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Research papers

An online state of health estimation method for lithium-ion batteries based on time partitioning and data-driven model identification

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ABSTRACT

In recent years, the request for batteries to employ in emerging technologies like smart grids or electric vehicles shows constant growth. To maintain these systems over time, it is crucial to have a mechanism to monitor the battery State of Health (SoH), determine when it is not of use for the current application, and eventually reuse it in another context a.k.a. *battery second life*. However, standard techniques from the literature provide an accurate estimation of the State of Health mainly by performing offline tests or with *a priori* knowledge of hyper-parameters. This paper proposes a novel algorithm, namely State of Health Estimator (SHE), that infers the battery model online, *i.e.*, during its operational life, and uses this characterization to provide a reliable and accurate estimation of both actual battery capacity and internal resistance, considering both ohmic and polarization components. The experimental campaign, performed on real-world data, shows satisfactory performance, with an average error of 1.2 % and of 4 % in the estimate of the maximum battery capacity and internal resistance, respectively.

1. Introduction

The battery market has been increasing rapidly in recent years, driven by its use for electric vehicles [1] and stationary applications [2]. Batteries, thanks to their storage capacity with a high charge and discharge cycle efficiency, allow increasing the exploitation of renewable energy sources by facing the energy transition of the electrical system safely and efficiently. As the market grows, making the entire storage chain as eco-sustainable as possible is essential. For this purpose, several research activities have been launched aiming at extending battery lifetime. In this context, battery diagnostic tools play a crucial role. Indeed, they provide all the inputs a battery management system needs to optimize the control of the storage system.

There are several battery status indicators. Some of them, such as State of Charge (SoC), State of Energy (SoE), and State of Power (SoP), provide information about the status of the battery for the current instant of the battery lifetime, which in its turn depends on the battery working condition. These indicators are significant for short-term battery usage, assuming that the battery characteristics remain the same over short time periods. However, batteries are subject to aging phenomena. Time, environmental conditions, and working mode affect the rate of aging [3]. Hence, other battery status indicators that aim to provide information about the current aging and remaining lifetime are more suitable for battery life indicators. The most popular index of this family is the State of Health (SoH) which represents the current condition of the battery compared to the ideal ones, *i.e.*, factory conditions. Knowing the SoH over time allows applying charge/discharge strategies that minimize the stress on the battery to increase the battery lifetime [4]. Moreover, the SoH index allows the battery owner to understand when the battery performance is not sufficient to cover the needs of a particular service, *e.g.*, the range of electric vehicles, before any inconvenience occurs. Typically, the SoH is calculated through dedicated tests [5], such as full-charge/full-discharge, pulse discharge, and Electrochemical Impedance Spectroscopy (EIS) tests, which require temporarily preventing the battery from being used for its normal operations. However, this might not be possible in some scenarios, *e.g.*, automotive applications. In all such cases, *i.e.*, when a physical measurement to get the SoH is not feasible, methods to estimate battery aging can be used.

This work aims to provide a useful battery diagnostic tool to assess aging by monitoring battery voltage and current profiles during operational life without a specific electrochemical test. The proposed solution combines a data-driven method to partition the voltage and current

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measurements over time with an algorithm to characterize the electrical model of the battery, originally used for State of Charge (SoC) estimation, into a new algorithm, namely State of Health Estimator (SHE), to evaluate the current battery State of Health (SoH) related to both capacity and internal resistance.

The paper is structured as follows: Section 2 reviews the currently available methods to estimate the SoH in Lithium-ion batteries; Section 3 describes the necessary background to introduce the presented method; Section 4 describes the proposed algorithm in details; Section 5 provides a thorough experimental analysis of the proposed method; Section 6 draws some conclusions on the presented work, and delineates the possible future works.

2. Related works

In this section, the recent literature about SoH estimation is presented. In particular, this analysis focuses on the works about Lithium-Ion batteries [6].[1] Depending on the application, the definition of SoH is computed based on the battery capacity or internal resistance. In what follows, an overview of the studies available in the literature on both these aspects is provided. As a final remark, a method will be denoted as *online* if it performs the estimation during the operational life of the battery, while it is denoted as *offline* if it requires suspending the battery operations to estimate the battery SoH.

2.1. Capacity

The most common method used to measure the current capacity of the battery is Coulomb Counting (CC) [13]. However, its application requires an offline procedure that, as mentioned, requires temporarily suspending the system's normal operations. Feng et al. [14] propose an online method based on probability density functions that use random variables to determine the capacity. This solution extends the ones based on Incremental Capacity Analysis (ICA) [15], and Differential Voltage Analysis (DVA) [16]. Notice that these offline methods are time-consuming since their curves are obtained by imposing a low current, *e.g.*, $C/20$ for the work in [17], C being the battery c-rate. Baghdadi et al. [18] propose a method to estimate the maximum capacity by estimating the OCV after a CC-CV charge and a relaxation period. Taking into account data-driven methods, several works are presented to estimate the capacity-related State of Health, based on fuzzy rules [19], Support Vector Machines (SVM) [20], Neural Networks [21,22], and Genetic Algorithms [23]. We remark that such black-box methods require the availability of data from the beginning to the end of multiple batteries.

