A Light-weight Model for Run-time Battery SOC-SOH Estimation While Considering Aging

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KEYWORDS

Lithium-ion battery, Electrical equivalent circuit model, State of charge, State of health, Extended Kalman filter

ABSTRACT

Batteries are becoming one important part to power varieties of devices including electro-mechanical robots and vehicles. Understanding the behaviour of the battery and its state of charge can help the control systems to significantly improve the decision-making and risk management at run-time, after the device starts its operation. Currently, there is an increased interest in tracking battery dynamics as a function of health in both academia and industry. In this paper, we propose a light-weight approach for modeling the state of charge of lithium-ion (Li-ion) batteries during the life-time of the system. We also consider the battery capacity of charge degradation over its usage. To do that, we use electrical equivalent circuit model (EECM) modeling as the basis for modeling the battery and add the aging model to it to consider the effect of battery usage in the long term. Experimental results show that our proposed technique successfully estimates the battery state of charge at different states of health for the National Aeronautics and Space Administration (NASA) randomized usage battery dataset in comparison with the state-of-the-art. The obtained estimation error in the worst case is 2.2%.

I. INTRODUCTION

Lithium-ion batteries are one of the most popular forms of energy storage systems. It is estimated that in 2015 up to 85% of deployed energy storage systems has been Li-ion batteries [1]. These batteries are able to be recharged several times and tend to have lower self-discharge rate compared with similar energy storage systems [2]. One important aspect of optimizing an energy storage system's usage is to predict the behaviour of the battery at run-time [3]. This behaviour can be demonstrated through different parameters such as state-of-charge (SOC) and state-of-health (SOH) of the battery; the former is the level of battery charge over the usage of the battery and the latter refers to the capacity of the battery, in contrast with the nominal capacity value, over the battery aging process [4]. This battery aging process results in a continuous battery energy capacity reduction over the battery life-time. Accurate online estimation of battery SOC/SOH results in more optimal battery-aware control and risk management in autonomous systems. Another parameter that can be used to show the battery aging is the battery's internal impedance in the way that battery impedance is increased by in the aging process [5]. Therefore, SOH usually is quantified by the battery impedance or battery capacity. Unfortunately, SOC and SOH can not be measured directly and they have to be estimated by employing advanced algorithms with the use of measurable quantities, such as current drawn from the battery, output voltage and temperature of the battery [6].

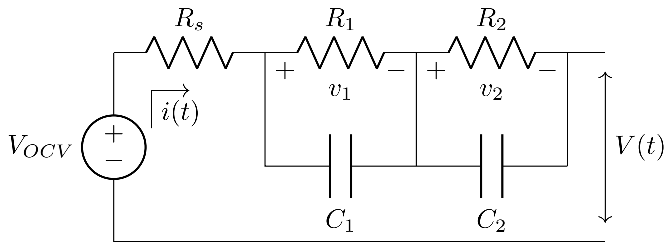

Fig. 1: Schematic diagram of second-order equivalent circuit model.

There have been several works on battery SOC and SOH estimation. However, most of the proposed techniques do not give a suitable approach that can execute continuously at run-time during the battery's life-time. Some problems of the state of art are the heaviness of the estimation algorithm, that is not suitable for run-time estimation of the parameters, and ignorance of the effect of aging on the parameters. In this paper, we use the EECM model to describe the battery behaviour and we propose a light-weight method to identify the parameters of EECM model. Then, an extended Kalman filter (EKF) is used to co-estimate of the battery SOC and SOH during the activity of the battery in its life-time. We show the robustness of our method by applying the extracted model on different NASA datasets generated by different instructions. The rest of the paper is organized as follows. Section 2 describes and analyzes some related works. Section 3 presents the EECM to model the battery dynamics. Section 4 introduces the proposed method to estimate the battery parameters. In the section 5, used dataset is introduced. Section 6 presents the results and validation of the proposed model, while Section 7 provides some concluding remarks.

