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# A modified model based state of charge estimation of power lithium-ion batteries using unscented Kalman filter

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## HIGHLIGHTS

- A modified equivalent circuit model is presented.
- A linear-averaging method is presented to compute correction factors.
- The UKF algorithm for SOC estimation based on the presented model is introduced.
- Performance of the proposed method is verified by comparison results.

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## ABSTRACT

Accurate estimation for the state of charge (SOC) is one of the most important aspects of a battery management system (BMS) in electric vehicles (EVs) as it provides drivers with the EVs' remaining range. However, it is difficult to get an accurate SOC, because its value cannot be directly measured and is affected by various factors, such as the operating temperature, current rate and cycle number. In this paper, a modified equivalent circuit model is presented to include the impact of different current rates and SOCs on the battery internal resistance, and the impact of different temperatures and current rates on the battery capacity. Besides, a linear–averaging method is presented to calculate the internal resistance and practical capacity correction factors according to data collected from the experimental bench and saved as look-up tables. The unscented Kalman filter (UKF) algorithm is then introduced to estimate the SOC according to the presented model. Experiments based on actual urban driving cycles are carried out to evaluate the performance of the presented method by comparing with two existed methods. Experimental results show that the proposed method can reduce the computation cost and improve the SOC estimation accuracy simultaneously.

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## 1. Introduction

With the soaring energy crisis and environmental pollution, electric vehicles (EVs) have gained increased attention in recent years. Many industrialized nations have declared their plans for EVs development and production. For example, the US government has planned to have one million EVs on the road by 2015, and the Chinese government has set a goal of owning five million EVs by 2020 [1]. Power battery plays an important role in EVs, just like the oil does in the internal combustion engine vehicles (ICEVs). Comparing with other batteries, such as the lead-acid, nickel–cadmium and NiMH batteries, lithium-ion battery (LIB) has merits in high voltage, high energy and power density, no memory effect, low self-discharge rate and long cycle life, so it has been widely used in EVs [2]. In the EVs application, accurate state of charge (SOC) estimation for LIB is essential to ease the "range anxiety" [1], realize the reasonable energy management and efficient utilization of the battery. Besides, it prevents the battery from over-charging or over-discharging that leads serious damage to the battery.

Previously, various methods for SOC estimation have been proposed. A common method is the Ampere-hour (Ah) counting method [3–5], in which the residual charge is calculated by integrating the current over time. The Ah method only needs to measure the battery current, so it is simple and can be easily implemented on-board. However, it requires accurate knowledge of the initial SOC value and suffers accumulated error from the integration process due to current drift. The open-circuit voltage

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(OCV) [6,7] is another common method, which estimates the SOC based on the relationship between the OCV and the SOC. Nevertheless, it is not suitable for online estimation due to the long rest time to reach the battery's steady-state. Computational intelligence algorithms, such as the artificial neural networks (ANNs) [8–10], fuzzy-logic [11–13], and support vector machines (SVMs) [14–16] have also been developed to estimate the SOC. These methods do not require detailed knowledge of battery systems. Thus, they can be applied to all battery types and have excellent estimation performance if the training data are sufficient to cover the whole loading conditions. However, collecting training data that cover all of the loading conditions is time consuming and nearly impossible. Besides, all the aforementioned methods are open-loop estimation algorithms and do not require the battery model.

More recently, efforts have been focused on model-based and closed-loop estimation methods, among which the most famous two methods are the sliding mode observer (SMO) [17,18] and Kalman filter (KF) [1,19–26]. In these two methods, a battery is regarded as a power system and can be described by various models. They have high real-time and precise performance which strongly depends on the model accuracy related to its complexity.