2.2. Internal resistance

The first approach to measuring the resistance-related State of Health consists of the measurement of voltage reactions to current pulses [24], which is an offline method. Remmlinger et al. [25] highlight the importance of including the dependence on the SoC and temperature for a consistent estimation of the internal resistance. Other approaches make use of instruments called Electrochemical Impedance Spectroscopy (EIS) that directly measure internal resistance, using sine-wave signals [26,27] but they require an offline test to measure the internal resistance. Instead, Eddahech et al. [28] propose an offline method to precisely estimate internal resistance by looking at charging curves using the CC-CV approach, which therefore requires suspending the nominal activities of the battery. Finally, also in the case of internal resistance State of Health, several works use data-driven methods such as SVM [29] and Neural Networks [30]. The drawbacks remarked for the capacity estimates also apply in this case.

[1] For a complete review of this topic, see [7–12].

2.3. Complete Solutions

Other approaches for SoH estimation are based on the model's estimation and produce as a byproduct the estimation of the capacity and internal resistance, from which the State of Health is computed. These approaches usually rely on equivalent models and filtering techniques [31] to adapt in an online fashion the model estimation using the measurements. In particular, these equivalent models for lithium-ion batteries are RC models from which one can retrieve the measures of current and voltage. From these measures, equivalent models can be designed and estimated using Kalman Filter derivation such as Extended Kalman Filter (EKF) [29,32,33], Sigma-Point Kalman Filter [34], Unscented Kalman Filter [35] or Particle Filters [35,36]. Such methods, even if allowed to work online (*i.e.*, without disconnecting the battery and suspending its normal operations), from the practical point of view, fail in avoiding the request for previous information for hyperparameter tuning. More specifically, they require the initialization of values such as the EKF error covariance matrix, which does not allow to run these techniques unless one has extensive domain knowledge. Xiong et al. [37] use EKF and Least Squares to perform an estimate of the SoH. In this work, the tests are conducted on a new battery and the nominal capacity is provided to the model. A model-based method based on Least Squares is proposed by Prasad and Rahn [38]. This solution partially solves problems related to prior information requests for hyperparameter tuning. Tang et al. [39] propose a solution to perform SoH estimation in the case in which the battery has an embedded Battery Management System. However, this is not the case in most of the commonly used battery models. Other solutions based on machine learning methods are the ones based on SVM [40] that use non-parametric methods to extract non-linear behavior and estimate both capacity and internal resistance. A solution based on Bayesian model integrating SVM is proposed by Saha et al. [41,42].

In general, there is a wide range of machine learning and data-driven models to estimate the SoH, but they require either prior knowledge or a large amount of preliminary collected data.

3. Preliminaries

Since there is no standardized way to define the SoH [43], several formulas to calculate battery aging have been presented in the literature. In what follows, the most common definitions present in the literature for the State of Health are presented. More specifically, they are based either on the battery's maximum capacity or internal resistance. The measurement units for the quantities mentioned in what follows are summarized in Table 1.

3.1. Capacity state of health

The Capacity State of Health $SoH_C(t) \in [0,1]$ at a specific time t is defined as:

$$SoH_C(t) := \frac{Q_{\max}(t) - \alpha Q_N}{(1-\alpha)Q_N}, \tag{1}$$

where $Q_{\max}(t)$ is the current maximum capacity that can be stored in the

Table 1
Measurement units for the quantities used in the paper.

Quantity	Unit
t	s
$Q_{\max}(t)$, Q_N	Ah
$R(t)$, R_S, R_P, R_N	Ω
C	F
$I(t)$	A
$V(t)$	V

battery, Q_N is the nominal capacity declared by the manufacturer, *i.e.*, the one had by the battery at the system deployment, and α is the fraction of capacity for which the battery becomes depleted for the specific application.

3.2. Internal resistance state of health

The Resistance State of Health $SoH_R(t) \in [0,1]$ at a specific time t is defined as:

$$SoH_R(t) := \frac{(1+\beta)R_N - R(t)}{\beta R_N}, \tag{2}$$

where $R(t)$ is the current internal resistance, R_N is the internal resistance of the battery measured at system deployment, and β is the fraction of increase of the internal resistance for which the battery can be considered elapsed. When the battery degrades, the internal resistance increase, and the value of the ratio in Eq. (2) tends to decrease. Notice that it is common in the literature, *e.g.*, in the work by Lievre et al. [44], to consider the internal resistance referring only to the ohmic resistance of the battery, which can be calculated as the ratio between voltage and current variation over a few seconds. However, the total voltage dip of a battery also includes a transient due to the polarization that is more complex to measure online. Notice that the use of either one of these definitions of SoH is mainly related to the context in which the battery is used.

Commonly, the index used for battery degradation in power applications is SoH_R, while in energy applications, it is more common to use SoH_C. Indeed, for stationary applications such as the self-consumption scenarios in smart-grids is more common to consider the SoH component related to capacity since this kind of application is less stressful in terms of power than other applications, *e.g.*, automotive. Usually, the battery is considered to be elapsed, *i.e.*, $SoH_C(t) = 0$, when the value of $Q_{\max}(t)$ drops below the 80 % of the nominal capacity Q_N [9], formally $\alpha = 0.8$. Conversely, it is common for batteries used for automotive applications to rely on the $SOH_R(t)$, since the power density is one of the most relevant requirements [45] for such settings. In this setting, it is common to have $SoH_R(t) = 0$ when the internal resistance reaches 160 % of its initial value at the same condition of temperature and SoC [46], formally $\beta = 0.6$.

