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Estimation of state-of-charge and state-of-power capability of lithium-ion battery considering varying health conditions

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HIGHLIGHTS

- Robustness of the SoC estimator against varying health conditions is analyzed.
- Robustness of the SoP estimator against varying health conditions is analyzed.
- The need of parameter updates of battery model is analyzed and discussed.
- Accurate SoC and SoP joint estimator against varying health conditions is proposed.

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ABSTRACT

Battery state-of-charge (SoC) and state-of-power capability (SoP) are two of the most significant decision factors for energy management system in electrified vehicles. This paper tries to make two contributions to the existing literature. (1) Based on the adaptive extended Kalman filter algorithm, a data-driven joint estimator for battery SoC and SoP against varying degradations has been developed. (2) To achieve accurate estimations of SoC and SoP in the whole calendar-life of battery, the need for model parameter updates with lowest computation burden has been discussed and studied. The robustness of the joint estimator against dynamic loading profiles and varying health conditions is evaluated. We subsequently used data from cells that have different aging levels to assess the robustness of the SoC and SoP estimation algorithm. The results show that battery SoP has close relationship with its aging levels. And the prediction precision would be significantly improved if recalibrating the parameter of battery capacity and resistance timely. What's more, the method reaches accuracies for new and aged battery cells in electrified vehicle applications of better than 97.5%.

1. Introduction

To address the two urgent tasks nowadays of protecting the environment and achieving energy sustainability, it is of strategic significance on a global scale to replace oil-dependent vehicles with electric vehicles. Battery, as important on-board electric energy storage, has been widely used in various electrified vehicles. The most important factor determining their successful commercialization is technologies safeguarding the reliable and safe battery operations. Battery management systems (BMS) have been designed to provide monitoring, diagnosis, and control functions to enhance the operations of battery. A critical function of BMS is to accurately estimate battery state-of-charge (SoC) and state-of-power capability (SoP) in real-time [1–3].

On one hand, the accurate battery SoC estimate is a key decision factor to manage batteries efficiently and to carry out the power distribution strategy in various electrified vehicles [4,5]. On the other hand, the accurate SoP estimate is critical in practical BMS applications since it is necessary to determine the available power in the moment to meet the acceleration, regenerative braking and gradient climbing power requirements without fear of over-charging or over-discharging. More importantly, accurate SoP estimates will be helpful to optimize the battery capacity and size and benefit the vehicle's general potency [6–8]. Therefore, to provide an efficient guarantee for the optimization of energy management system in electrified vehicles, a reliable SoC and SoP prediction algorithm is particularly necessary.

In terms of SoC estimation, a wide variety of methods has previously been summarized for constructing the SoC estimator, each one having its own advantage, as reviewed in Ref. [3]. Compared with direct measurement method, Coulomb counting method,

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voltage and impedance measures based methods, filter algorithms or integrated algorithm based on multiple filters are attracting more attentions [9–18]. This is because that these kinds of approaches can hardly applied to electric vehicles directly, but the filters based approach can effectively avoid the problems from noise, inaccurate current sensor, accumulated round off error and so on. Ref. [9] used output injection-based PDE observer to predict the state of battery. Ref. [10] presented a comparative study among the nonlinear state observers and extended Kalman filters for predicting battery SoC. Ref. [11] used extended Kalman filters to predict battery SoC. Ref. [12] presented comprehensive unobservable model-based battery SoC, unknown nonlinearities, and state-of-health (SoH) estimation method. Refs. [13–18] presented several kinds of filters for estimating battery SoC. The above methods have achieved acceptable accuracy for battery SoC estimation. However, to achieve an optimized performance and longer calendar-life of a battery, an accurate battery SoP prediction method is necessary in addition to the knowledge of its SoC [19–21]. It is noted that any power/energy management system only focusing on the battery SoC is not reliable enough for electric vehicles. It needs to be adjusted to meet the requirements of battery SoP for long term objectives. Thus, compared with the research experience in battery SoC, the battery SoP estimation method is urgent needed.

