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Comparative study of methods for integrated model identification and state of charge estimation of lithium-ion battery

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HIGHLIGHTS

- Three co-estimation methods are compared for lithium-ion battery application.
- A noise compensating method is exploited for co-estimation purpose.
- Noise effects on different methods are analyzed with simulations and experiments.
- The computing cost and tuning effort are discussed.

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ABSTRACT

Model-based observers appeal to both research and industry utilization due to the high accuracy and robustness. To further improve the robustness to dynamic work conditions and battery ageing, the online model identification is integrated to the state estimation, giving rise to the co-estimation methods. This paper systematically compares three types of co-estimation methods for the online state of charge of lithium-ion battery. This first method is dual extended Kalman filter which uses two parallel filters for co-estimation. The second method is a typical data-model fusion method which uses recursive least squares for model identification and extended Kalman filter for state estimation. Meanwhile, a noise compensating method based on recursive total least squares and Rayleigh quotient minimization is exploited for online model identification, which is further designed in conjunction with the extended Kalman filter to estimate the state of charge. Simulation and experimental studies are carried out to compare the performances of three methods in terms of the accuracy, convergence property, and noise immunity. The computing cost and tuning effort are further discussed to give insights to the application prospective of different methods.

1. Introduction

Due to the unique merits of high energy and power density, no memory effect, and friendly environment impact, lithium-ion batteries (LIBs) have been widely applied in many fields like portable electronic devices, renewables penetration and electric mobility [1,2]. Battery safety as a major concern in real applications can be enhanced by electrochemical methods such as the polymeric approaches [3–6]. However, safety management from system prospective is equally important for the reliable operation of LIB systems. In real applications, LIB packs are always equipped with a well-designed battery management system (BMS) that keeps monitoring the important battery states including state of charge (SOC), state of power (SOP), state of health (SOH), etc. to fulfill the expectation on safety, efficiency and life span.

The SOC is a critical state to be monitored in BMS that can be viewed as the fuel gauge of the LIB system. The accurate monitoring of SOC ensures the safe operation area and protects LIB from unsuitable over-charge or over-discharge. However, accurate and robust SOC monitoring is still challenging to date as it cannot be measured directly by any available sensors. The coulomb counting (CC) method is straightforward, but as an open-loop method, it lacks the self-correction

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mechanism and depends largely on an accurate guess of initial SOC. Estimation biases will also accumulate over time when the current measurement contains non-ignorable errors. The open circuit voltage (OCV) measurement method infers the SOC from the calibrated SOC-OCV look-up table. However, it needs a long relaxation time to release the polarization voltage thus may be difficult for use in the continuous and dynamic load condition.

Model-based SOC observers have been widely investigated due to the close-loop correction mechanism for enhanced robustness. Multiple types of battery models have been attempted for such observers, including the electrochemical model [7–10], equivalent circuit model (ECM) [11,12] and artificial intelligence (AI) model [13,14]. Amongst others, the ECMs have been recognized to be most promising for the application in real-time embedded systems, owing to the excellent trade-off between the computing cost and modeling accuracy. Leveraging the ECM, state-space equations are typically formulated and the system states of interests are observed with a variety of adaptive filters, such as Luenberger observer [15], extended Kalman Filter (EKF) [16–18], unscented Kalman filter [19], particle filter [20], proportional-integral (PI) observer [21], sliding mode observer [22], and the adaptive variants [23]. Such offline model-based observers can achieve accurate SOC estimation within a narrow range of working conditions or battery ageing status. However, their robustness cannot be guaranteed as the model parameters are impacted by multiply factors such as the battery temperature, current magnitude and direction, SOC, and ageing statues [24]. Without the self-adaption of model parameters, the ECM may lose accuracy under dynamic working conditions, and as a consequence the accuracy of SOC estimation will be declined inevitably.