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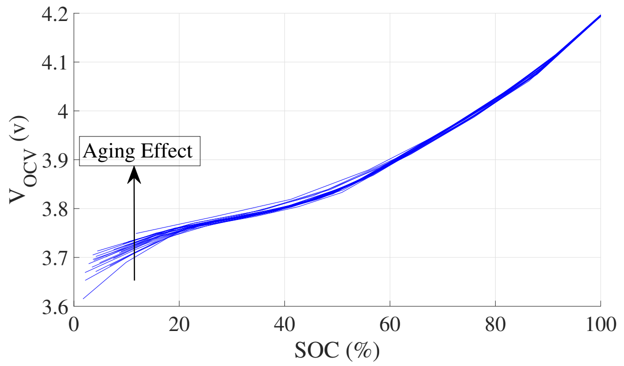


Fig. 2: Aging effect on open circuit voltage over SOC.

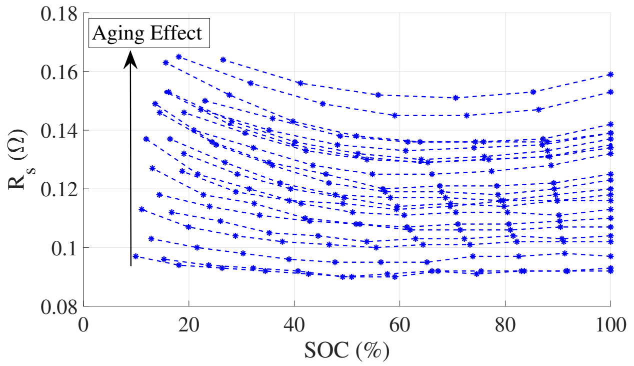


Fig. 3: Aging effect on internal resistance over SOC.

II. Related works

Several methods are presented to estimate SOC and SOH that could be classified in offline and online approaches. Coulomb counting is the simple way to compute the SOC, but it has a less accuracy. Also, estimate the initial state of SOC is the serious problem for employing this method [7]. Other simple method is to use the open circuit voltage (OCV) to estimate the SOC, but this method has the disadvantage of requiring a long period of time to stabilize the battery voltage. [8].

Data-driven approaches based on machine learning (ML) techniques can give reliable SOC and SOH estimation. There have been various learning-based methods for SOH/SOC estimation [9]. Some of the common non-deep learning methods are, e.g., nonlinear least squares regression (NLSR) [10], Gaussian process regression (GPR) [11], [12], and relevance vector machine (RVM) [13]. In these techniques, distinctive features, that are representative of cell states, are extracted manually from the voltage and current run-time/offline measurement data and then are given to the learning unit as the input. In contrast, deep learning methods employ the complete set of raw data during the cell charge/discharge process as the input without extraction and selection of distinctive features [14]. In Ref.[15], the authors present a deep convolutional neural network (DCNN) for battery cell level capacity estimation. In this work, comparing to the other shallow neural network and RVM method, proposed method shows high accuracy and robustness in the online estimation. However, training the proposed DCNN module is 7.6x longer than while using

Algorithm 1 EECM Parameters Identification Algorithm

$n \leftarrow$ number of DPPC Experiments ▷ number of SOH level
while $n \neq 0$ **do**
  $m \leftarrow$ number of pulse in DPPC ▷ number of SOC level
  while $m \neq 0$ **do**
    if $Pulse(i(t))$ **then** ▷ beginning of every pulsed discharge
      $t_0 \leftarrow t$
      $V^m_{OCV} \leftarrow V(t_0 - T_s)$
      $R^m_s \leftarrow \frac{V(t_0-T_s)-V(t_0)}{i(t_0)}$
    end if
    $m \leftarrow m - 1$
  end while
  $m \leftarrow$ number of pulse in DPPC ▷ number of SOC level
  while $m \neq 0$ **do**
    $V_{OCV}(t) \leftarrow (\frac{V^{m-1}_{OCV}-V^m_{OCV}}{T_p})t + V^m_{OCV}$ ▷ $0 \leq t \leq T_p$
    $v_{12}(t) \leftarrow -V(t) + V_{OCV}(t) - R^m_s i(t)$
    $[A, B, C, D] \leftarrow ssest(v_{12}(t), i(t))$ ▷ MATLAB function
    $canon(A, B, C, D)$ ▷ MATLAB function
    calculate EECM parameters based on Eq.2.
  end while
  $n \leftarrow n - 1$
end while

