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**Misyris, Georgios; Tengner, Tomas ; Marinopoulos, Antonis G. ; Doukas, Dimitrios I. ; Labridis, Dimitris P.**

*Published in:*
Proceedings of 2017 IEEE Manchester PowerTech

*Link to article, DOI:*
10.1109/PTC.2017.7980809

*Publication date:*
2017

*Document Version*
Peer reviewed version

# Battery Energy Storage Systems Modeling for Online Applications

George S. Misyris
Tomas Tengnér
Antonis G. Marinopoulos
ABB Corporate Research
Västerås, Sweden

Dimitrios I. Doukas
Dimitris P. Labridis
Department of Electrical and Computer Engineering
Aristotle University of Thessaloniki
Thessaloniki, Greece

***Abstract*—Over the last decade the use of battery energy storage systems (BESS) on different applications, such as smart grid and electric vehicles, has been increasing rapidly. Therefore, the development of an electrical model of a battery, capable to estimate the states and the parameters of a battery during lifetime is of critical importance. To increase the lifetime, safety and energy usage, appropriate algorithms are used to estimate, with the lowest estimation error, the state of charge of the battery, the battery impedance, as well as its remaining capacity. This paper focuses on the development of model-based online condition monitoring algorithms for Li-ion battery cells, which can be extended to battery modules and systems. The condition monitoring algorithms were implemented after considering an optimal trade-off between their accuracy and overall complexity.**

***Index Terms*—Battery energy storage systems (BESS), capacity, equivalent circuit model (ECM), internal resistance, model-based method, parameter identification, state of charge (SOC), state of health (SOH).**

## I. Introduction

An efficient battery model is a key for most online applications, in order to guarantee good grid or electric vehicles' performance in terms of accuracy, power performance and safety. The user should be able to identify the battery-cell condition, so that the prescribed operation can be ensured. The online battery condition can be diagnosed when state of charge (SOC) and state of health (SOH) are identified.

Several methods have been proposed related to those two states. Regarding the SOC, the most conventional way for its estimation is the Coulomb Counting (CC) method, which calculates the SOC by measuring the battery current and integrating it over time. However, measurements always introduce an error, which is also related to the device sensitivity and also an error which depends on the integration process (numerical, trapezoidal etc.). Therefore, CC method suffers from a long-term drift. Beside the drifting, CC uses the previously measured capacity to calculate SOC, so if battery capacity fades due to degradation, this may cause additional SOC estimation error. Moreover, when the initial point of SOC is not known then the estimation error is persistent or even increases during battery operation. In order for this method to be useful and accurate, the SOC must be re-calibrated on a regular basis, such as resetting the SOC to 100% when the charger determines that the battery is fully charged or taking open circuit voltage (OCV) after relaxation period. Model-based methods use both the measured current and voltage signals to estimate the SOC, in order to provide more accurate results since the estimation includes information from the battery voltage response as well. Those methods are often based on an equivalent circuit model (ECM), where the output voltage is expressed as the sum of an OCV and voltage drops over $R_{\text{series}}$ and RC branches. According to the literature, SOC estimation methods that are widely used are Kalman Filter (KF) and its extensions [1]–[3], Luenberger observer method [4], [5], smooth variable structure filter (SVSF) [6], proportional integral observer [7], [8] and sliding mode observer (SMO) [9], [10].

Regarding the SOH, its purpose is to provide an indication of the battery performance, which can be expected from the battery's current condition. The SOH is usually defined by the percentage of battery capacity that is remaining from its nominal initial value. In certain high power applications, where battery power capability is the limiting factor, battery impedance may define SOH. In order the internal impedance to be estimated, moving window least squares (MWLS) [11] and Lyapunov observer [12], [13], are commonly used.

As for the capacity estimation, there are several model-based methods that can be implemented. KF and its variants, such as dual extended KF (DEKF) [14] or sigma point KF (SPKF) [15], which estimate SOC and capacity simultaneously, are commonly used. Recently a total least squares (TLS)-based method [16], [17] was introduced in order to reduce the capacity estimation error caused by current measurement errors and SOC estimation error .

The scope of this paper is to examine how combinations of the aforementioned algorithms are able to provide an efficient solution to the problem of online battery state estimation. The contribution of this paper is to provide detailed modeling and mathematical formulation of the algorithms selected combination as well as experimental validation. The algorithms that have been chosen are recursive least squares (RLS) with varying forgetting factors for identifying the ECM's parameters, linear KF (LKF) for the SOC estimation, MWLS [11] for internal impedance identification and approximate weighted total least squares (AWTLS) [16] for the capacity estimation.

