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Multi-model probabilities based state fusion estimation method of lithium-ion battery for electric vehicles: State-of-energy ☆

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HIGHLIGHTS

- A novel multi-model probability battery SoE fusion estimation approach was proposed.
- The linear matrix inequality-based H_∞ technique is employed to estimate the SoE.
- Performance of the method was verified by different batteries at various temperatures.
- The results show that the proposed method can achieve accurate SoE estimation.

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ABSTRACT

State-of-energy (SoE) is an important index for batteries in electric vehicles and it provides the essential basis of energy application, load equilibrium and security of electricity. To improve the estimation accuracy and reliability of SoE, a novel multi-model fusion estimation approach is proposed against uncertain dynamic load and different temperatures. The main contributions of this work can be summarized as follows: (1) Through analyzing the impact on the estimation accuracy of SoE due to the complexity of models, the necessity of redundant modeling is elaborated. (2) Three equivalent circuit models are selected and their parameters are identified by genetic algorithm offline. Linear matrix inequality (LMI) based *H*-infinity state observer technique is applied to estimate SoEs on aforementioned models. (3) The concept of fusion estimation is introduced. The estimation results derived by different models are merged under certain weights which are determined by Bayes theorem. (4) Batteries are tested with dynamic load cycles under different temperatures to validate the effectiveness of this method. The results indicate the estimation accuracy and reliability on SoE are elevated after fusion.

1. Introduction

Since the lithium-ion batteries (LIBs) own the high energy/power density and superior cycle lifetime, they are regarded as the most promising energy candidate in automotive industry and have been widely employed in hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs) [1–3]. In terms of safety, high efficiency and sustainable application, especially after the batteries are connected in series or parallel forming packs, battery management system (BMS) is indispensable to monitor the state of every single cell and rule them in case of the abuse resulting in catastrophic issues. But it is still a tough task for BMS to acquire the accurate states by direct measurements because the sophisticated electrochemical process is occurring inside the battery during working operation which contains the strong nonlinearity and complex time-varying characteristic [4–6]. Normally, people will pay more attention to two indicators of LIBs-state of charge (SoC) and state of health (SoH) [7–9]. SoC is relevant to the residual capacity of a battery and it protects the battery working within the safe operating area (SOA) from being overcharged or over discharged. SoH is used to manifest the level of ageing of the battery and it helps to recalibrate the estimation results on SoC which relates to the actual available capacity. In recent years, SoC estimation methods have been extensively and deeply studied. The ampere-hour (A h) counting approach [10,11] is the most common one as it is simple and low-cost. But the estimation accuracy is vulnerable to noise, uncertain initial SoC knowledge and current drift. Based on equivalent circuit models, many estimation techniques are investigated. Kalman filter technique which is utilized for lead-acid battery originally and

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then some derivatives, such as extended Kalman filter (EKF) [12,13] and unscented Kalman filters (UKF) [14,15] are applied successively. Adaptive techniques [16,17] are explored to break the strict limitation with the noisy items of former methods. Besides, some other ways, including particle filter (PF) [18], and robust state observers [19–22] are studied as well, which yield the satisfactory estimation results and robustness. The data-driven methodologies [23–26] are also effective tools to address this nonlinear issue, but they are of over-dependency on the priori knowledge of experimental data. As for SoH estimation, particularly for capacity estimation, the model-based methods [27] are still the most practical because not only they can meet the demand of accuracy, but also the real-time capability is superior to others.

Back to the motivation to estimate the state of the battery, on one hand, these indexes are able to prohibit the abuse and guarantee the operating safety. On the other hand, how much the remaining driving range (RDR) of electric vehicles left is another critical point that people should concern. As a matter of fact, the state of energy (SoE), which signifies the residual available energy in the battery, is more qualified than SoC to estimate the RDR [28]. Some studies have existed with respect to the estimation of SoE. Liu et al. [29] presented the Back-Propagation Neural Network (BPNN) based method to estimate the SoE, considering the influence of the energy loss on the internal resistance, electrochemical reactions, the decline of open circuit voltage (OCV), the discharge rate and temperature fluctuation. Although the estimation results are satisfactory through validations, the complexity of this method is a vital defect for practical applications. Wang et al. [30] proposed a joint estimation approach based on PF algorithm to obtain the SoC and SoE respectively. However, the estimation accuracy of SoE relies on the prerequisite that the SoC has been well computed. Xiong et al. [31] chose the central difference Kalman filter (CDKF) and Gaussian model to estimate the SoE and controlled the estimation error within 1% both for $LiFePO_4$ and $LiMnO_2$ batteries. Dong et al. [32] adopted dual filters-EKF plus PF-to estimate the SoE. The former filter is employed to update parameters of battery model on-line and the other filter is used to estimate the SoE. By experimental validation, the estimation accuracy could converge to the authentic values within the error of ±4% under constant current conditions and dynamic current conditions. Wang et al. [33] applied recursive least square (RLS) with forgetting factor method to identify the battery model and adaptive technique to estimate the SoE. The simulation results demonstrated the effectiveness of the proposed method. Barai et al. [28] clearly illustrated the strong relationship between the RDR and SoE rather than that with SoC and presented a novel SoE estimation method based on the short-term cycling history.

