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Combined State of Charge and State of Health estimation over lithium-ion battery cell cycle lifespan for electric vehicles

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HIGHLIGHTS

- Performance degradation of lithium-ion battery over the cell lifetime is quantified.
- State estimators with the different time scales are developed for SOC and SOH identification.
- Capacity fade and power fade are accurately characterized.
- SOC estimator is accurate and robust over the life span of the battery cell.

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ABSTRACT

A combined SOC (State Of Charge) and SOH (State Of Health) estimation method over the lifespan of a lithium-ion battery is proposed. First, the SOC dependency of the nominal parameters of a first-order RC (resistor-capacitor) model is determined, and the performance degradation of the nominal model over the battery lifetime is quantified. Second, two Extended Kalman Filters with different time scales are used for combined SOC/SOH monitoring: the SOC is estimated in real-time, and the SOH (the capacity and internal ohmic resistance) is updated offline. The time scale of the SOH estimator is determined based on model accuracy deterioration. The SOC and SOH estimation results are demonstrated by using large amounts of testing data over the battery lifetime.

1. Introduction

Lithium-ion batteries have been widely used in modern electrified vehicles. The reliable, efficient, and safe operation of lithium-ion batteries requires monitoring, control and management. For battery management systems, a core function is to provide accurate estimates of State of Charge (SOC) and State of Health (SOH) of batteries, which is challenging due to the lack of sensors for electrochemical phenomena inside the cells.

Many methods were proposed to estimate the battery SOC, each with its own advantages and disadvantages, as summarized in Table 1. The Coulomb counting method and open circuit voltage method are widely used in battery management systems of electrified vehicles. They are easy to use and fast in computation, but the former highly relies on the performance of current sensor, and the latter is not effective for batteries with flat open-circuit-voltage curve. Another disadvantage for Coulomb counting is that this method is open-loop estimation and may have large accumulated error due to uncertainties or disturbances [1–5]. Moreover, it requires accurate initial SOC value. Many artificial intelligence-based methods have been applied to establish black-box SOC estimation models, such as neural network [6], fuzzy logic [7], and support vector regression (SVR) models [8]. The Kalman filter (KF) and sliding mode observer have also been used to predict the battery SOC. These approaches are model-based, closed-loop, and thus can use output feedback to keep better robustness than non-feedback methods. In Refs. [9–11], the extended Kalman filter (EKF) concept, based on nonlinear state-space models, was used to

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Table 1
Advantages and disadvantages of existing SOC and SOH estimation methods.

State of charge (SOC)			State of health (SOH)			
Method	Advantage	Disadvantage	Method		Advantage	Disadvantage
Coulomb counting [1–4]	Simple	Open-loop, sensitive to the current sensor precision, and uncertain to initial SOC	Durability model-based open-loop method	Durability mechanism [23,24]	Comprehensive understanding	Complex, need accurate input parameters
Open circuit voltage method [5]	Simple	Open-loop, sensitive to the voltage sensor precision, unsuitable for cells with flat OCV–SOC curves		Durability external characteristic [25–28]	Simple and easy to predict capacity fade and internal resistance increment	Based on a large number of experiments
Neural network [6]	Generic, good nonlinearity mapping approximation	Sensitive to the amount and quality of training data	Battery model-based parameter identification closed-loop method	DC resistance [21]	Simple	Not accuracy, sensitive to disturbances
Fuzzy logic [7]	Generic, good nonlinearity mapping approximation	Sensitive to the amount and quality of training data		AC impedance [22]	Accuracy	Complex
Support vector machine [8]	Generic, good nonlinearity mapping	Sensitive to the amount and quality of training data		Extend Kalman filter [11,29]	Quite easy to implement, accurate	Sensitive to modeling accuracy
Kalman filter [9–18]	Closed-loop, online, accuracy	More computationally expensive than non-feedback methods, and highly depend on the model accuracy.		Fuzzy logic [30]	Accuracy simple, accurate	Slow convergence
				Sample entropy [31–33]	Simple	Need large amount of data
Sliding mode observer [19,20]	Closed-loop, online, and accurate	More computationally expensive than non-feedback methods, and highly depend on the model accuracy.		Discharge voltage [30]	Easy	Not accurate
				Adaptive control system [31]	Online	Sensitive to modeling accuracy

estimate the SOC of a Li-polymer battery. Several other variants of Kalman filter, e.g. sigma-point KF [12,13], adaptive KF [14–16], Dual KF [17] and derivative KF [18] have also been used for battery SOC estimation. The sliding-mode observer technique has also been used to monitor battery SOC trajectories [19,20].