RLS has been chosen among other estimation algorithms cause of the fast rate of convergence and the good accuracy

that provides when there is persistent excitation of battery [6].

KF method has been chosen because it offers a computationally efficient and accurate option for SOC estimation. Furthermore, KF and its extensions are the most used methods for SOC estimation and have been validated extensively.

AWTLS is an extension of the TLS algorithm and has been chosen due to its simplicity, no need to store any value and it can be very easily computed in a recursive manner, which makes it suitable for the MATLAB/Simulink® environment. The same goes for MWLS which implements the Internal Impedance identification.

Section II of the paper is divided into three parts, which are model parameter identification, SOC and SOH estimation respectively. Finally, in Section III, experimental validation and results from two different types of batteries and also different load profiles are presented.

## II. Electrical Battery Model

ECMs are selected to simulate a battery-cell. A comparative study of the ECM that can be used to simulate the battery-cell is presented in [18]. Although for online applications, the Thevenin model is the one that has been used most, it is not accurate enough since its elements can change, depending on the SOC, temperature and aging respectively. To improve model's accuracy more RC branches can be added to Thevenin model in order to compensate the transient response of the battery's voltage. Increasing number of RC branches leads to better accuracy but also affects negatively the model complexity. Therefore, the number of RC components to be chosen, is a trade-off between accuracy and complexity. In most cases, the most efficient number of RC branches is considered to be two [19]. However, to make the model simpler only one RC branch is used in this paper. One RC branch gives sufficiently well results [18] if the excitation of the system is high [20]. In Fig. 1 the ECM is shown.

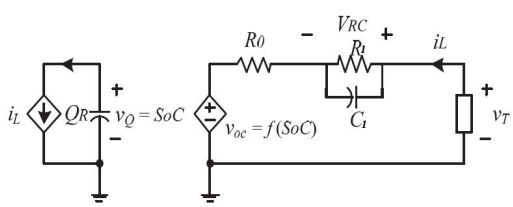


Fig. 1. Battery-equivalent circuit.

*1) OCV-SOC Relationship:* The OCV has a non-linear relationship with the SOC, which makes the battery parameter identification and the SOC estimation rather challenging in terms of the stability and performance of the battery model. To deal with the non-linearity, the average OCV-SOC curve is divided into discrete number of linear segments. Therefore, a piece-wise linear relationship between OCV and SOC at each operation point of the battery is considered. Based on [5], the equation which describes each segment of the OCV-SOC relationship is:

$$V_{\mathrm{OC}} = b_0 + b_1 \cdot \mathrm{SOC} \tag{1}$$

where $b_0$ is the $y$-intercept and $b_1$ the equation slope.

It should be mentioned that for $LiFePO_4$ batteries, OCV-SOC curve cannot be differentiated between 0.3 and 0.7 (it is too flat). That adds a restriction to battery's operation, when piecewise linearization is chosen, since the SOC observability is very low. Therefore if this way of modeling is applied to $LiFePO_4$, the cycling of the battery should occur between SOC breakpoints, in which the OCV is conspicuously different (e.g., between 0.1 and 0.85 of SOC).

*2) Hysteresis Effect:* The equilibrium potential is higher during the charging process than during the discharging one [21], an effect called hysteresis effect. To simplify the model, hysteresis effect will be simulated by considering the average of the equilibrium potentials of charging and discharging.

*3) Capacity Degradation:* The maximum (nominal) capacity $Q$ of a battery cell can be defined by the following equation:

$$\int_{t_1}^{t_1} \frac{\eta i(\tau)}{3600} d\tau = Q(\mathrm{SOC(t_2)} - \mathrm{SOC(t_1)}) \tag{2}$$

where $\eta$ is the coulombic efficiency, $i(\tau)$ the current at time $\tau$, $Q$ the capacity, and $\mathrm{SOC}(t_1)$ the state of charge at $t_1$. It is obvious that (2) has a linear structure of $y = Qx$. An accurate estimation of the battery capacity is very important, in order to face the capacity fading as the battery ages. The capacity will be estimated by using an extension of TLS algorithm.