In terms of SoP estimation, there are some methods have been presented to guarantee safe, efficient, and durable operations of the traction batteries under demanding driving conditions, which have been reviewed by Xiong, in Ref. [19]. The most commonly used approach is hybrid pulse power characterization (HPPC) method proposed by the Idaho National Engineering & Environmental Laboratory, which determines the static peak power in laboratory environments, but the estimates are over optimism. However, it is not suitable to estimate the continuous peak currents that are available for the next multi sampling intervals, additionally, the method neglects design limits like cell current, cell power or SoC [6]. As an improvement, the voltage-limited method was proposed by Plett [8]. However, these two *Rint* model-based methods hardly could simulate the relaxation effect performance and the estimates would diverge from the practical capability. To solve this problem, the authors in Ref. [7] proposed a dynamic electrochemical polarization battery model-based multi-parameter SoP estimation method. Then, to efficiently estimate the battery SoP under multiple sampling intervals, Ref. [21] has proposed a SoC and SoP joint estimator, which has achieved a good accuracy in real-time.

However, most of the above estimation methods were verified by the narrow set of scenarios of battery data, without exploring varying battery aging levels. In other words, the reliability of these estimation algorithms was not sufficiently assessed. For example, many estimation approaches mentioned above were evaluated under only one battery aging level. As a result, the performance of these algorithms against different health conditions was not adequately studied.

1.1. Contribution of the paper

In addition to the knowledge of SoC, the real-time SoP is also important for reliable battery operation in energy storage system, and these two states have close interactions in each other. Thus a data-driven SoC and SoP joint/dual estimator is urgently needed. However, battery performance is greatly restricted by its aging levels. As a consequence, little literature explores prediction methods for long term using. A key contribution of this study is to develop an accurate estimation method for battery SoC and SoP against varying health conditions. Thus the need of parameter update in real-time has been discussed and analyzed. What's more, the relationship between the battery parameter and its state has been evaluated by the data from cells that have different aging levels. The result is helpful for improving the performance of SoC and SoP joint estimator in its whole service period.

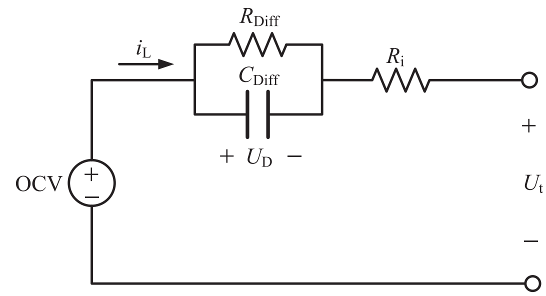

Fig. 1. The schematic diagram of the lumped parameter battery model.

1.2. Organization of the paper

A description of the lumped parameter battery model, battery experiments on several $LiFePO_4$ lithium-ion battery (LiB) cells and parameters identification method are given in Section 2. The data-driven SoC and SoP joint estimator is depicted in Section 3. The evaluation for the proposed battery parameters updating approach is illustrated in Section 4. Finally, conclusions are drawn in Section 5.

2. Modeling for the lithium-ion battery

2.1. The dynamic lumped parameter battery model

To achieve a reliable battery state estimation, an accurate battery model needs to be built at first. The lumped parameter battery model, which uses Nernst model to make the SoC as part of the model, is developed. The schematic of the battery model is shown in Fig. 1, it is very important to correctly identify the model parameter, including the open circuit voltage (OCV) which is used to describe the voltage source, series resistance (R_i) which is used to describe the electrical resistance of various battery components or with the accumulation and dissipation of charge in the electrical double layer, diffusion resistance (R_{Diff}) and diffusion capacitance (C_{Diff}) which consist of a RC network to describe the mass transport effects and dynamic voltage performances. The electrical behavior of the proposed model can be expressed by Eq. (1).

$$\begin{cases} \dot{U}_D = -\dfrac{1}{C_{Diff}R_{Diff}}U_D + \dfrac{1}{C_{Diff}}i_L \\ U_t = U_{oc} - U_D - i_L R_i \end{cases} \tag{1}$$

where U_D is the polarization voltage across C_{Diff}, U_t is the terminal voltage. Then the open circuit voltage U_{oc} can be described as follows:

$$U_{oc} = K_0 + K_1 \mathrm{SoC} + K_2/\mathrm{SoC} + K_3 \ln\mathrm{SoC} + K_4 \ln(1 - \mathrm{SoC}) \tag{2}$$

where K_i ($i = 0, 1, \ldots, 4$) are five polynomial involving different capacities and temperatures chosen to make the model fitting the test data accurately. However, the battery behavior of different temperatures will be discussed in our future work.

Table 1
Five aging levels of $LiFePO_4$ lithium-ion battery cells.

Aging level	SoH_1	SoH_2	SoH_3	SoH_4	SoH_5
Capacity/Ah	12.5	11.76	11.4	10.7	9.6
SoH	1.04	0.98	0.95	0.89	0.80