquad \{I\} = \{I_0, I_1, \ldots, I_N\}$$

$$\{SOC\} = \{SOC_0, SOC_1, \ldots, SOC_N\}$$

where x_k $(k = 0, \ldots, N)$ represents the sample $x_k = x(kT)$. The next steps are all executed offline:

S1: Define a mathematical function to describe the curve (2) with some given parameters as

$$V_{OC} = f_{OC}(\theta_{OC}, SOC) \tag{5}$$

where θ_{OC} refers to the parameters that define the curve and must be identified. Discretize differential equation (3) to obtain an explicit difference equation

$$V_{DYN,k} = f_{DYN}(\theta_{DYN}, V_{DYN,k^-}, I_{k^-}) \tag{6}$$

where θ_{DYN} refers to the parameters that define the difference equation and must be identified, and V_{DYN,k^-}, I_{k^-} refers to $[V_{DYN,k-1}, V_{DYN,k-2}]$ and $[I_k, I_{k-1}, I_{k-2}]$, respectively.

S2: Set iteration counter $i = 1$. Set ε an small constant. Under assumption A2 set initially an estimated sequence[2] of dynamical voltages at each sampling period as

$$\{\hat{V}_{DYN}\}_{i-1} = \{0, \ldots, 0\}.$$

S3: Obtain the virtual measurements of $\{V_{OC}\}$ as

$$\{V_{OC}^m\}_i = \{V\} - \{\hat{V}_{DYN}\}_{i-1}.$$

Obtain $\hat{\theta}_{OC,i}$, the current estimate of parameters θ_{OC} in (5) by minimizing some metric of the error

$$\{e_{OC}\}_i = \{V_{OC}^m\}_i - f_{OC}(\hat{\theta}_{OC,i}, \{SOC\})$$

Obtain the estimation of values $\{V_{OC}\}$ with the current available parameters as

$$\{\hat{V}_{OC}\}_i = f_{OC}(\hat{\theta}_{OC,i}, \{SOC\}) \tag{7}$$

S4: Obtain the virtual measurements of $\{V_{DYN}\}$ as

$$\{V_{DYN}^m\}_i = \{V\} - \{\hat{V}_{OC}\}_i.$$

Obtain $\hat{\theta}_{DYN,i}$, the current estimate of parameters θ_{DYN} in (6) by minimizing some metric of the error

$$\{e_{DYN}\}_i = \{V_{DYN}^m\}_i - f_{DYN}(\hat{\theta}_{DYN,i}, \{V_{DYN}^m\}_i, \{I\})$$

Obtain the estimation of values $\{V_{DYN}\}$ with the current available parameters, called $\{\hat{V}_{DYN}\}_i$, where each element is denoted as $\hat{V}_{DYN,k,i}$, by using the difference equation from $k = 2$ to $k = N$ as

$$\hat{V}_{DYN,k,i} = f_{DYN}(\hat{\theta}_{DYN,i}, \hat{V}_{DYN,k^-,i}, I_{k^-}) \tag{8}$$

S5: Estimate the output voltage sequence as $\{\hat{V}\}_i = \{\hat{V}_{OC}\}_i + \{\hat{V}_{DYN}\}_i$ and obtain a given metric of the estimation error sequence $\{\tilde{V}\}_i = \{V\} - \{\hat{V}\}_i$. If the error metric is low stop and compute the electrical parameters in (1) from $\hat{\theta}_{DYN,i}$. Else set $i = i + 1$, and go to step 3.

3.1 Acquiring the data for identification (S0)

A measurement test to obtain the data that covers almost the full range of cell SOC is described by the following steps (see as an example Figure 2):

S0a: The cell is preconditioned [3] at $25°C$ for 3 hours, and charged using Constant Current (CC) and Constant Voltage (CV) charging steps until voltage reaches $U = U_{max}$.

S0b: Then a CC discharge is deployed with $I = C/2$ until the voltage reaches $U = U_{min}$.[4]

S0c: Next a CV discharge step is deployed until $I <= C/20$.

[2] $\{x\}_i = \{x_0, x_1, \ldots, x_N\}_i$ refers to a sequence used in the i-th iteration. When referring to a given element k in the sequence $(k = 0, \ldots, N)$ during that iteration i, we use notation $x_{k,i}$

[3] The preconditioning step is not part of the measurement test.

[4] Cells are cycled in an 80% depth of discharge (dSoC) range (4.085-3.534 V). Hence the measured capacity (including CV at both limits) is assumed to be 80% of the cell's capacity. Through linear extrapolation the 100% dSoC capacity is calculated by dividing the logged capacity by 0.8 in the formula section. All further C-rates in the test measurement are based on the actual cell capacity test.

S0d: Subsequently, a CC charging step is deployed with $I = C/2$ until $U <= U_{max}$.