Finally, it is worth noting that some works in the capacity-related SoH estimation field use a different definition, *i.e.*, $SoH_C := Q_{\max}(t)/Q_N$, *e.g.*, [39]. However, using such a definition does not provide explicit information about the usability of the battery in the specific context, and, therefore, we resort to the definition in Eq. (1) that by setting the value of α adapts to different applications.

4. Algorithm

4.1. Problem formulation

Since the direct measurement of the SoH is not a viable option, the goal of this work is to determine the battery SoH, both in its capacity SoH_C and internal resistance SoH_R formulation. Recall that the computation of these values requires estimating either the maximum capacity $Q_{max}(t)$, or the internal resistances $R(t)$ at the current time instant t.

The SHE method relies on the use of the current $I(t)$ and voltage $V(t)$ measurements, the SoC of the battery $SoC(t)$, and the battery temperature $T(t)$ gathered during the operational battery life, at the beginning of its life and in its last period of usage.[2] Formally, the proposed method requires having the above information over two time periods:

- A dataset $\mathscr{D}_{init} := \{I(t), V(t)\}_{t \in \mathscr{T}_{init}}$ of the measurements over an initial time period $\mathscr{T}_{init}$ characterizing the initial stages of the battery usage, and a dataset $\mathscr{E}_{init} := \{SoC(t), T(t)\}_{t \in \mathscr{T}_{init}}$ of the SoC and temperature over the same period $\mathscr{T}_{init}$;
- A dataset $\mathscr{D}_{old} := \{I(t), V(t)\}_{t \in \mathscr{T}_{old}}$ of measurements over a time period $\mathscr{T}_{old}$ characterizing the current state of the battery, and a dataset $\varepsilon_{old} : \{SoC(t), T(t)\}_{t \in \mathscr{T}_{old}}$ of the SoC and temperature over the same period $\mathscr{T}_{old}$.

4.2. Proposed solution

This work proposes the use of an electrical model, *i.e.*, the Thevenin's equivalent model [48,49], to characterize the battery behavior and, subsequently, infer the SoH from it. Indeed, it has been shown that the use of Thevenin's model, *i.e.*, a first-order electric RC model of the battery, provides enough accurate approximation of lithium-ion battery dynamics [50]. In this model, depicted in Fig. 1, the battery is characterized by an equivalent model specified by the following parameters: the internal resistance R_S in series with an RC group (consisting of a resistance R_P, and capacitance C), and a voltage source, *i.e.*, the Open Circuit Voltage OCV. In this model, the value of the Q_{max} is inferred from the behavior of the OCV source w.r.t. the current passing through it, while the variations in the internal resistance value are approximated by the behavior of the resistance $R := R_S + R_P$. It is worth noting that the use of the SHE allows evaluating SoH_R based on the whole internal resistance, considering both the ohmic and recovery effect, giving a comprehensive knowledge of the battery aging.

Fig. 2 summarizes the whole procedure, which combines a time series segmentation approach [51] and the Voltage Dynamic-Based State Estimation (VDB-SE) algorithm, providing an online approach to the battery modeling [47] to estimate either the maximum capacity $Q_{max}(t)$ and the resistance $R(t)$.[3]

4.3. Capacity

Let now consider the capacity State of Health SoH_C. Applying the VDB-SE algorithm to $\mathscr{D}_{init}$, it outputs a parameter vector $\hat{\theta}$ characterizing the battery, whose elements include $\hat{Q}_{max,init}$, *i.e.*, an estimate of the Thevenin's model maximum capacity for the nominal conditions of the battery.[4] Repeating the same process on $\mathscr{D}_{old}$, the algorithm obtains an estimate of the same quantity $\hat{Q}_{max,old}$ for the current conditions for the battery. The final estimates $\widehat{SoH}_C$ of the actual SoH_C are computed as follows:

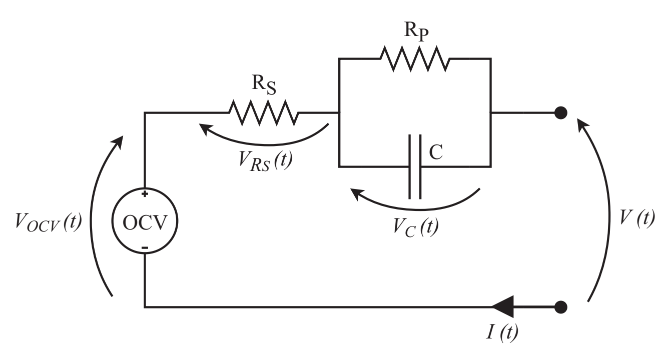


Fig. 1. Thevenin equivalent model of the battery.

[2] If the information about the SoC is not available, one can rely on its estimation provided by using the CC [13], or the VDB-SE [47] methods.

[3] Notice that the original purpose of the work in [47] was the SoC estimation. Conversely, in what follows, it will be used for its ability to provide a model of the battery, including estimates for the Q_{max}, R_S, and R_P values.

[4] See [47] for more details.