RVM model (around 500 seconds). The memory usage for DCNN and RVM has been estimated around 144 MB and 20 GB respectively. It shows high computational and memory resources are needed to implement machine learning based approached for battery management systems.

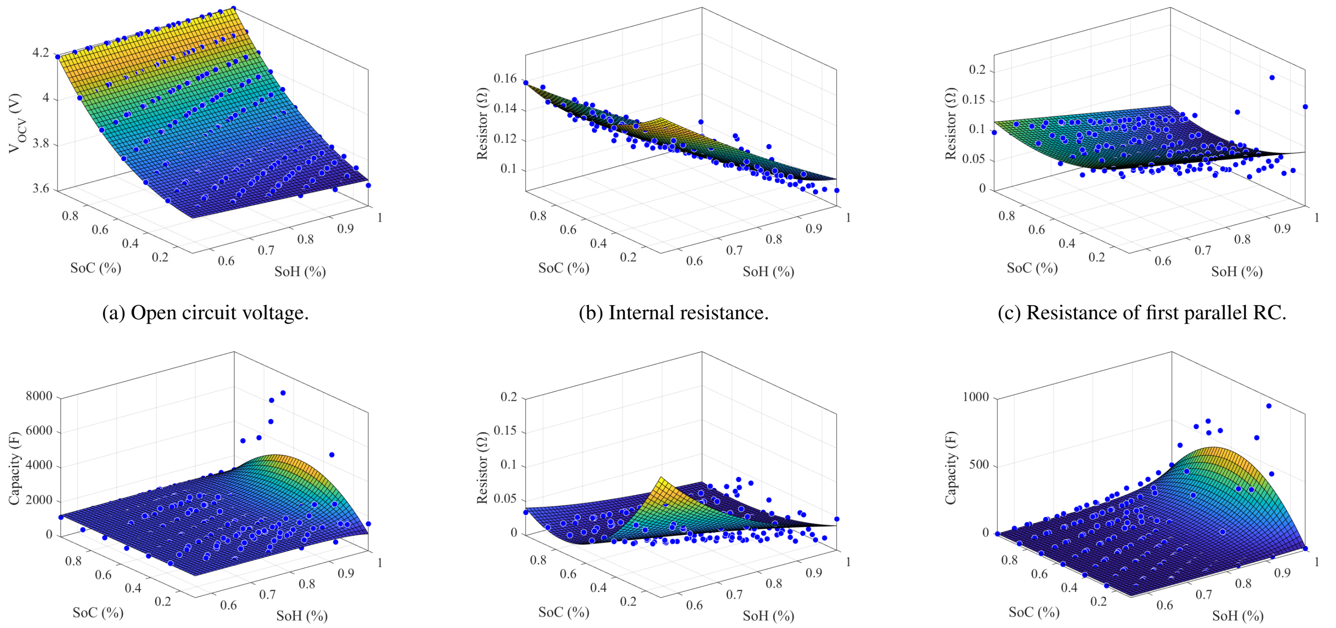
In contrast with accurate by heavy ML-based techniques for battery SOC/SOH estimation, some works use simple model-based estimation methods such as electrical equivalent circuit model (EECM), electrochemical model (ECM), and empirical models (EM) [6]. Based on the established EECM, some adaptively filtering algorithms such as, extended Kalman Filter (EKF) [16] , Particle filter (PF) [17] and adaptive extended Kalman filter (AEKF) [18], were employed to identify the electrical parameters such as resistance and capacity for the battery SOH estimation. In [19] two extended Kalman filters have been used to model the Li-ion batteries based on frictional order models [20]. One EKF has been used to estimate the combined SOC and SOH while the other has been used to update the EECM parameters. However, as mentioned in the paper, the SOH and EECM parameters could not be fit at the different aging levels of the battery, due to lack of proper data showing the battery aging over the activity of the system.