A number of battery models have been proposed, such as the first principle models, black box models and equivalent circuit models (ECMs) [27]. Among them, the ECMs are widely used due to their advantages in simulating the dynamic behaviors of LIB [28,29]. Furthermore, LIB parameters, such as the practical capacity, internal resistance are related to operating temperature, current rate and cycle number. Therefore, corrections on battery parameters have been reported to improve the SOC estimation accuracy. In Ref. [1], the internal resistance was estimated online to improve the model accuracy. However, it increases the computation cost. In Ref. [29] and Ref. [30], variations of model parameters (e.g., the ohmic resistance, electrochemical polarization resistance and capacitance, concentration polarization resistance and capacitance) with the SOC have been discussed. However, the variations of battery capacity with temperature, current rate and cycle number are neglected. In Ref. [31], a cycle life model was developed to predict the battery capacity degradation with the increase of cycle, but the variations of battery capacity with the temperature and current rate, and the variations of internal resistance with the temperature, current rate and SOC are ignored. In Ref. [32], an enhanced battery model was presented to include the impact of different discharge rates and temperatures on the battery capacity. Unfortunately, it compensates the impact of different factors on battery capacity separately. Besides, the ohmic resistance is regarded as a state-variable in this method, leading to the increase of computation cost.

In this paper, a modified equivalent circuit model is presented. An offset voltage is employed to compensate the model error based on the fact that a small bias exists between the estimated OCV and the measured OCV [1]. To further improve the model accuracy, a combined resistance correction factor that simultaneously describes the variations of battery internal resistance with the current rate and SOC, as well as a combined capacity correction factor that simultaneously indicates the variations of battery capacity with the temperature and current rate are introduced. A linear-averaging method is proposed to calculate the values of the correction factors according to data collected from the experimental bench and saved as look-up tables. Comparing with the methods proposed in Ref. [1] and Ref. [32], the presented method compensates the impact of different temperatures and current rates on battery capacity simultaneously, so it is more accurate. Besides, the presented method compensates the impact of different current rates and SOCs on battery internal resistance with the look-up table method rather than the online estimation method, so it reduces the computation cost.

The following sections of this paper are organized as follows: Section 2 presents a modified simple equivalent circuit model and a linear-averaging method used to calculate the internal resistance and practical capacity correction factors. Section 3 introduces the UKF-based SOC estimation method with the presented battery model. Section 4 describes the experimental setup. Section 5 presents the experimental results and discussion, and Section 6 makes conclusions of the paper.

## 2. Battery modeling

### 2.1. Battery equivalent circuit model

The equivalent circuit models, consisting of resistors, capacitors and inductors, perform well in describing the battery dynamic characteristics, so they are usually used in SOC estimation [2,24,29]. A complicated model is able to accurately capture the characteristics of a battery, but it increases the computation cost which is not suitable for an on-board estimator [24]. On the contrary, a simple model can reduce the computation cost, but it may not be accurate enough to describe the LIB characteristics.

In this paper, a modified simple equivalent circuit model shown in Fig. 1 is presented to reduce the computation cost and improve the model accuracy. In this model, variable $R$ represents the internal resistance at different current rates and SOCs, which can be calculated by a simple linear-averaging method (introduced in Section 2.3) according to the two-dimension $R_b$–$I$–SOC look-up table; OCV stands for the open circuit voltage (OCV), which is a nonlinear function of SOC; and $V_c$ is introduced as an offset voltage based on the fact that a small bias exists between the estimated OCV and the measured OCV [1].

Based on Fig. 1, the discrete state-space equations can be derived as:

$$\mathrm{SOC}(k+1) = \mathrm{SOC}\left(k\right) - \frac{I(k) \times \Delta T}{Q_n} \tag{1}$$

$$V(k) = \mathrm{OCV}[\mathrm{SOC}(k)] - I(k) \times R(k) - V_c \tag{2}$$

where $\Delta T$ is the sample period, and $Q_n$ represents the battery nominal capacity.

### 2.2. Model parameters estimation

In the presented equivalent circuit model shown Fig. 1, the parameters, including $R$, $V_c$ and the OCV–SOC relationship need to be determined. In this paper, the battery's discharging internal resistance was tested as the following process:

i) Charge the battery to its cut-off voltage with the standard charging method at the temperature of 25 °C;
ii) Rest the battery for 1 h;

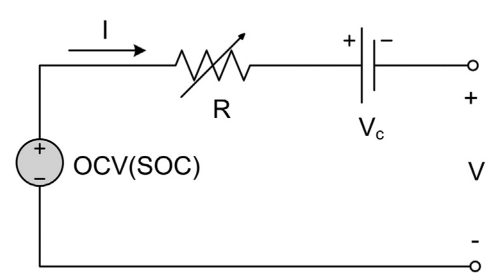


**Fig. 1.** Modified battery equivalent circuit model.

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