Most recent ECM-based observers tend to give more emphasis on the incorporation of online model adaption to the existing observing techniques, in seeking to enhance the robustness of observer within a wide range of working scenarios. In terms of the online adaptive ECM-based SOC observation, the dual estimation methods and data-model fusion methods are most widely studied in the literature [21]. The dual estimation methods such as dual extended Kalman filter (DEKF) [25] use two filters run in parallel, one for state estimation and one for model parameters identification. Xiong et al. [26] further adopted multiple timescales for the dual EKF to improve the estimation accuracy and meanwhile reduce the computing cost. In contrast, the data-model fusion methods combine the online data-driven methods for model identification and the model-based observers for SOC estimation. Recently, the dual estimation method with different filtering techniques, i.e. EKF-based model identification and PF-based state estimation, was proposed for LIB management [27]. For the data-model fusion methods, the online model identification is mostly achieved with the recursive least squares (RLS) method, based on which different type of observers are further designed to estimate the battery states [17,28–31]. In recent years some modified methods like the vector-type RLS [32] and adaptive forgetting RLS [33] were proposed to improve the performance of model parameters identification. In spite of the difference of underlying theories, both the two category of methods have been widely verified with high accuracy and robustness under lab testing conditions. However, BMSs commonly work in adverse conditions where the measurements are contaminated with large amount of random noises due to the external interference, sensor resolution and rounding processes [34]. The key BMS algorithms may be adversely impacted by such noises. To date, however, the effect of measurement noises on the model identification and SOC estimation has not been scrutinized yet. The performances of existing techniques under the adverse condition of noise corruption have not been evaluated.

In this paper, the DEKF and RLS-EKF as the representative of dual estimation and data-model fusion methods, respectively, are reviewed and evaluated in terms of their robustness to noise corruption. Furthermore, an improved data-model fusion method called noise compensating EKF (NC-EKF) is also exploited by using recursive total least squares (RTLS) and Rayleigh quotient (RQ) minimization for online model identification and using EKF for SOC estimation. The total least squares method is promising to address the input and output disturbances, thus has been used for battery parameter and capacity estimation [35,36]. Simulation and experimental studies are carried out to evaluate the performances of different methods from both theoretical and practical prospective. A comprehensive comparison of the accuracy, noise immunity, computing cost and tuning effort is performed to reveal the features and application scenarios of the three types of methods.

The rest of this paper is organized as follows. The battery modeling is described in Section 2. In Section 3, the DEKF and RLS-EKF are reviewed and the NC-EKF is detailed for the co-estimation of model parameters and SOC. Section 4 and 5 discuss the simulation and experimental results to evaluate the feasibility of different methods. Section 6 further discusses the computing cost and tuning effort, and makes an overall comparison among the three methods. The main conclusions are drawn in Section 7.

2. Equivalent circuit modeling

A variety of battery models have been investigated for LIBs in the literature [11]. A battery model suitable for the real-time application generally has a simple topology while captures the major dynamics of LIB. In light of this, the first-order RC model as shown in Fig. 1 (a) is used in this paper. The voltage source represents the battery OCV. R_s is the ohmic resistance. The single RC branch is used to simulate the polarization effects due to passivation layers on the electrodes, charge transfer between electrode and electrolyte, diffusion, migration and convection processes. The dynamics of the ECM in use is written as:

$$\begin{cases} C_p\frac{dV_p}{dt} + \frac{V_p}{R_p} = I \\ V_t = V_{oc} - V_p - IR_s \end{cases} \tag{1}$$

where I is the load current which is defined as positive for discharge and negative for charge, V_{oc} is the OCV, V_p and V_t denote the polarization and terminal voltages, respectively.

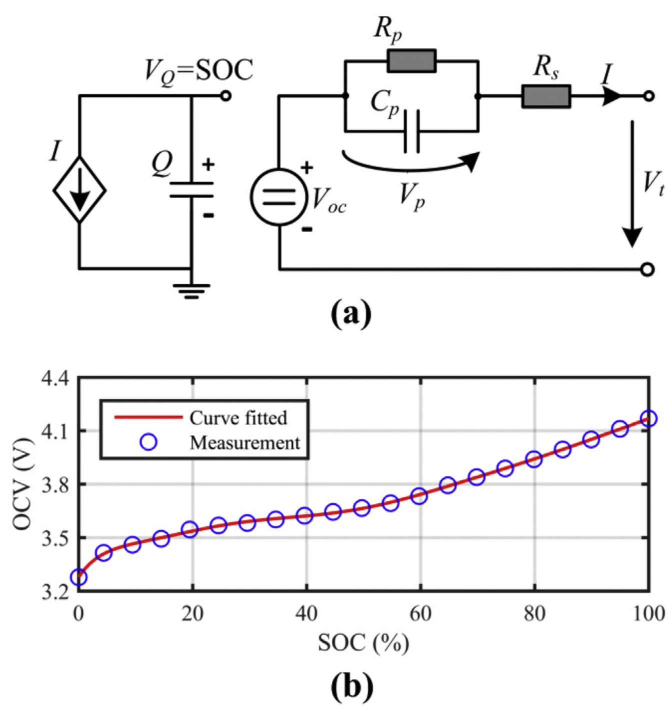

Fig. 1. First-order RC model: (a) circuit diagram of the battery model; (b) measured and curve-fitted SOC-OCV correlation.