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An integrated approach for real-time model-based state-of-charge estimation of lithium-ion batteries

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HIGHLIGHTS

- An auto-regression battery model is built considering hysteresis nonlinearity.
- A hybrid model training method combining TLBO and least square is proposed.
- WRLS and joint-EKF approaches are used for real-time model-based SOC estimation.
- Flat OCV problem is tackled by combining WRLS method with coulomb counting.

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ABSTRACT

Lithium-ion batteries have been widely adopted in electric vehicles (EVs), and accurate state of charge (SOC) estimation is of paramount importance for the EV battery management system. Though a number of methods have been proposed, the SOC estimation for Lithium-ion batteries, such as LiFePo4 battery, however, faces two key challenges: the flat open circuit voltage (OCV) vs SOC relationship for some SOC ranges and the hysteresis effect. To address these problems, an integrated approach for real-time model-based SOC estimation of Lithium-ion batteries is proposed in this paper. Firstly, an auto-regression model is adopted to reproduce the battery terminal behaviour, combined with a non-linear complementary model to capture the hysteresis effect. The model parameters, including linear parameters and non-linear parameters, are optimized off-line using a hybrid optimization method that combines a meta-heuristic method (i.e., the teaching learning based optimization method) and the least square method. Secondly, using the trained model, two real-time model-based SOC estimation methods are presented, one based on the real-time battery OCV regression model achieved through weighted recursive least square method, and the other based on the state estimation using the extended Kalman filter method (EKF). To tackle the problem caused by the flat OCV-vs-SOC segments when the OCV-based SOC estimation method is adopted, a method combining the coulombic counting and the OCV-based method is proposed. Finally, modelling results and SOC estimation results are presented and analysed using the data collected from LiFePo4 battery cell. The results confirmed the effectiveness of the proposed approach, in particular the joint-EKF method.

1. Introduction

Due to the imminent challenges of environment protection and the exhaustion of non-renewable fossil fuels, electric vehicles (EVs) and hybrid electric vehicles (HEVs) are rapidly gaining popularity worldwide in recent years as an effort of replacing the internal combustion engine (ICE) vehicles to improve the fuel efficiency and reduce the emissions in the transport sector. Many countries have proposed their national plans to increase the EV/HEV penetration in the coming decades [1]. The battery system is a key component in the EV/HEV system. Among different cell types, Lithium-ion batteries, such as LiFePo4 that is under investigation in this paper, are favoured power supplies for EVs and HEVs due to their high power and high energy densities, long service life, high efficiency and environmental-friendly figures [2]. A battery management system (BMS) is essential in EV/HEV applications for safe and

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efficient operation where hundreds or even thousands of battery cells are connected in series/parallel configuration to fulfil the high power and high voltage needs of the vehicles [3]. One key functionality of the BMS is to estimate the state-of-charge (SOC) of the battery, which is not directly measurable. SOC indicates the charge left in the battery available for further service, which determines the remaining range an EV can travel without re-charging the battery. Battery SOC indicator is similar to the fuel gauge in an ICE vehicle. Therefore accurate real-time SOC estimation is of great importance to prevent stranding halfway and to relieve the range anxiety. Further, SOC estimation can be used for preventing overcharging and over-discharging operations of the battery, thus reducing the harm caused to the battery. Some EVs require to cycle the battery within a specific SOC range, e.g., 20% to 70%, to achieve higher efficiency and longer service life, which again relies on accurate SOC estimation. On the other hand, inaccurate SOC estimation will result in an over-sized battery system, therefore a significant increase of the overall cost of EVs.

Another application of SOC estimation is for battery cell balancing. There are slight differences between different cells within the same pack, such as different cell capacity or internal impedance. As time goes by, this difference will become more and more significant [4]. The overall capacity of battery cells connected in series is limited by the cell with the least capacity, and without a balancing method this cell will be stressed more than other cells under the same working condition, leading to a deteriorating unbalancing problem. Therefore cell balancing is another essential functionality of the BMS, and the cell SOC can be used as an indicator for balancing the battery [3]. There are other advantages brought by accurate SOC estimation, such as accurate available power estimation, and battery SOC estimation can also be used for developing power and energy management strategies, etc.