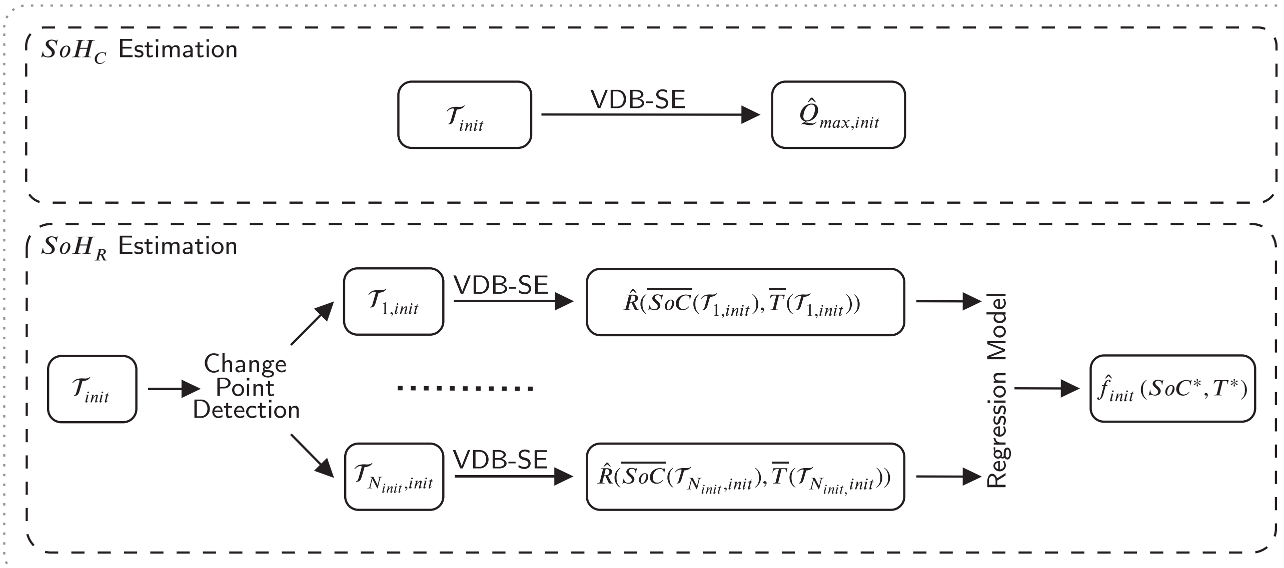


Fig. 2. Schema of the SHE algorithm at time period $\mathcal{T}_{init}$. The same schema holds if we apply the scheme at $\mathcal{T}_{old}$ by substituting the indexes corresponding to $\mathcal{T}_{init}$ with the ones corresponding to $\mathcal{T}_{old}$.

$$\widehat{SoH}_C = \frac{\widehat{Q}_{max,old} - \alpha \widehat{Q}_{max,init}}{(1-\alpha)\widehat{Q}_{max,init}}.$$

Alternatively, one can use the information about Q_N, if it is available, instead of the estimate of $\widehat{Q}_{max,init}$ to estimate $\widehat{SoH}_C$.

4.4. Internal resistance

For what concerns the internal resistance, as stated by Huet [52], the resistance R_S depends on different factors, *i.e.*, the current SoC and temperature. This implies that the estimation procedure should follow a different path. In what follows, the algorithm makes use of the dataset $\mathcal{E}_{init}$ and $\mathcal{E}_{old}$ to partition $\mathcal{T}_{init}$ and $\mathcal{T}_{old}$, respectively. This approach ensures that the SoC and temperature are jointly homogeneous over each one of the elements of the partition. Finally, these intervals are used to partition the datasets $\mathcal{D}_{init}$ and $\mathcal{D}_{old}$, respectively, and estimate the internal resistance R using the VDB-SE algorithm.

At first, applying a change point detection algorithm on $\mathcal{E}_{init}$, a partition $\mathcal{T}_{1,init}, \ldots, \mathcal{T}_{N_{init},init}$ of the original period $\mathcal{T}_{init}$ is obtained, formally $\cup_i \mathcal{T}_{i,init} \equiv \mathcal{T}_{init}$ and $\mathcal{T}_{i,init} \cap \mathcal{T}_{j,init} = \varnothing$ for each $i \neq j$. The number of sub-intervals N_{init} is determined by the change point detection algorithm, either fixing a number of splits or a penalty factor balancing the number of splits with the homogeneity of each $\mathcal{T}_{i,init}$ set.[5] Using the above defined subsets $\mathcal{T}_{1,init}, \ldots, \mathcal{T}_{N_{init},init}$, a partition of the measurement data into the datasets $\mathcal{D}_{1,init}, \ldots, \mathcal{D}_{N_{init},init}$ is obtained, where each set $\mathcal{D}_{i,init}$ corresponds to the measurements gathered during one of the period $\mathcal{T}_{i,init}$ or, formally, $\mathcal{D}_{i,init} := \{(I(t)\, V(t)) \in \mathcal{D}_{init} \text{s.t.} t \in \mathcal{T}_{i,init}\}$.