S0e: Next, a CV charging step is executed until $I <= C/20$.

S0f: After the last CV charging step, a rest time of 10 minutes is deployed, and experiment steps **S0b** to **S0e** are repeated to cover twice the SOC range.

During the experiment, current, voltage, and time are recorded. With these data we compute SOC by Coulomb counting using (1a). This calculation is considered reliable because: (i) we have a good estimation of the initial SOC ($SOC(0)$) thanks to step **S0a**; (ii) the accumulated error due to measurement noise, decalibration of current sensor or resolution in digital acquisition is negligible thanks to the limited time span of the experiment.

*3.2 Defining the models to identify (**S1**)*

In this section we define the parameters included in (5) and (6) to approximate (2) and (3) using, respectively, fuzzy approximates and discretization of differential equations.

S1a: First, we propose to approximate curve (2) by general approximators by means of a fuzzy function of the form

$$V_{OC} = \sum_{j=0}^{n_m} c_j \mu_j(SOC) = \left[\mu_1(SOC) \; \cdots \; \mu_{n_m}(SOC)\right] \underbrace{\begin{bmatrix} c_1 \\ \vdots \\ c_{n_m} \end{bmatrix}}_{\theta_{OC}} \tag{9}$$

where θ_{OC} is the vector of parameters needed in (5), and where $\mu_j(\cdot)$ $(j = 1, \ldots, n_m)$ represent triangular membership functions fulfilling $0 \leq \mu_j(SOC) \leq 1$ and $\sum_{j=1}^{n_m} \mu_j(SOC) = 1$. Each $\mu_j(\cdot)$ is defined by the piecewise function

$$\mu_j(SOC) = \begin{cases} 0, & SOC \leq t_{j-1} \\ \frac{1}{\Delta}(SOC - t_{j-1}), & t_{j-1} \leq SOC \leq t_j \\ \frac{1}{\Delta}(t_{j+1} - SOC), & t_j \leq SOC \leq t_{j+1} \\ 0, & SOC \geq t_{j+1} \end{cases} \tag{10}$$

where t_j $(j = -1, \ldots, n_m + 1)$ is the set of ordered values

$$t_j = j \cdot \Delta, \qquad \Delta = \frac{1}{n_m} \tag{11}$$

being t_j the vertex position of each triangle, and 2Δ the width of each triangle. The number of triangular sets n_m is a tuning parameter that must be chosen as a compromise between the achievable $OCV - SOC$ curve accuracy and data availability. The parameters to be identified (θ_{OC}) refers then to the weight of each membership value in the curve.

S1b: Under assumption of constant current $I(t)$ between samples, the differential equation (3) can be discretized using the zero-order-hold equivalent leading to difference equation

$$V_{DYN,k} = a_1 V_{DYN,k-1} + a_2 V_{DYN,k-2} + b_0 I_k + b_1 I_{k-1} + b_2 I_{k-2} \tag{12}$$

being

$$a_1 = \alpha_1 + \alpha_2, \quad a_2 = -\alpha_1 \alpha_2, \quad b_0 = R_0 \tag{13a}$$

$$b_1 = \beta_1 + \beta_2 - \alpha_1 R_0 - \alpha_2 R_0, \; b_2 = \alpha_1 \alpha_2 R_0 - \alpha_2 \beta_1 - \alpha_1 \beta_2 \tag{13b}$$

$$\alpha_1 = e^{\frac{-T_s}{\tau_1}}, \; \alpha_2 = e^{\frac{-T_s}{\tau_2}}, \; \beta_1 = R_1 (1 - e^{\frac{-T_s}{\tau_1}}), \; \beta_2 = R_2 (1 - e^{\frac{-T_s}{\tau_2}}) \tag{13c}$$

With this, the difference equation (12) can be rewritten in regression form as

$$V_{DYN,k} = \underbrace{\left[V_{DYN,k-1} \; V_{DYN,k-2} \; I_k \; I_{k-1} \; I_{k-2}\right]}_{\phi(k)} \underbrace{\begin{bmatrix} a_1 \\ a_2 \\ b_0 \\ b_1 \\ b_2 \end{bmatrix}}_{\theta_{DYN}} \tag{14}$$

where θ_{DYN} is the vector of parameters needed in (6).

*3.3 Parameter identification (**S3, S4**)*

Once we have defined the static and dynamic functions with linear dependence w.r.t. vectors of parameters θ_{OC} and θ_{DYN}, we propose to obtain these vectors by means of least squares (LS) problems, which we detail mathematically in the following. First of all, let us define the membership values as:

$$\mu_{j,k} = \mu_j(SOC_k), \qquad j = 0, \ldots, n_m, \qquad k = 0, \ldots, N$$

Once this is obtained, we can execute steps **S3** and **S4** with the following detailed operations.