*4) Equivalent Circuit Model:* The state-space equations for ECM with one RC branch, as in Fig. 1, are:

$$\begin{cases} \begin{bmatrix} \dot{\mathrm{SOC}} \\ \dot{V_{\mathrm{RC}}} \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & e^{-\frac{1}{\mathrm{R_1C_1}}} \end{bmatrix} \begin{bmatrix} \mathrm{SOC} \\ V_{\mathrm{RC}} \end{bmatrix} + \begin{bmatrix} \frac{1}{Q_{\mathrm{R}}} \\ R_1(1 - e^{-\frac{1}{\mathrm{R_1C_1}}}) \end{bmatrix} i_L \\ V_T = \begin{bmatrix} b_1 & 1 \end{bmatrix} \begin{bmatrix} \mathrm{SOC} \\ V_{\mathrm{RC}} \end{bmatrix} + R_0 i_L + b_0 \end{cases} \tag{3}$$

where the state variables of the system are the SOC and the voltage drop on the RC-branch. The unknown variables of the system are $R_0$, $R_1$ and $C_1$, while the known ones are $b_1$, $b_0$ and $Q_R$ (nominal capacity). Those parameters can be extracted from the OCV-SOC curve and laboratory measurements respectively. Lastly, it should be mentioned that $Q_R$ does not affect the identification of the other parameters [22], so it does not need to be updated during the simulation.

The transfer function that describes the battery system is:

$$\frac{\mathbf{Y}(s) - b_0}{\mathbf{U}(s)} = \frac{R_0 s^2 + (\frac{b_1}{Q_{\mathrm{R}}} + \frac{1}{C_1} + \frac{R_0}{\mathrm{R_1C_1Q_R}})s + \frac{b_1}{\mathrm{R_1C_1Q_R}}}{s(s + \frac{1}{\mathrm{RC}})} \tag{4}$$

while the discrete form of the transfer function is:

$$\frac{\mathbf{Y}_(z^{-1}) - b_0}{\mathbf{U}(z^{-1})} = \frac{c_0 + c_1 z^{-1} + c_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} \tag{5}$$

Defining the transfer function is the initial step to identify the battery parameters and then estimate the battery states.

### A. Parameter Identification

Based on the excitation and dynamics of the battery system, RLS with different forgetting factors is proposed [20]. On the battery equivalent circuit $R_0$ and RC estimation has different

sensitivity for variations in load current and battery voltage. In particular, $R_0$ varies with a slower rate and converges to its actual value faster than $R_1$ and $C_1$ do. Therefore, $R_0$ forgetting factor must have higher value than the one for $R_1$ and $C_1$.

The coefficients of the discrete transfer function can be estimated by using bi-linear transformation [22]. Afterwards, the battery parameters are calculated based on the equations between the battery parameters and the coefficients of the transfer function. Calculation is based on [22].

### B. SOC Estimation

As a next step, SOC can be estimated by using LKF algorithm. Battery state equations are:

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + Du + b_0 \end{cases} \tag{6}$$

where $x_1 = SOC$, $x_2 = V_{RC}$, $A = \begin{bmatrix} 0 & 0 \\ 0 & e^{-\frac{1}{R_1 C_1}} \end{bmatrix}$, $B = \begin{bmatrix} \frac{1}{Q_R} \\ R_1(1 - e^{-\frac{1}{R_1 C_1}}) \end{bmatrix}$, $C = \begin{bmatrix} b_1 & 1 \end{bmatrix}$, $D = R_0$, $u = I_L$, $y = V_T$ and $x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ and $Q_R$ represents the nominal capacity of the battery. During battery lifetime the capacity degrades, so if the capacity is not updated the SOC estimation error will increase. However, due to LKF algorithm, the system converges to steady state if the matrices A and C, as shown in (6), are observable, which in this case depends on $b_1$, $R_1$ and $C_1$. Therefore, an accurate parameter identification is crucial for SOC estimation.