Considering the uncertainty on equivalent circuit models (ECMs) that we have discussed in our previous work in Ref. [34], we have investigated the multi-model probabilities based fusion estimation method for the battery SoC estimation. There have three differences between the previous paper and this study. (1) In this paper, the goal to be estimated is the SoE rather than SoC; (2) Due to the different object, the corresponding systematic functions are slightly of discrepancy; (3) To emphasize the robustness of the algorithm against temperatures. Experiments are carried out with three temperatures and the method is verified by data which own distinct temperature characteristics. The single model-based methods are still used for counterparts. Through the comparison, the proposed method is revealed being superior to the single model ones and the estimated SoE has been improved no matter in the aspects of accuracy or reliability.

The remainder of this paper is listed as follows: Section 2 introduces the battery model and LMI-based *H*-infinity (H_∞) state observer. Section 3 analyzes the reason why the estimated results should be fused about SoE, and subsequently the novel fusion estimation method is presented. The test bench and the experimental verification are introduced in Section 4. Some conclusions are drawn in the final section.

2. Model-based SoE estimation

2.1. Definition of SoE

SoE which is a percentage represents the residual energy of the total in a battery and its form is analogous to the SoC, which is shown as follows:

$$z(t) = z(t_0) + \frac{1}{E_{\mathrm{act}}}\int_{t_0}^{t} P(\tau)d\tau \tag{1}$$

where $z(t)$ denotes the SoE at sample time t similarly hereinafter, $z(t_0)$ denotes the initial SoE value, E_{act} denotes the actual available energy of the battery, and $P(\tau)$ denotes the instantaneous power of the battery. The continuous form can be written as:

$$\dot{z}(t) = \frac{P(t)}{E_{\mathrm{act}}} \tag{2}$$

2.2. Battery models

Due to the complicated electrochemical process occurring inside the battery, it is difficult to evaluate the accurate performance by simple measurements. Consequently, equivalent circuit model, the combination of several electrical circuit components, is designed to simulate the dynamic characteristics of the battery. Using ECMs can solve many problems about states estimation, but the lack of physical explanation is its fatal weakness. Common ECMs contain the *Rint* model, *N*th-RC networks model, *RC* model, and *PNGV* model. Among these ECMs, the *N*th-RC networks model, seen in Fig. 1, occupies the dominant position. It basically consists of three parts, the potential resource U_{oc} to describe the open circuit voltage (OCV) which holds the monotonous relationship with SoC (SoE), the ohmic resistance R_o to mimic the direct current voltage drop, and several Resistance-Capacitor (RC) networks $R_{\mathrm{D}i}$, $C_{\mathrm{D}i}$ forming the polarization voltage $U_{\mathrm{D}i}$ to express the polarization and diffusion effect, where, $i = 1, 2, 3, \ldots, N$, U_t denotes the terminal voltage.

There still exists the trade-off between the complexity of model and estimation accuracy. Although the more RC pairs placed in the circuit can improve the accuracy [35], it sacrifices a large amount of calculation resource of the hardware at the cost. Therefore, usually the order of RC networks model is confined within three. According to electric knowledge, dynamic equations of Thevenin model, double polarization model and 3rd-RC model are listed in Table 1.

The OCV of the battery has a monotonous relation with SoE shown in Fig. 2.

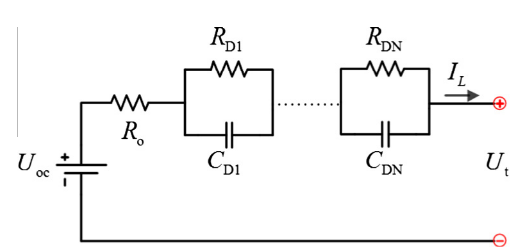

Fig. 1. The diagram of general RC networks ECM.

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