S3a: Obtain virtual measurements:

$$V^m_{OC,k,i} = V_k - \hat{V}_{DYN,k,i-1}, \qquad k = 0, \ldots, N.$$

S3b: Construct regression and output matrices

$$X_{OC} = \begin{bmatrix} \mu_{1,0} & \cdots & \mu_{n_m,0} \\ & \vdots & \\ \mu_{1,N} & \cdots & \mu_{n_m,N} \end{bmatrix}, \qquad Y_{OC} = \begin{bmatrix} V^m_{OC,0,i} \\ \vdots \\ V^m_{OC,N,i} \end{bmatrix}$$

S3c: Compute the current parameter estimation:

$$\hat{\theta}_{OC,i} = (X_{OC}^T X_{OC})^{-1} X_{OC}^T Y_{OC}$$

S3d: Compute the current estimation of V_{OC} as[5]

$$\hat{V}_{OC,k,i} = \left[\mu_{1,k} \; \cdots \; \mu_{n_m,k}\right] \hat{\theta}_{OC,i}, \qquad k = 0, \ldots, N.$$

S4a: Obtain virtual measurements:

$$V^m_{DYN,k,i} = V_k - \hat{V}_{OC,k,i}, \qquad k = 0, \ldots, N.$$

[5] Can also be obtained through $\{\hat{V}_{OC}\}_i = X_{OC} \hat{\theta}_{OC,i}$.

S4b: Construct regression and output matrices

$$X_{DYN} = \begin{bmatrix} V^m_{DYN,1,i} & V^m_{DYN,0,i} & I_2 & I_1 & I_0 \\ & & \vdots & & \\ V^m_{DYN,N-1,i} & V^m_{DYN,N-2,i} & I_N & I_{N-1} & I_{N-2} \end{bmatrix}, Y_{DYN} = \begin{bmatrix} V^m_{DYN,2,i} \\ \vdots \\ V^m_{DYN,N,i} \end{bmatrix}$$

S4c: Compute the current parameter estimation:

$$\hat{\theta}_{DYN,i} = (X^T_{DYN} X_{DYN})^{-1} X^T_{DYN} Y_{DYN}$$

S4d: Compute the current explainable V_{DYN} values along time through the model, by executing the difference equation in open loop, i.e., for $k = 2, \ldots, N$ compute

$$\hat{V}_{DYN,k,i} = \left[\hat{V}_{DYN,k-1,i}\ \hat{V}_{DYN,k-2,i}\ I_k\ I_{k-1}\ I_{k-2}\right] \hat{\theta}_{DYN,i},$$

with $\hat{V}_{DYN,0,i} = V^m_{DYN,0,i}$, $\hat{V}_{DYN,1,i} = V^m_{DYN,1,i}$.

Once the discrete dynamical model is obtained, we can recover the electrical parameters R_i $(i = 0, 1, 2)$ and C_i $(i = 1, 2)$ by inverting (13).

4 Experimental results

In this paper, measurements shown in Figure 2 were used to test the proposed approach. The experiments were conducted under laboratory conditions using *ARBIN BT2000 - Battery Test Equipment* and *Memmert ICP* thermal chamber. In the figure, the SOC obtained by Coulomb counting is also shown. Figure 3 shows the virtual measurements and the estimation with the model obtained at iterations $i = 1$ to $i = 5$. In the top row we can see the OCV-SOC curve evolution, where we have also included the available OCV-SOC curve (called V_{OC}) from an standard long-time procedure. We see how the static curve is well fitted in just few iterations. In the bottom row, we show for the dynamical voltage, both the virtual measurement, and its estimation through the difference equation. We can also see how the virtual measurements tend progressively to follow the expected behaviour of the proposed linear model. This allows our algorithm to fit better the dynamic behaviour at each iteration. For each identification iteration i we have obtained the explainable voltage V at each sampling k $(k = 1, \ldots, N)$ through the model and the estimation error as

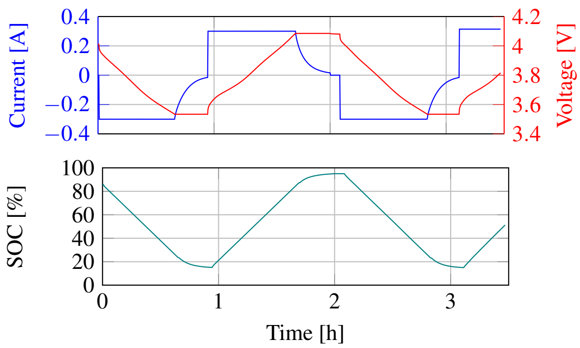

Fig. 2 Acquired experimental data for identification.

$$\hat{V}_{k,i} = \hat{V}_{OC,k,i} + \hat{V}_{DYN,k,i} \qquad \tilde{V}_{k,i} = V_k - \hat{V}_{k,i} \qquad (15)$$