For LKF implementation, the state matrix, the co-variance and the process and measurement noise of the LKF algorithm need to be initialized. After the initialization, the LKF can be divided into 5 steps, which are repeated at each time step. The 5 steps of the algorithm are:

1) State estimate time update:

$$\widehat{x_k^-} = A_{k-1}\widehat{x_{k-1}^+} + B_{k-1}u_{k-1} \tag{7}$$

2) Error co-variance time update:

$$\sum \widehat{x_k^-} = A_{k-1}\sum \widehat{x_{k-1}^+} A_{k-1}^T + \sum w \tag{8}$$

3) Kalman gain matrix:

$$L_k = \sum \widehat{x_k^-} C_k^T [c_k \sum \widehat{x_k^-} C_k^T + \sum u]^{-1} \tag{9}$$

4) State estimate measurement update:

$$\widehat{x_k^+} = \widehat{x_k^-} + L_k[y_k - C_k\widehat{x_k^-} - D_k u_k] \tag{10}$$

5) Error co-variance measurement update:

$$\sum \widehat{x_k^+} = (I - L_k C_k)\widehat{x_k^-} \tag{11}$$

### C. SOH Estimation

The SOH is a metric that reflects the general battery condition and its ability to deliver the specified performance compared with a fresh battery. SOH can be determined by the capacity degradation and the internal impedance increase.

TABLE I
BATTERIES NOMINAL CHARACTERISTICS

| | Battery 1 | Battery 2 |
|---|---|---|
| Maximum Capacity (Ah) | 20.0 | 15.1 |
| Nominal Voltage (V) | 2.7 | 4.2 |
| Chemistry | Li-ion LTO/Mixed Oxide | Li-ion Graphite/LMO-Spinel |

*1) Internal Impedance:* To estimate the internal impedance of the battery, an online method is implemented, as presented in [11]. The resistance is identified by the voltage drop that occurs across the cell. Then a filter is used to limit the measurement noise effect. Since the SOH is relative to the condition of a new battery, the system must keep the initial internal impedance of a fresh cell in memory, as a reference.

*2) Capacity Estimation:* To estimate capacity degradation, an extension of TLS algorithm is used [16]. The algorithm identifies the slope of the equation $y = Q\hat{x}$, where $x = \mathrm{SOC(t_2)} - \mathrm{SOC(t_1)}$ and $y = \int_{t_1}^{t_1} \frac{\eta i(\tau)}{3600} d\tau$. It is assumed that $\eta = 1$ at all values of current and temperature within normal operation conditions. For operations out of this range, e.g., low temperature and high C-rate, $\eta$ must be specifically adjusted. The steps of this algorithm are extensively described in [16].

## III. EXPERIMENTAL VALIDATION & RESULTS

To verify battery modeling accuracy, three experiments have been conducted, at varying temperatures and different C-rates for two batteries. In Table I their nominal characteristics are shown. Experiments load profiles for the first experiment are given in Figs. 2 and 3 and for the second in Figs. 4 and 5.

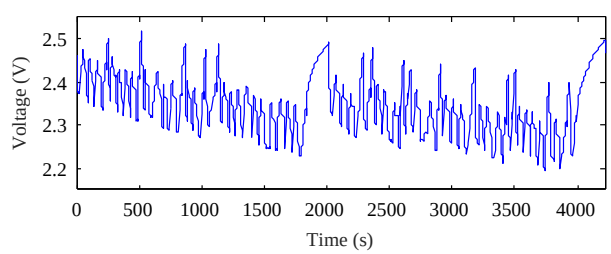


Fig. 2. Load-profile (voltage) for experiments 1 and 3.

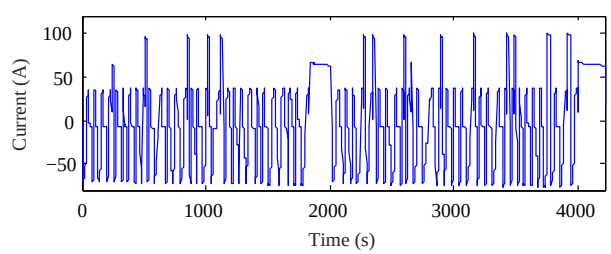


Fig. 3. Load-profile (current) for experiments 1 and 3.

The temperature for both experiments varies between 20 and 30 degrees. The same load-profile with the first experiment has been used for the third experiment, but it includes more cycles and the temperature varies between 39 to 42 degrees

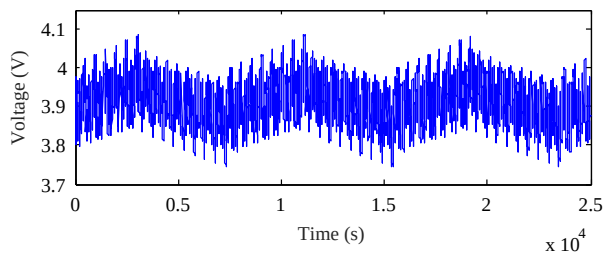


Fig. 4. Load-profile (voltage) for experiment 2.