In this paper, we try to employ the light-weight model to estimate the battery behaviour by considering the aging effect on battery performance. Proposed model provides the accurate battery SOC estimation over the whole battery lifetime, while it degrades continuously. Less complexity and light computation cost make the proposed model to worth practical approach to implement on the battery management systems (BMS) which usually have simple processors and low memory capacities.

III. Model description

A. Electrical equivalent circuit model

The schematic view of the second-order EECM that has been used in this paper is shown in Figure 1. This model



(a) Open circuit voltage. (b) Internal resistance. (c) Resistance of first parallel RC.

(d) Capacitor of first parallel RC. (e) Resistance of second parallel RC. (f) Capacitor of second parallel RC.

Fig. 4: Fitting surface on identified EECM parameters.

TABLE I: Fitting function variables.

Parameter	a_0	a_1	a_2	a_3	a_4
R_s	-0.0736	0.1059	-0.1487	0.3995	0.7725
R_1	-2.25	0.1401	-0.1854	2.481	0.0513
R_2	0.0013	2.887	-4.368	1.789	3.692
C_1	1270	-0.0001	0.0001	-0.00001	-18.57
C_2	13.89	-0.001	0.0011	-0.0001	-14.48

is used to calculate the battery voltage in response to the current being drawn from the battery. The V_{OCV} is the ideal voltage source, which is dependant on the battery SOC and SOH. R_s accounts for the ohmic internal resistance of the battery, and the parallel RC circuits, i.e., R_1, C_1, R_2 and C_2, represent the voltage diffusion phenomenon [21].

Let v_1 and v_2 denote the voltage across the subcircuits consisting of R_1, C_1, R_2 and C_2. The measured battery voltage, $V(t)$, is calculated as follows:

$$V(t) = V_{OCV} - R_s i(t) - v_1 - v_2 \tag{1}$$

where $i(t)$ denote the load current (assumed positive for the discharging process) and v_1 and v_2 dynamics are:

$$\begin{bmatrix} \dot{v_1} \\ \dot{v_2} \end{bmatrix} = \begin{bmatrix} \frac{-1}{R_1 C_1} & 0 \\ 0 & \frac{-1}{R_2 C_2} \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} + \begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C_2} \end{bmatrix} i(t)$$
$$v_{12} = v_1 + v_2 = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \tag{2}$$

B. *Definition of state of charge*

The SOC is the ratio between the remaining capacity and the current maximum available capacity which the battery can deliver [22]. Then, the current remaining capacity in the battery is used to quantify SOC:

$$SOC(t) = SOC(0) - \frac{1}{C_p^{ag}} \int_0^t \eta i(\tau) d\tau \tag{3}$$

where C_p^{ag} indicate the current maximum available capacity, which decrease with the aging of the battery. Also, η denote the Coulombic efficiency and in this study, is assumed 1 [23].

C. *Definition of state of health*

Over time, batteries will age and their performance will degrade. They will eventually reach a point where they no longer satisfy the expected requirements from the battery, the time when is considered as the battery's *end of life.*. SOH is defined as the following equation:

$$SOH(t) = \frac{C_p^{ag}}{C_{init}} \tag{4}$$

where C_{init} indicates the initial maximum available capacity when the battery is new. According to the Eq. (2), Eq. (3). and Eq. (4), can be discretized battery model as the following equation:

