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An adaptive state of charge estimation approach for lithium-ion series-connected battery system

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HIGHLIGHTS

- An equivalent circuit model is built based on a model parameter regulator.
- An AUKF based on a noise statistics estimator and parameter regulator is developed.
- The AUKF method is applied to estimate SOC of a series-connected battery system.
- The SOC estimation accuracy is validated by simulations and experimental results.

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ABSTRACT

Due to the incorrect or unknown noise statistics of a battery system and its cell-to-cell variations, state of charge (SOC) estimation of a lithium-ion series-connected battery system is usually inaccurate or even divergent using model-based methods, such as extended Kalman filter (EKF) and unscented Kalman filter (UKF). To resolve this problem, an adaptive unscented Kalman filter (AUKF) based on a noise statistics estimator and a model parameter regulator is developed to accurately estimate the SOC of a series-connected battery system. An equivalent circuit model is first built based on the model parameter regulator that illustrates the influence of cell-to-cell variation on the battery system. A noise statistics estimator is then used to attain adaptively the estimated noise statistics for the AUKF when its prior noise statistics are not accurate or exactly Gaussian. The accuracy and effectiveness of the SOC estimation method is validated by comparing the developed AUKF and UKF when model and measurement statistics noises are inaccurate, respectively. Compared with the UKF and EKF, the developed method shows the highest SOC estimation accuracy.

1. Introduction

Renewable energy sources (RESs), such as wind energy and photovoltaic energy, are developing rapidly around the world [1]. However, owing to the intermittent and fluctuant nature of these sources, their large-scale integration into the grid can lead to voltage and frequency fluctuation of existing power networks [2]. Battery energy storage systems (BESSs) are widely regarded as an effective solution to integrate large-scale RESs into the grid [3]. They can smooth the fluctuating power of the RESs and balance the active and reactive power of the grid when the RESs are integrated into the grid. There are many kinds of batteries according to the commercial application [4], including lead-acid, nickel-cadmium, lithium-ion, vanadium redox flow, and sodium-sulfur batteries. Compared to lead-acid and nickel-cadmium batteries, lithium-ion batteries have become the preferred choice in BESSs because of their higher power and energy densities, lower self-discharge rate, and longer cycles [5]. To meet higher power and capacity requirements, BESSs conventionally consist of thousands of low-voltage and low-power lithium-ion batteries connected in series and/or parallel. A well-designed battery management system (BMS) is required to enhance the reliability, efficiency, and lifetime of the BESSs. As one of the core indicators of the BMS, state of charge (SOC) can illustrate the available capacity of the BESSs and can enhance other functions for the BESSs, such as reliability and safety [6]. However, accurate estimation of SOC in the BESS application is challenging because a battery is a dynamic nonlinear and complex electrochemical system and the

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SOC is not easily and directly measured.

Methods to improve battery SOC estimation accuracy have recently been presented. The coulomb counting (ampere-hour counting) method integrates the currents flowing into and out of the batteries over time to obtain SOC estimation. This method is easy to implement in practical use. However, as an open-loop approach, it is not accurate because it needs prior knowledge of the initial SOC and easily suffers from measurement errors and accumulated errors [7]. The open-circuit voltage (OCV) method is another approach that is extensively used independently or with other approaches [8]. However, this method requires a long time to measure terminal voltage and there is often a small voltage variation of lithium-ion batteries around the battery nominal voltage, which degrades the SOC estimation accuracy. The electrochemical impedance spectroscopy (EIS) method can be applied to accurately decipher the chemical and physical processes that take place in a battery, but it is too complicated to estimate SOC for online applications due to the requirement of Nyquist plots [9].

Recently, some advanced algorithms have been used to accurately estimate the SOC. The advanced algorithms, such as the fuzzy logic method [10], artificial neural networks [11], support vector machine [12], and sliding mode observers [13], demonstrate improved SOC estimation precision without demanding exact knowledge of the battery dynamics. However, it is difficult to use these advanced methods online because they require extensive samples, complex algorithms, and extensive computation [14].

Amongst others, the methods based on equivalent circuit model (ECM) and closed-loop SOC estimation iteration process have been developed and have proved to be accurate and implementable for battery SOC estimation. For these methods, the battery charging and discharging characteristics are predicted by the ECM, while the SOC is estimated online in the iteration process of different adaptive filters, such as Kalman filter (KF) [15], extended Kalman filter (EKF) [16], and unscented Kalman filter (UKF) [17]. The KF is a widely used adaptive filter for linear models, but is not suitable for nonlinear models. As an extended method of the KF, the EKF can be used in more complex and nonlinear models. However, because the EKF requires a linearized approximation of the nonlinear function using first-order or second-order terms of Taylor's formula and a computation of the Jacobian matrix, it is also not very accurate. To overcome these drawbacks, the UKF is presented as a sigma-point KF (SPKF) method for SOC estimation [18]. The UKF based on unscented transform not only does not require the calculation of the Jacobian matrix, but has a higher SOC estimation accuracy than the EKF [19].