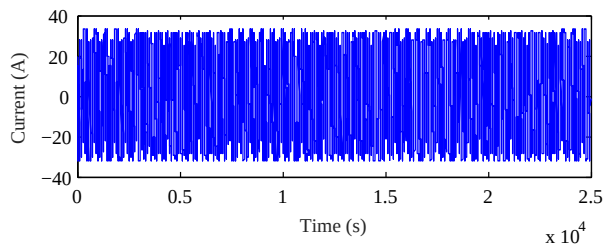


Fig. 5. Load-profile (current) for experiment 2.

in order to validate SOH estimation. Experiments 1 and 3 had been conducted for Battery 1 while the second one for Battery 2. All experiments have high excitation load-profile, so that the wind-up problem of the RLS does not affect the battery states' estimation. The sample time is 0.5 s, so that the short transient response of the voltage can be captured and also not increase the RLS sensitivity [23]. Running times of the three experiments is 2, 4 and 32 days respectively. The LifeTest SBT0550 battery cell tester from PEC Corporation was used to integrate current for coulomb counting SOC estimation and used as a reference for SOC estimation.

### A. Parameter Identification

For parameter identification, RLS algorithm with different forgetting factors has been utilized [20]. Afterwards, the results for each parameter of the ECM are displayed.

In Figs. 6, 7 and 8 are the results of $R_0$, $R_1$ and $C_1$ for the experiment 1, while in Figs. 9, 10 and 11 respective results for experiment 2 are depicted. The results have been validated based on the fitting of the estimated voltage, which is derived from the RLS algorithm, to the measured voltage.

As shown in Figs. 12 and 13, the estimated voltage from the RLS algorithm fits the measured one with great accuracy, so parameter identification is considered accurate. The values of the ECM parameters depend on the experiments sample time. In particular it is based on the amount of information (voltage and current) with which the RLS tries to fit the parameters.

RLS algorithm provides better accuracy when the sample rate is within [0.5, 0.8]. If the value for sample time is chosen out of this range RLS cannot give accurate results. The reason for this is either sensitivity problems of RLS or lack of information for the battery voltage. The different forgetting factor is crucial for the parameter identification [20], since the dynamics of the parameters are different between the $R_0$, $R_1$ and $C_1$.

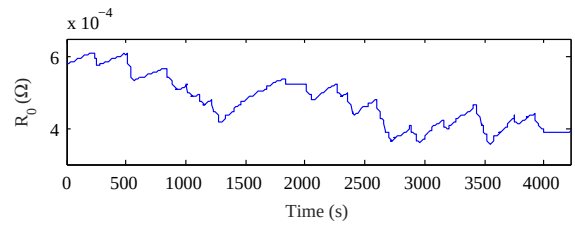


Fig. 6. $R_0$ identification for experiment 1.

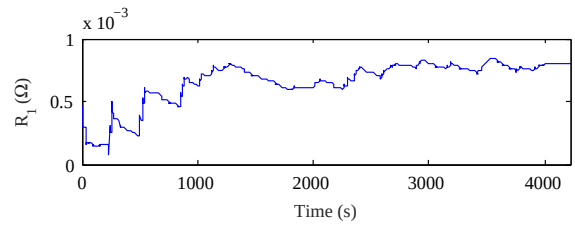


Fig. 7. $R_1$ identification for experiment 1.

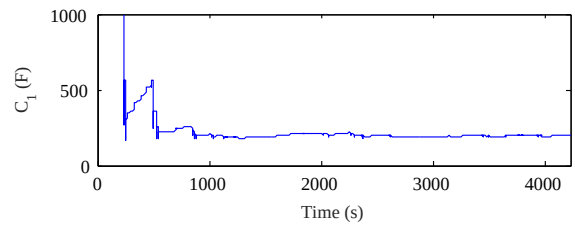


Fig. 8. $C_1$ identification for experiment 1.

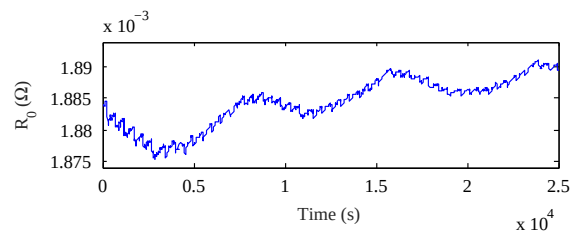


Fig. 9. $R_0$ identification for experiment 2.