State of Health (SOH) is a metric to evaluate the aging level of batteries, which often includes capacity fade and/or power fade. The commonly used indicators include battery capacity [11], DC resistance [21], and AC impedance [22]. The SOH estimation methods mainly include durability model-based open-loop methods and battery model-based closed-loop method [5]. The former methods directly predict the changes in capacity fade and internal resistance. The durability models describe the increase of SEI film resistance and battery terminal voltage [23,24]. Based on durability characteristics, a storage life model for lithium cobalt oxides batteries was given in Ref. [25]. Bloom et al. [26] obtained the relationship between the battery performance degradation and ambient temperatures and cycle time. Matsushima [27] also found that capacity loss exhibits a square root relationship with time. Li et al. [28] developed an extended Arrhenius model. The battery model-based closed-loop methods use least-squares methods, Kalman filtering [29] and other adaptive algorithms (such as fuzzy logic [30]), to identify the battery capacity and internal resistance according to the operating data. Sample Entropy was also used to estimate the battery SOH in Refs. [31–33]. The advantages and disadvantages of these SOH methods are summarized in Table 1.

Most of the above mentioned battery-state-estimation methods were developed for either SOC or SOH estimation, and not both. The intimate coupling feature between SOC and SOH was overlooked. The accuracy of SOC estimation is heavily influenced by battery degradation. As batteries degrade, SOC-only estimation algorithms may lead to large errors. The inaccurate SOC estimations in turn may mislead the battery SOH calibration. Therefore, simultaneous estimation of SOC and SOH is quite beneficial. Compared to the battery SOC variation, battery SOH typically change much more slowly, necessitating multi-timescale state estimators. In order to determine the appropriate time scale for the SOH estimator, it is critical to examine the performance degradation of the battery model in the context of battery aging. The multi-scale EKFs are used to estimate SOC and SOH, and the capacity estimation is periodically introduced in SOC update equation [34,35]. It is more computational efficient than a joint estimation [34]. However, the determination of the two time scales is heavily dependent on the tuition and calibration.

This paper discusses a model-based combined SOC/SOH estimation method over the lifespan of LiNMC batteries. First, the SOC dependence of the nominal parameters of a first-order RC (resistor–capacitor) model is determined, and the performance degradation of the nominal model is quantified over the battery lifetime. Second, two EKFs with different time scales are applied to implement the combined SOC/SOH monitoring: one observer is for real-time SOC estimation; the other for offline SOH (capacity and internal resistance) update. The time scale of the SOH estimator is determined based on the quantified model accuracy degradation. The SOC and SOH estimation results are demonstrated by using large amounts of testing data over the battery lifetime.

The remainder of the paper is arranged as follows: Section 2 introduces the battery model structure and battery tests; the degradation of a nominal battery model is described in Section 3; the combined SOC/SOH estimation approach and associated results are discussed in Section 4; Section 5 concludes this paper.

2. Battery modeling

2.1. Equivalent circuit model

Hu et al. [36] compared 12 commonly used equivalent circuit models and concluded that the first-order RC model is the best choice considering model complexity, accuracy, and robustness. Fig. 1 shows the model structure considered. The battery capacity C_{cap} is used to quantify SOC level by Eq. (1)

$$\dot{\mathrm{SOC}} = -\frac{\eta \cdot I_{\mathrm{batt}}}{3600 \cdot C_{\mathrm{cap}}} \tag{1}$$

The Coulombic efficiency η is simplified as the constant value, 1.0 during the discharge and 0.98 in charging.