However, all KF methods suppose that the battery noise statistics, such as model and measurement noise covariances, are accurate. That is to say, SOC estimation based on the KFs described above will be unstable or even divergent and excessively slow to adapt if the noise statistics are inaccurate [20]. To deal with these problems, the adaptive Kalman filter (AKF) [21], the adaptive extended Kalman filter (AEKF) [22], and the adaptive sigma-point Kalman filter (ASPKF) [23] are used to estimate noise statistics online, but at the cost of additional computation. A novel adaptive H-infinity filter (AHIF) based on covariance matching technique is also proposed as another solution [24]. Contrary to the KFs, the AHIF does not require accurate knowledge of the model and measurement noise covariances. However, due to the existing steady-state estimation errors of the covariance matching method, the battery SOC estimation accuracy is still degraded and is unstable using AHIF [25].

Moreover, the other challenge in estimating model and measurement noises is that these noises should be assumed to be Gaussian white noises with zero mean value. In real applications, this assumption is difficult to be realized because the noises that suffer from environmental disturbances may illustrate a biased distribution, which has a negative effect on the accuracy and convergence behavior of SOC estimation using KFs [26]. To resolve the problem, a particle filter (PF) [27] and an unscented particle filter (UPF) [28] are applied to estimate battery SOC. However, due to large computation requirements and memory consumption (e.g., by a factor of 50 compared to the UKF as shown in Ref. [29]), these filters are not suitable for online SOC estimation in real applications, especially for series-connected battery systems.

The SOC estimation accuracy of battery system using the above methods can be degraded by focusing mainly on the cells and neglecting the cell-to-cell variation in battery system. In general, to meet the requirements of high capacity and high voltage in the BESSs, the battery system is usually composed of thousands of cells connected in series and/or in parallel. The performance of series-connected battery system is mainly tied to the state of the weakest cell. For example, in the charging process, the weakest cell will reach the maximum charge capacity before the other cells in spite of whether the battery system reaches its upper cut-off voltage. Moreover, in the discharging process, the weakest cell will first reach the minimum discharge capacity even if the battery system reaches its lower cut-off voltage. As a result, the battery system model and its SOC estimation precision are degraded when cell inconsistency is ignored [30].

Recently, much effort has been made to improve the SOC estimation precision of series- and/or parallel-connected battery system. Plett [31] presented a method called “bar-delta filtering” that employs a more sophisticated SPKF-based method to estimate the pack-average SOC and applies a simplified EKF-based method to estimate each cell's SOC. It is assumed that the difference between the pack-average SOC and the SOC of each cell is small and this difference is estimated for each cell. Similarly, Roscher at al [32]. developed a Luenberger observer to estimate the pack-average SOC, and the differences between the pack-average SOC and the SOC of each cell were estimated via some simple calculations. Dai at al [33]. employed a sophisticated EKF to estimate the pack-average SOC, and the differences between the pack-average SOC and the SOC of each cell were estimated by a single-state EKF. As a result, this method shows sufficient SOC estimation accuracy, but it is not suitable for use in actual vehicular operation owing to its high computation cost. To estimate accurately the SOC of a battery system of multiple cells in series, a method based on minimal cell load voltage of the battery system was proposed [34]. The battery system SOC can be estimated dynamically with a sophisticated EKF. One of the limitations of this method is that it ignores the problem of overcharge from the cell with maximum terminal voltage. More importantly, the SOC estimation error will be larger if the cell with minimal load voltage is not the one with the lowest capacity. In Refs. [35,36], a method based on a screening process was developed to build an ECM for a lithium-ion battery system in series and improve the model-based SOC estimation accuracy using EKF. Through the screening process, including capacity and resistance screening, the proposed ECM of the battery system can be easily expressed from a single-cell model and the accuracy of the SOC estimation is improved. However, this method also has limitations: (i) the acceptance proportion of the tested cells will be reduced because most of the cells have been eliminated in the screening process, (ii) the key factor for improving the acceptance proportion is not discussed, such as the variance threshold of the cells, and (iii) SOC estimation using EKF is vulnerable to divergence owing to inaccurate noise statistics. To overcome these drawbacks, Xiong at al [30]. employed a method based on a filtering process to build the ECM for a battery system in series and introduced an AEKF-based SOC estimator to improve estimation accuracy. This method can ensure the SOC estimation accuracy for each cell and battery system, however, it also has limitations: (i) the cell-to-cell variations are not discussed in the battery system model although they influence the accuracy of the battery system model, and (ii) SOC estimation based on the AEKF will be unstable or even divergent when the noise statistics are inaccurate or unknown.

This study improves SOC estimation accuracy of a lithium-ion series-connected battery system two ways. First, a battery system model based on a model parameter regulator, which exhibits the influence of