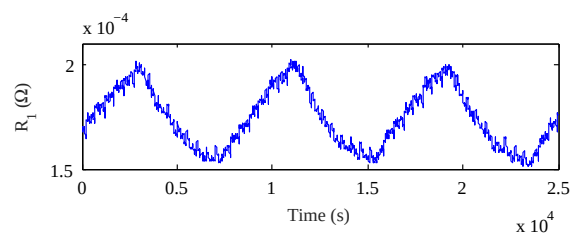


Fig. 10. $R_1$ identification for experiment 2.

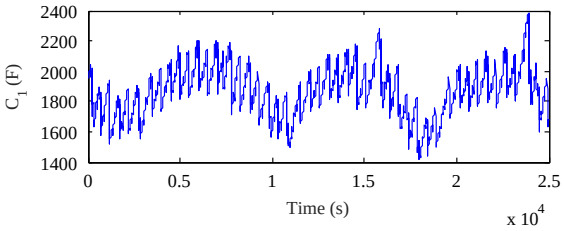


Fig. 11. $C_1$ identification for experiment 2.

In Figs. 12 and 13 curve fitting of the estimated to the measured voltage is shown.

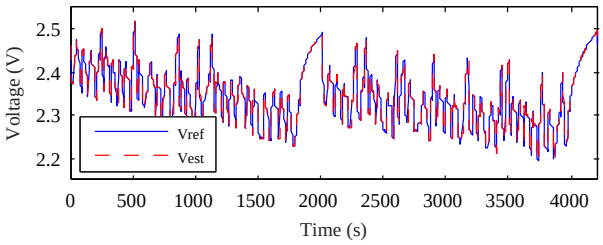


Fig. 12. Estimated and measured voltage for experiment 1.

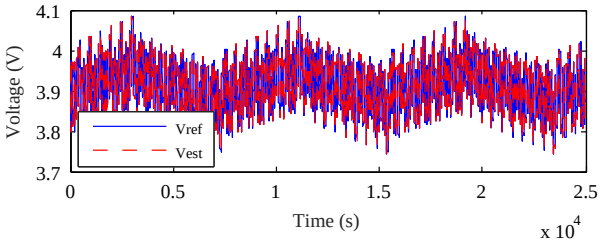


Fig. 13. Estimated and measured voltage for experiment 2.

## B. SOC Estimation

Having identified the battery parameters, the results for the SOC estimation are presented. ECM parameters are used as inputs to the LKF. The algorithm offers great accuracy regarding the SOC estimation. Maximum and rms error of SOC estimation are also presented. In Fig. 14, for experiment 1, the maximum error is 2.16% and the rms error is 1.23%. For experiment 2, in Fig. 15, the maximum error is 3.41% and the rms error is 1.24%.

## C. SOH Estimation

For SOH estimation results are derived from the experiments 2 and 3, in which the temperature and the C-rates vary.

*1) Internal Impedance:* Regarding the Internal Impedance of the battery, two kind of results are presented. The first one refers to the change of the internal impedance due to the temperature while the second refers to its increase due to battery aging. In Fig. 16, it is shown how the internal impedance of Battery 2 changes due to the fluctuation of the temperature. As it was expected, for increasing temperature, the internal impedance decreases while the opposite occurs

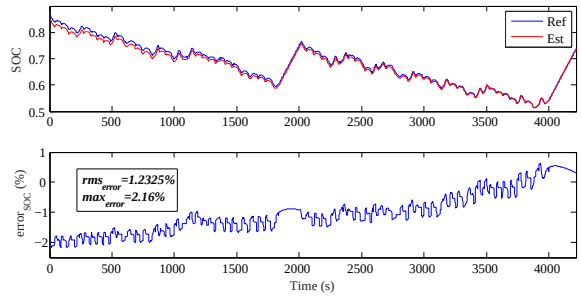


Fig. 14. SOC estimation and error for experiment 1.

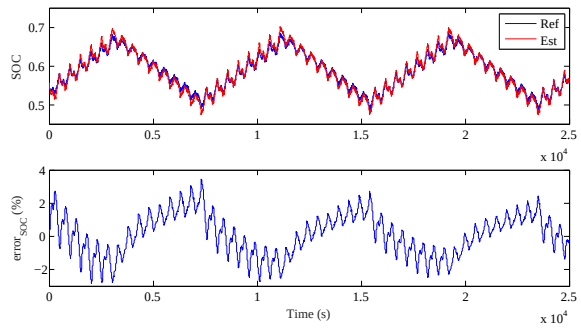


Fig. 15. SOC estimation and error for experiment 2.