Applying the VDB-SE algorithm over each one of the datasets $\mathcal{D}_{i,init}$, generates a parameter vector characterizing the electrical model of the battery during the $\mathcal{T}_{i,init}$ period. Among the parameters estimated from the battery by VDB-SE, the values of the resistances $\widehat{R}_{S,i,init}$ and $\widehat{R}_{P,i,init}$, for all $i \in \{1, \ldots, N_{init}\}$, are the ones of interest for estimating the SoH. Indeed, their summation is an estimate $\widehat{R}_{i,init}$ of the internal resistance $R(t)$, *i.e.*, $\widehat{R}_{i,init} := \widehat{R}_{S,i,init} + \widehat{R}_{P,i,init}$. Finally, define the average values of the SoC and temperature over each period $\mathcal{T}_{i,init}$ as follows:

[5] See [53] to properly choose one of these two options according to the information available on the dataset.

$$\overline{SoC}_{i,init} = \frac{\sum_{t \in \mathcal{T}_{i,init}} SoC(t)}{|\mathcal{T}_{i,init}|}; \tag{3}$$

$$\overline{T}_{i,init} = \frac{\sum_{t \in \mathcal{T}_{i,init}} T(t)}{|\mathcal{T}_{i,init}|}; \tag{4}$$

respectively, where $|\mathcal{T}_{i,init}|$ is the cardinality of the set $\mathcal{T}_{i,init}$. The above data defines a regression problem where the input vectors are $(\overline{SoC}_{i,init}, \overline{T}_{i,init})$ and the corresponding output is $\widehat{R}_{i,init}$. This problem is solved by means of standard machine learning techniques, *e.g.*, Linear Regression, Regression Trees, and Neural Networks, the choice of which depends on the complexity and availability of the data analyzed.

As a result, the above-mentioned techniques generate a function $\widehat{f}_{init}(SoC, T)$ that approximates the relationship between the pair State of Charge SoC and temperature T, and the internal resistance $R(t)$. Finally, the value of the internal resistance $\widehat{f}_{init}(SoC^*, T^*)$ is evaluated at SoC^* and T^*, which are the reference values at which the resistance is evaluated for SoC and temperature, respectively.

The same approach, *i.e.*, partitioning and subsequent regression, is applied to the dataset $\mathcal{D}_{old}$ corresponding to the current battery status. This generates the function $\widehat{f}_{old}(SoC, T)$ characterizing the relationship between the generic State of Charge SoC and temperature T with the current internal resistance $R(t)$. Finally, the estimates of the SoH_R is computed as follows:

$$\widehat{SoH}_R = \frac{(1+\beta)\widehat{f}_{init}(SoC^*, T^*) - \widehat{f}_{old}(SoC^*, T^*)}{\beta \widehat{f}_{init}(SoC^*, T^*)}. \tag{5}$$

5. Experiments

In this section, the SHE methodology is tested using real data coming from a battery degradation test.

5.1. System Under Test

All the data used for this experimental campaign are retrieved from degradation tests performed in standard conditions using Nickel-Manganese-Cobalt (NMC) cell manufactured by KOKAM, model SLPB100216216H. The main characteristics of the cell are reported in

Table 2
Characteristics of the simulated cell.

Feature	Value
Rated voltage	3.6 V
Minimum voltage	2.7 V
Maximum voltage	4.2 V
Rated capacity	44 Ah
Rated charging/discharging current	40 A

Table 2. The current and voltage composing the data used for the experiment are provided in Fig. 3. The degradation test is performed in the RSE's Battery Lab using thermal chambers to control temperature and measurement instruments that register sample time, current, voltage, and temperature information. In particular, the test bench used to perform the aging test is a Hoecherl & Hackl bidirectional power supply, model NL1V20C80. This, controlled by a host computer, can charge and discharge the battery at a maximum rate of 80 A. All the tests were carried out inside a temperature test chamber (ACS DY 250 BT), which was used to maintain the desired cell temperature within $\pm 0.5\ K$. A data logger based on National Instruments Compact DAQ was used for measuring the cell voltage (NI9206), the current through an external LEM, and the ambient and battery temperatures (NI9213). The dataset over which the solutions are tested is composed of 24 discharges with a spacing of approximately 200 cycles between each period of characterization. Each characterization is composed of a full discharge and a pulse discharge aiming at measuring the maximum capacity and internal resistance, respectively. To run the experiments, it has been used the Matlab implementation of SHE.[6] The code used for the results provided in this section has been run on an Intel(R) I5(R) 8259U @ 2.30GHz CPU with 8 GB of LPDDR3 system memory. The operating system was macOS 12.2.1, and the experiments have been run on Matlab(R) *R2021b*. All the experiments shown in this section take ≈7 minutes to be performed.

5.2. Performance indexes

As performance indexes, authors used the percent errors over the battery parameters and SoH, formally defined as follows. The percent error $e_C(t)$ corresponding to the capacity at time instant t is defined as:

$$e_C(t) = \frac{\left|Q_{\max}(t) - \widehat{Q}_{max,old}(t)\right|}{Q_{\max}(t)} \cdot 100,$$

where $\widehat{Q}_{max,old}(t)$ is the corresponding estimate for the maximum capacity provided by the proposed method, the ground truth $Q_{\max}(t)$ is provided by a measurement conducted offline through Coulomb Counting. Both are defined for each $t \in \{0, 200, \ldots, 4600\}$, *i.e.*, the last time instants of each one of the 24 discharges. The percent error $e_R(t)$ corresponding to the internal resistance at time instant t is defined as:

$$e_R(t) = \frac{|R(t, SoC^*, T^*) - \widehat{f}_{old}(t, SoC^*, T^*)|}{R(t, SoC^*, T^*)} \cdot 100,$$

where the ground truth $R(t, SoC^*, T^*)$ is provided by a measurement conduced at time t during the pulse discharge test when the battery is at State of Charge SoC^* and Temperature T^*.