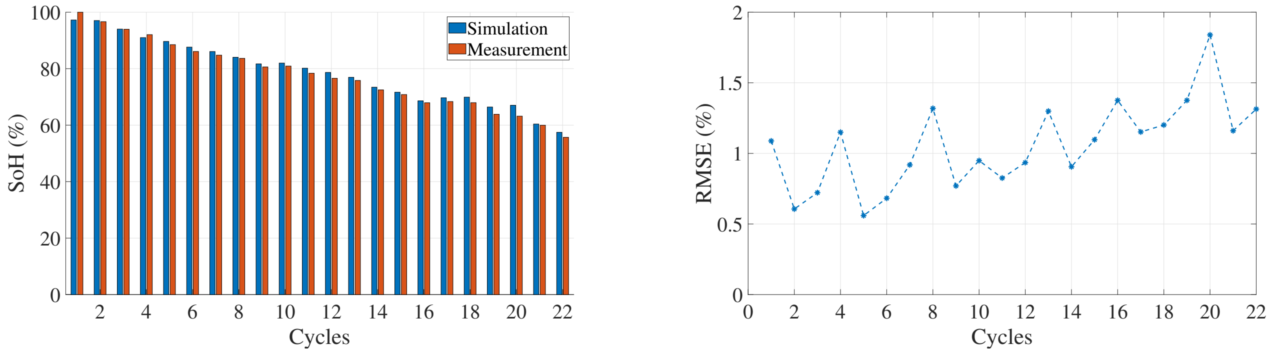
$$\begin{aligned} SOC_{k+1} &= SOC_k - \frac{\eta T_s}{C_{init} SOH_{cycle}} i_k \\ v_{1_{k+1}} &= (1 - \frac{T_s}{R_1 C_1}) v_{1_k} + \frac{T_s}{C_1} i_k \\ v_{2_{k+1}} &= (1 - \frac{T_s}{R_2 C_2}) v_{2_k} + \frac{T_s}{C_2} i_k \end{aligned} \tag{5}$$

where T_s is sampling time.

IV. Parameters Estimation

A. *Identify the EECM parameters*

The goal of the parameter identification algorithm is to identify the six parameters of the second-order EECM, that is shown in Figure 1, under specific SOC and SOH. In our work, we use the proposed method in [24] to identify the



(a) Real and estimated SOH values of DPPC experiments

(b) RMSE of SOC estimation of DPPC experiments

Fig. 5: Jointly SOC/SOH estimation under the RW3 dataset.

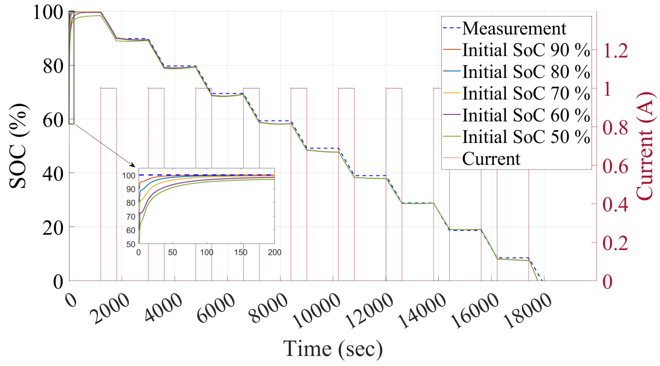


Fig. 6: Estimation of SoC with different initial states.

EECM parameters. Algorithm 1 describes the parameter estimation method from discharge pulse power characterization (DPPC) measurement. Based on this method, in each DPPC cycle, that presents an SOH value, EECM parameters are calculated for discrete SOC values, Line 3-11 in Algorithm 1, explain the proposed method to calculate open circuit voltage and battery internal Resistance. At first, the last value of the battery voltage before the onset of discharge pulse, is considered as the open circuit voltage at the current SOC. Then, initial drop of battery voltage, when the pulsed discharge starts, is used to calculate the internal resistance. Line 12-19 describe the method to calculate the RC subcircuit values. Based on Eq. (1), the voltage of RC subcircuits (v_{12}) is calculated in one pulsed discharge period (T_P) and used to obtain a second-order linear time invariant (LTI) model for RC subcircuit by using Matlab Estimate State-Space Model ($ssest$) function. By transferring the obtained LTI model to a diagonal state-space model and comparing state-space matrices with Eq. (2), values for RC parameters will be calculated. As mentioned before, battery capacity reduces by aging effect, in consequence, the number of pulses in each DPPC experiment and number of extracted values for the EECM parameters reduce by increasing aging effect. Figure 3, shows this fact that the extracted values for the internal resistance are 12 when the battery is new, while they are only 6 for the oldest battery.