For this $\tilde{V}$ error we have obtained the following metrics $MAX_i = \max_k |\tilde{V}_{k,i}|$, $MAE_i = \frac{1}{N}\sum_k |\tilde{V}_{k,i}|$, $RMS_i = \sqrt{\frac{1}{N}\sum_k \tilde{V}^2_{k,i}}$, $ME_i = \frac{1}{N}\sum_k \tilde{V}_{k,i}$ that refer to the maximum absolute error, the mean absolute error, the root mean square error, and the mean error. Figure 4 shows these metrics in mV at the end of each identification iteration. The mean error shows that the approach performs a bias free voltage estimation. Furthermore, we see that the algorithm only needs 10 iterations to converge, being the metrics at the end of the identification $MAX = 12.9$ mV, $MAE = 2.2$ mV, $RMS = 3$ mV and $ME = 0$ mV. Finally, Figure 5 shows the measured voltage, its estimation through the full model with the final identified parameters and the error (on the right plot, in mV). Results show a proper fitting, but also a somewhat deterministic dynamical behaviour, advising that some higher order model could be used.

5 Conclusions

In this work we have presented a co-identification procedure for estimating offline the parameters that define an equivalent circuit model for batteries. The iterative nature of the algorithm has allowed us to obtain a simultaneous refinement of both the static OCV-SOC model and the dynamic RC circuit model, making effective use of minimal experimental data. The proposed identification method makes use of virtual measurements of OCV and voltage drop at RC branches to improve model accuracy. The experimental results show the efficacy of the approach to capture the interplay between static and dynamic components, making it potentially useful for practical applications. Further research work will deal with sequentially identify different RC branches to improve the modelling of the dynamic behaviour; considering dependency of Rs and Cs with respect to SOC and temperature; and how to extend this approach to capture aging processes by recursive least squares algorithms.

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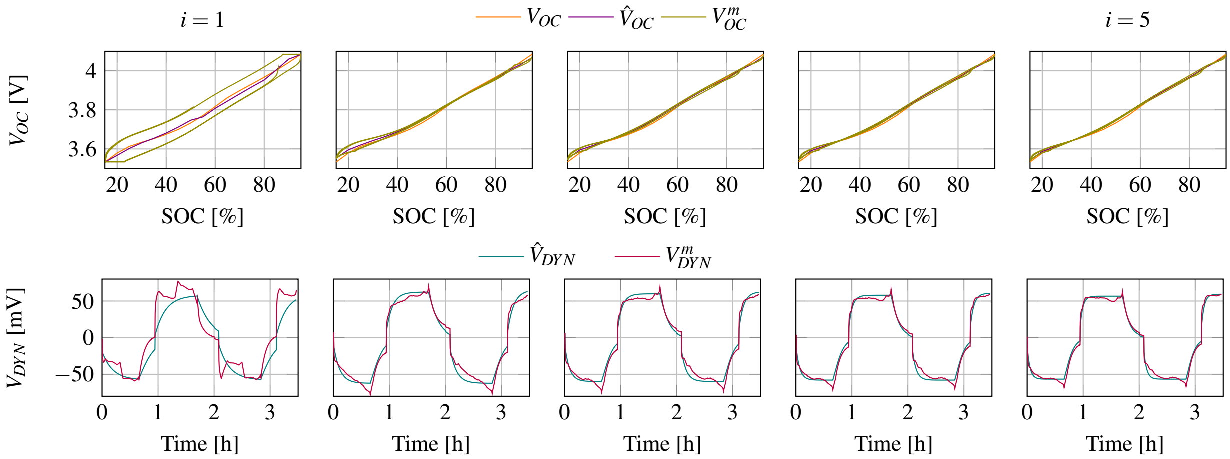

Fig. 3 Virtual measurements and estimations along iterations.

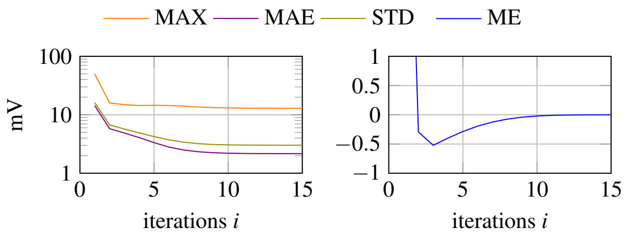

Fig. 4 Metrics of the estimation error along iterations

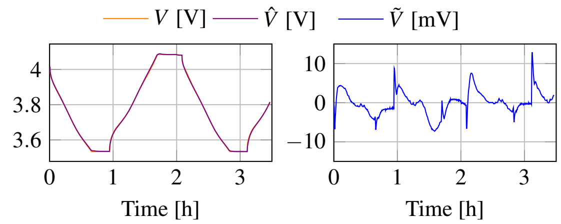

Fig. 5 Voltage estimation [V] and error [mv]

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