The error over the SoH estimate are evaluated in the same way for both capacity-related (SoH_C) and resistance-related (SoH_R) State of Health. Formally, the errors e_{SoH_C} and e_{SoH_R} are:

$$e_{SoH_C}(t) = |SoH_C(t) - \widehat{SoH}_C(t)| \cdot 100,$$

$$e_{SoH_R}(t) = |SoH_R(t) - \widehat{SoH}_R(t)| \cdot 100,$$

where $\widehat{SoH}_C(t)$ and $\widehat{SoH}_R(t)$ are the estimates provided by the proposed methods at time $t \in \{0, 200, \ldots, 4600\}$, respectively.

5.3. Capacity

To estimate the capacity State of Health SoH_C, an estimate over time of the maximum capacity $\widehat{Q}_{max}(t)$ is performed. The estimated values over the charge/discharge cycles, reported on the x-axis, are provided in Fig. 4, and are compared with the ones made in a specific discharge test through CC performed by applying a Constant Current-Constant Voltage (CC-CV) profile to the battery as depicted in Fig. 5. Recall that the computation of this CC baseline requires an offline test and, therefore, in practical application is not feasible to apply such a method without removing the battery from its operational context.

The performances are satisfactory since the error in the estimate is $e_C(t) < 3\%$ over the entire estimation period, with an average error of less than 1.2 % in the estimate of the $Q_{max}(t)$ (averaged over the cycles composing the entire discharge test data).

Fig. 6 represents the behavior of the estimated SoH $SoH_C(t)$ over the cycles, considering $\alpha = 0.8$. The error in the SoH_C estimate $e_{SoH_C}(t)$ averaged over time is less than 5.9 %. This suggests that the proposed method provides a reliable estimate of the SoH over the entire operational life of the battery, as long as it is provided with the current and voltage measurements from it.

5.4. Internal resistance

To estimate the SoH_R, a change point detection algorithm on both SoC and temperature signals has been applied. Since in the tests under analysis, the temperature is maintained constant using a thermal chamber, the proposed analysis will focus on the relationship between SoC and internal resistance, which has been shown to be the most significant one [52]. To partition the signal, the authors adopt an approximated splitting criterion using a penalty factor to be more flexible w.r.t. the different kinds of signals the algorithm faces during the operational life of the battery. In particular, bottom-up search methods, *i.e.*, the ones by Killick et al. [51], Chen and Gupta [54], using an *L1–norm* as a cost function, have been used. The above-mentioned search method has been chosen due to its computational efficiency, *i.e.*, its computational complexity is linear w.r.t. the number of samples, and since the cost function has empirically demonstrated to be the most flexible among the ones allowed by this search method (for further information about cost function, refer to Moreno et al. [55]). As mentioned in Section 4, once the dataset has been partitioned, the proposed algorithm estimates using VDB-SE multiple values of the internal resistance and builds a model of the internal resistance. In this test, the models are computed using Ridge Regression [56] with second-order polynomial features.

The results are shown in Fig. 7a, where the models of the internal resistance are compared over the charge/discharge cycles with the resistance measurements obtained from the pulse discharge characterization tests (Fig. 3) denoted as Ground-Truth, whose computation requires an offline procedure. The results show how, at ≈2,500 cycles, the resistance starts to increase rapidly, and at ≈1000 cycles, it reaches the value of internal resistance such that the battery stops being reliable for the given application. The error on the internal resistance $R(t)$ in standard condition $\widehat{f}_{old}(t, SoC^*, T^*)$, *i.e.*, $SoC^* = 0.5$, and $T^* = 20^\circ C$, averaged over time is less than 4 %.

Fig. 7b shows the same analysis without the Regression model, considering only data from subset with average State of Charge $\overline{SoC}$ and average temperature $\overline{T}$ closer to normal conditions, *i.e.*, $\overline{SoC} \approx 0.5$ and $\overline{T} \approx 20^\circ C$. In this case, the analysis is more subject to noise, with an average error $e_R(t)$ over time equal to 6.7 %, resulting in an increase of 68 % in the estimate w.r.t. using the model. This analysis empirically

[6] https://github.com/marcomussi/she.