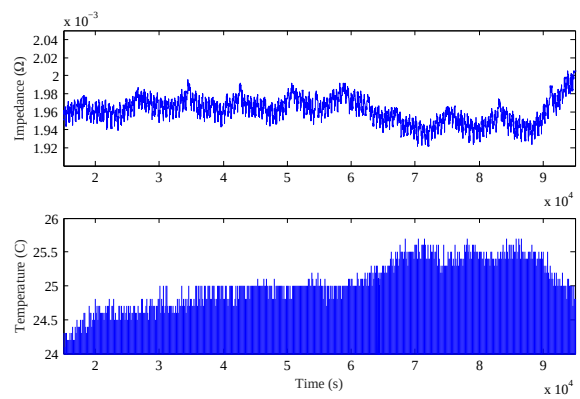


Fig. 16. Internal impedance variation of Battery 2 for experiment 2.

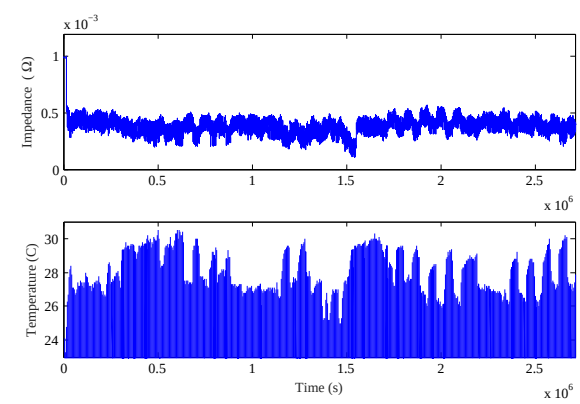


Fig. 17. Internal impedance variation of Battery 1 for experiment 3.

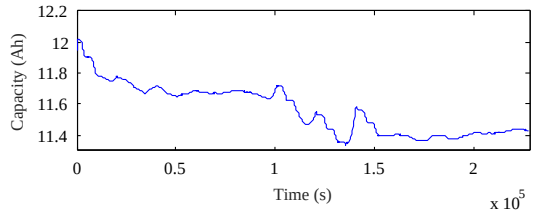


Fig. 18. Capacity estimation of Battery 2 for experiment 2.

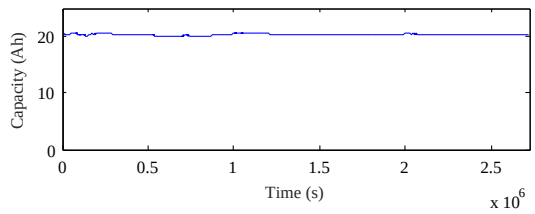


Fig. 19. Capacity estimation of Battery 1 for experiment 3.

when the temperature decreases. In Fig. 17, internal impedance variations during experiment 3 are presented. Experiment 3 lasted 32 days and the change of the resistance is caused by battery-SOC change and battery-aging. Regarding battery-aging it is seen that the average value of the impedance has not increased due to the battery's LTO chemistry, which presents a very long life cycle (in the range of 10000 full cycles).

*2) Capacity Estimation:* Regarding the capacity estimation, Figs. 18 and 19 refer to experiment 2 and 3 respectively. For results validation, at the end of each experiment a measurement of the remaining capacity was taken. The estimation error for the experiment 2 is 1.29%, while for experiment 3 is 3.21%. Note that Battery 2 had a capacity fading of 23.3%, *already before* the experiment had been set up. That explains why the initial capacity estimation is below 12 Ah.

## IV. Conclusions

In this paper, BESS online state estimation based on ECM has been presented. Accurate battery states estimation has been proposed using an innovative combination of existing algorithms, which work together in a common system i.e. RLS with MFF for parameter identification, combined with LKF for SOC estimation and TLS for capacity estimation. The proposed solution is fully automated and no re-estimation of initial parameters or model re-calibration is needed during operation lifetime. Consequently, proposed modeling is ideal for online applications. Overall formulation has been validated with test measurements in two different battery cells and the results have shown good accuracy regarding SOC and SOH.

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