Extracted values are used to fit the functions of SOC and SOH on the EECM parameters. To keep the method simple, exponential function of SOH with second-order polynomial function of SOC is assumed for EECM parameters except the V_{OCV}. As shown in the Figure 2, V_{OCV} is more dependant to SOC than SOH. Therefore, proposed function for V_{OCV} is third-order polynomial function of SOC with first-order function of SOH. Eq. (6) and Eq. (7) show the fitting function on V_{OCV} and other EECM elements, respectively.

$$\begin{aligned} V_{OCV}(SOC, SOH) &= p_0 + p_1 SOH + p_2 SOC + p_3 SOHSOC \\ &+ p_4 SOC^2 + p_5 SOHSOC^2 + p_6 SOC^3 \end{aligned} \tag{6}$$

$$f(SOC, SOH) = a_0 + (a_1 SOC^2 + a_2 SOC + a_3)e^{-a_4 SOH} \tag{7}$$

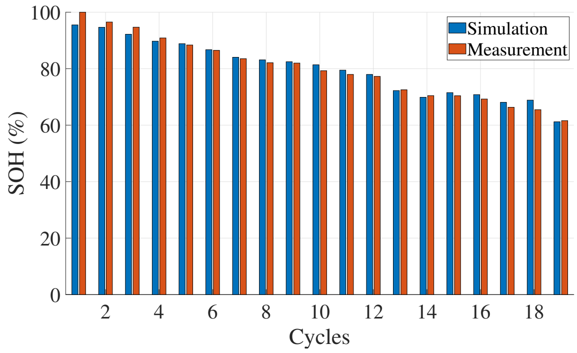
B. Jointly SOC and SOH Estimation

In order to achieve online estimation of the SOC and SOH, an extended Kalman filtering algorithm is proposed. Eq. (5) are used directly to estimate the SOC, while the ohmic internal resistance is used to characterize the battery SOH. As shown in Figure 3, extracted values for the internal resistance follows the same behaviour compared with battery aging. In fact, the average value of the internal resistance is increased by battery aging. Therefore, by monitoring the internal resistance over the discharge cycles, battery SOH is determined. In fact, by estimating the internal resistance value and battery SOC, a fitting function on the internal resistance is used in order to calculate the SOH of the battery. To do that, by defining $x_k = [SOC, R_s, v_1, v_2]^T$ as a EKF states, the EECM model (5) can be rewritten as:

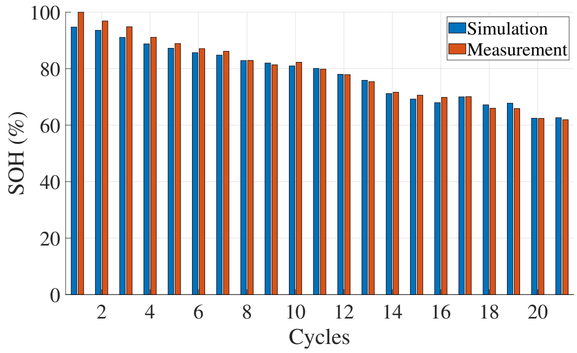
$$x_{k+1} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 - \dfrac{T_s}{R_1 C_1} & 0 \\ 0 & 0 & 0 & 1 - \dfrac{T_s}{R_2 C_2} \end{bmatrix} x_k + \begin{bmatrix} -\dfrac{\eta T_s}{C_p^{ag}} \\ 0 \\ \dfrac{T_s}{C_1} \\ \dfrac{T_s}{C_2} \end{bmatrix} i_k$$