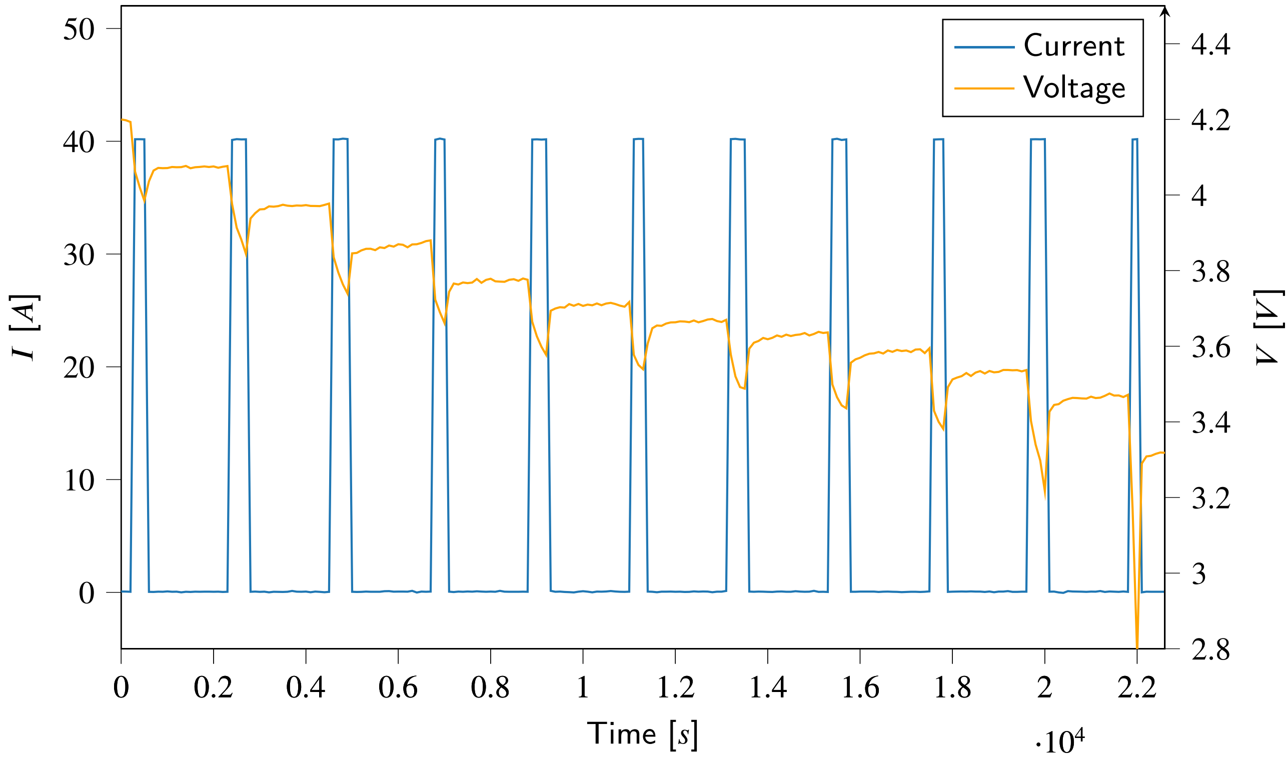


Fig. 3. Profiles during the full discharge test.

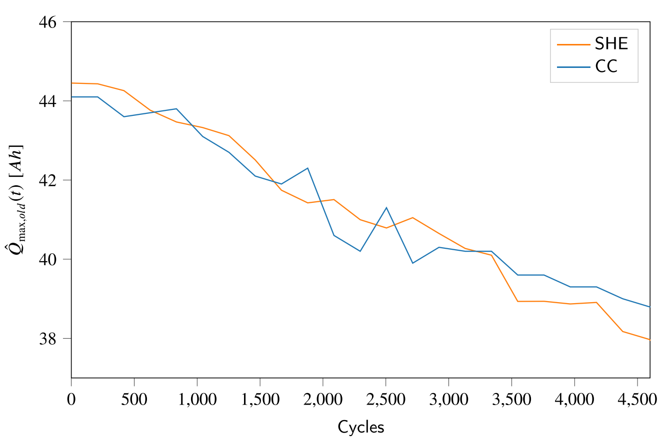


Fig. 4. Estimate of the value of $\widehat{Q}_{max,old}(t)$ over time.

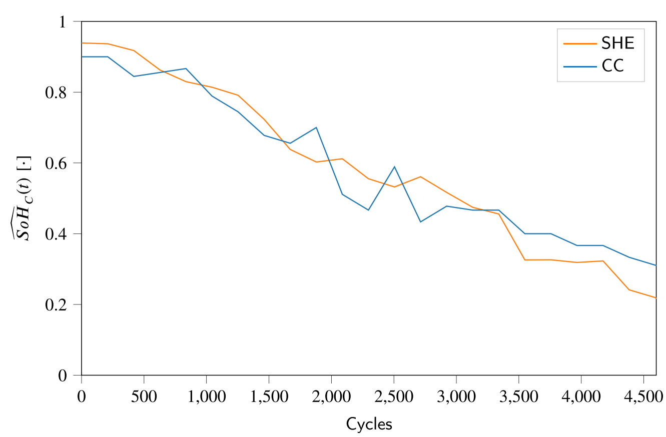


Fig. 6. Estimate of the values of SoH_C over time.