and the Jacobian matrix can be expressed as

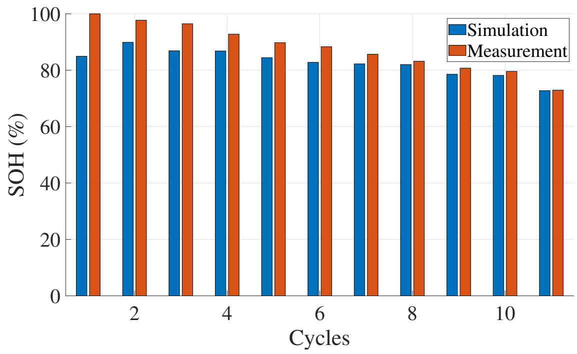
$$H_k = \frac{\partial V}{\partial x} = \begin{bmatrix} \frac{\partial V_{OCV}}{\partial SOC} & -i_k & -1 & -1 \end{bmatrix} \tag{8}$$



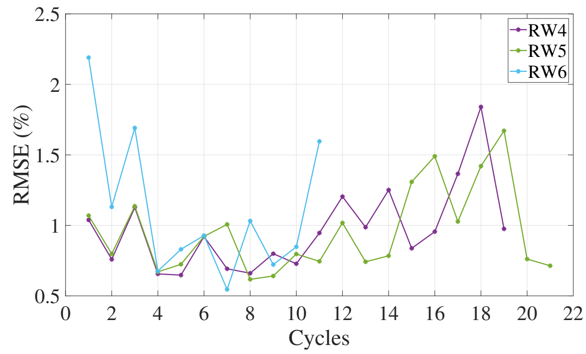
(a) Real and estimated SOH of RW4's DPPC measurements



(b) Real and estimated SOH of RW5's DPPC measurements



(c) Real and estimated SOH of RW6's DPPC measurements



(d) RMSE of SOC estimation of DPPC experiments under RW4,RW5 and RW6

Fig. 7: Validation results of jointly SOC/SOH estimation.

where, to compute the $\frac{\partial V_{OCV}}{\partial SOC}$, extracted function in the Eq. (6) is used. We update the battery SOH when the battery is operating in discharge mode rather than rest mode, and when the SOC estimation is greater than 60%, otherwise we keep the last estimated value of SOH. This avoids a battery nonlinear dynamics effect and improves SOH calculation accuracy. As shown in the Figure 2. and Figure 3, V_{OCV} has a linear relationship with SOC and internal resistance has less fluctuations in the high SOC values. Opposite to SOH estimation process, SOC and internal resistance will be estimated in the whole discharge cycles. In fact, SOH is a feature of the battery that changes slowly and there is no expect SOH changes significantly at one discharge cycle. Therefore, estimating the SOH in the part of the cycle is not illogical.

V. Experimental setup

The experimental data of the half-year cycling test was collected by NASA on a set of 18650 Li-ion batteries [25]. In our study, we used the second five groups of cells from the NASA dataset. The five groups consist of a total of 20 cells, with each group being composed of four cells with five different test instructions. Second group of NASA dataset's cells (RW3, RW4, RW5 and RW6) were cycled at room temperature throughout the duration of the test. They were continuously operated by repeatedly charging them to 4.2V and then discharging them to 3.2V using a randomized sequence of discharging currents between 0.5A and 4A. After every fifty randomized discharge cycles, a series of reference charging/discharging cycles with constant current and DPPC were performed in order to provide reference benchmarks for battery state health. In this paper, provide the EECM model by the first measurement (RW3) of second group of the NASA dataset, and use the other measurements (RW4, RW5, RW6) as a test data to validate the proposed method.

VI. Results and discussion

A. EECM parameter identification

In order to verify the accuracy of the proposed method, the battery SOC and SOH estimation are conducted under the NASA tests. As previously mentioned, the EECM parameters of battery model are computed by applying the algorithm 1, then introduced functions in the Eq. 6 and Eq. 7 are used to fit the surface on them. Figure 4 , shows the fitting surfaces on the EECM elements values over the SOC and SOH. The fitting functions information are provided in table I. Fitting results show that EECM parameters' dependence on SOC is reduced by battery aging. In addition, internal resistance and subcircuits' resistances increase significantly by battery aging, while capacitors' capacities decrease. Also, the dual RC subcircuits in EECM present both slow and fast dynamic of the voltage diffusion that means one of them has a higher time constant than the other. The calculated values reflect that fact when the parameter C_1 is almost 10 times larger than C_2.

B. SOC/SOH online estimation

Before the proposed method enters the iteration, initial values of the SOC and internal resistances are set to 0.8 and

0.1 ohm, respectively. Joint SOC/SOH estimation results are shown in the Figure 5, where real SOH and SOC values are calculated by Eq.4 and Eq.3 in every DPPC experiments, respectively. EKF states are updated in every DPPC measurement, while the battery SOH is updated by the estimated internal resistance. As can be seen in the Figure 5a, the estimated SOH follows the real SOH behaviour over the 22 DPPC experiments. The results show the root mean square error (RMSE) factor of SOH estimation is 1.62 %. Simultaneously, estimated SOH is used to estimate the battery SOC. In every DPPC experiment, EKF estimates the battery SOC in the whole period of experiment when the battery charge decreases from 100% to 0%. RMSE factor of SOC estimation for each DPPC experiments are shown in Figure 5b, that illustrates SOC estimation errors remain under the 2 % for all DPPC experiments.

Also, Figure 6 shows the convergence of SOC as a result of varying initial value of SOC. Furthermore, in this figure we can see the estimation of SOC over the entire period of DPPC cycle when the battery SOH is 0.8. The plot show that the proposed EKF state estimation method is able to converge to the actual SoC value after a transient period (shown as close-up view inside the plot), regardless of the initial value.

C. Method validation

To validate the proposed method, extracted model is used to compute the battery SOC and SOH on other experiments of the dataset group. As mentioned in section V, NASA dataset has four different measurements with same type of battery, while the discharging current profile is random. Therefore, expect to have different degradation dynamics in the measurements. Extracted model is applied on the RW4, RW5, RW6 measurements and the simulation results are shown in the Figure 7. Figure shows the EKF can estimate the battery degradation trend. However, accuracy of SOH estimation improves by increasing the battery aging. Probably, the low accuracy of the battery SOH estimation when it is new has to do with the initial health state of the battery when it was stored. Figure 7d shows the RMSE factor of SOC estimation over the battery operation during the different measurements. In every DPPC experiments, SOC estimation remains under the 2.2% that approve the accuracy and reliability of proposed EKF state estimation during the different consuming way.

VII. Conclusion

In this paper, a light-weight second-order EECM is employed to model the battery, and based on the model a EKF algorithm is proposed for co-estimation of the SOH and SOC. However, EKF estimates the SOC and internal resistance directly, while SOH is calculated by considering the relationship between internal resistance, SOC and SOH. We explained the EECM model's parameters, their identification, applying the EKF method and model validation by both in-sample and out-of-sample experimental DPPC data. The model can accurately estimate the SOH of the LTO cell in different dynamic experiments. In addition, the results show that the proposed model can obtain more accurate SOC value by considering the aging effect on the model parameters.

An important topic for the future work is studying the thermal effect on the EECM parameters. In a way, by adding the temperature of the battery operation to EKF, one could be able to estimate the SOC and SOH of the battery more accurately. Another interesting future direction of this work is to utilize this battery model and jointly SoC-SOH estimation in optimal control of resource-constrained mobile robots. Specifically, proposed battery model can be integrated into robotic control systems to address energy efficient resource-aware operation planning.

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