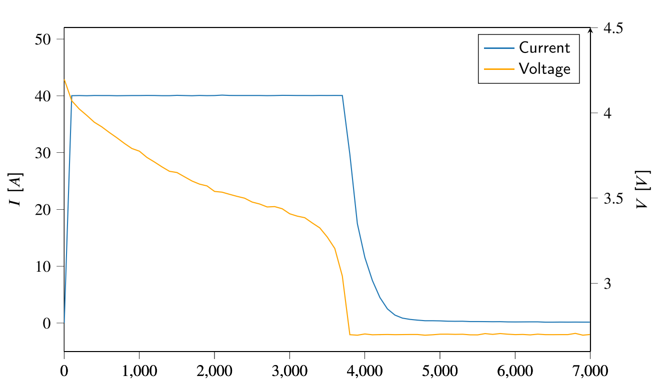


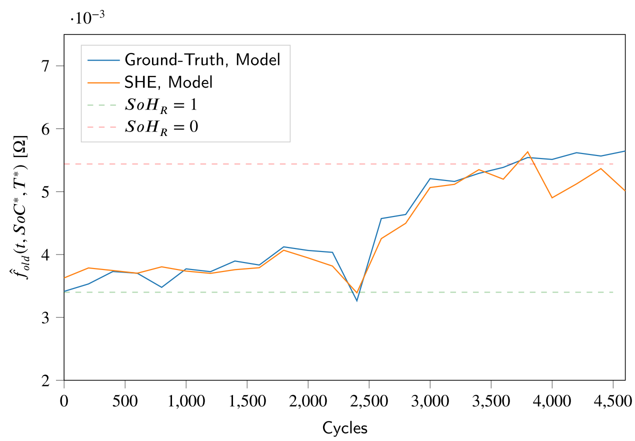
Fig. 5. Profiles during a single CC-CV discharge.

confirms the good properties of adopting a regression model in the estimate phase for the datasets under analysis.

Finally, Fig. 8 shows the SoH_R estimate corresponding to the estimated values of the internal resistance $\widehat{R}(t)$, considering $\beta = 0.6$. In this analysis, considering a battery exhausted when the current capacity is above the 160 % of the one estimated at system deploy, the average error in the estimate is e_{SoH_R} is equal to 7.5 %. The behavior is consistent with the one presented in Fig. 7a.

6. Conclusions and future works

In this work, a different method to estimate online the SoH of a battery, either in its maximum capacity or internal resistance flavor, is presented. The method has the advantage w.r.t. existing methods to require only the operational measurements provided by the battery, *i.e.*, current and voltage, and estimate a model over partitions of such signals



(a) Internal resistance for $SoC^* = 0.5$ and $T^* = 20°C$.

(b) Internal resistance values extrapolated from batches with $\overline{SoC} \approx 0.5$ and $\overline{T} \approx 20°C$.

Fig. 7. Internal resistance estimates for the SHE and Ground-Truth. Dashed lines represents the nominal condition (blue line for $SoH_R = 1$) and the elapsed condition (orange line for $SoH_R = 0$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

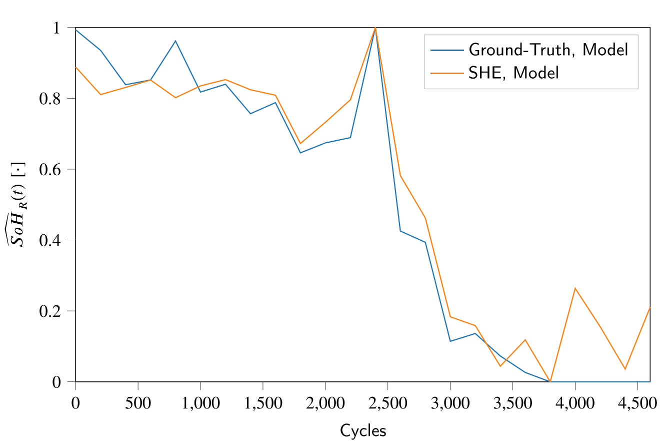


Fig. 8. SHE SoH_R estimates using internal resistance retrieved through regression models, considering $SoC^* = 0.5$ and $T^* = 20°C$.

without requiring lab experiments. Moreover, differently from what has been proposed before, the proposed method estimates the internal resistance, including the ohmic resistance and the polarization one.

Tests on real-world data coming from a battery cell empirically show that the performances of the algorithms in both flavors are satisfactory. In particular, the average error in terms e_C and e_R is 1.2 % and 4 %, respectively. These values result in an error on the capacity-related State of Health e_{SoH_C} below 6 %, and an error on the resistance-related State of Health e_{SoH_R} of 7.5 %.

An interesting future line of research is using such estimation to improve the management of batteries in smart grids.

NomenclatureThe acronyms used in the paper are the following:

Acronym	Description
SoH	State of Health
SHE	State of Health Estimator
OCV	Open Circuit Voltage
EIS	Electrochemical Impedance Spectroscopy
SoC	State of Charge
CC	Coulomb Counting
ICA	Incremental Capacity Analysis
DVA	Differential Voltage Analysis
SVM	Support Vector Machines
VDB-SE	Voltage Dynamic-Based State Estimation
NMC	Nickel-Manganese-Cobalt
CC-CV	Constant Current-Constant Voltage

CRediT authorship contribution statement

Luigi Pellegrino: Term, Investigation, Resources, Supervision. **Marco Mussi:** Methodology, Software, Validation, Data Curation, Visualization. **Francesco Trovò:** Methodology, Formal Analysis, Writing - Original Draft. **Marcello Restelli:** Conceptualization, Supervision, Writing - Review & Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We included a git repository to replicate the experiments

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