Despite the demanding necessity, accurate real-time SOC estimation is not easy to acquire. First of all, all the estimation methods in the EV applications should be based on the on-board measured signals, such as the battery terminal voltage, load current and the temperature. Due to the high-voltage, high-current and highly dynamic profile of the load, voltage and current measurements are often corrupted with noises. Besides, some SOC estimation methods, such as the open circuit voltage (OCV) based methods, are sensitive to the voltage measurement error. Secondly, the battery behaviour is highly non-linear and non-stationary, and some internal chemical reactions, such as the parasitic reaction, self-discharge and ageing process that affect the battery SOC, are extremely difficult to model.

Over the years, researchers have developed different SOC estimation methods [5–10]. These methods can be generally divided into two groups: direct measurement methods and model-based estimation methods. Direct measurement methods, or model-free methods, estimate battery SOC by a directly measurable physical property, such as coulombic counting method (or Ah method) and OCV based methods. For model-based SOC estimation methods, a model is firstly built to reproduce the battery terminal behaviour. Then the battery SOC can be linked to one or several of the model parameters. After the model parameters are identified, the battery SOC can be inferred. Another approach is to model the battery behaviour using a state-space model with the battery SOC as one state, then different state estimation methods, such as Kalman Filter (KF) and Unscented Kalman Filter (UKF), can be used for SOC estimation. Direct measurement methods are generally open-loop methods. They are easy to implement, but sensitive to current and voltage measurement errors. On the other hand, the model-based methods are generally close-loop methods and not sensitive to measurement errors, but they rely on an accurate battery model, which is difficult to acquire.

Further, the SOC estimation for Lithium-ion batteries faces two key challenges. Firstly, batteries like $LiFePo_4$ show a flat OCV-vs-SOC curve within some SOC ranges, and therefore a small voltage measurement error can cause a large SOC estimation error for the OCV-based SOC estimation methods. Another difficulty is that the battery shows a hysteresis effect, i.e., the battery OCV depends on the direction of the load current, which needs to be considered during battery modelling and SOC estimation. To address these problems, an integrated approach for real-time model-based SOC estimation of Lithium-ion batteries is proposed in this paper. The contributions of this paper are summarized as follows. Firstly, a new battery model is proposed, including an auto-regression relaxation model together with a non-linear complementary model to capture the hysteresis effect. Secondly, the model parameters are divided into two groups, namely the linear parameters and the non-linear parameters, and a hybrid optimization method that combines a meta-heuristic method (i.e., the teaching learning based optimization (TLBO) method) and the least square method is used to optimize the two distinctively different sets of parameters. This leads to a high modelling accuracy. Thirdly, based on the off-line trained model, two real-time SOC estimation methods are then proposed using the weighted recursive least square (WRLS) method and the Kalman Filter method, respectively. Finally, to tackle the problem caused by the flat OCV-vs-SOC curve of Lithium-ion batteries, a new method combining coulombic counting method and OCV-based method is also proposed.

The rest of this paper is organized as follows. Section 2 presents a brief introduction to different SOC estimation methods, including direct measurement methods and model-based methods. The battery test system and the test data used in this paper are presented in Section 3. Then the auto-regression model is presented in Section 4, together with the hysteresis model. The model parameters are optimized using TLBO and least square method. The modelling results are then presented. The two different model-based SOC estimation methods are given in Section 5, and the SOC estimation results are analysed in Section 6. Finally, Section 7 concludes this paper.

2. Different SOC estimation methods

2.1. Direct measurement methods

Based on the onboard measurable signals, i.e., battery terminal voltage and current, there are two popular direct measurement methods for SOC estimation, i.e., coulombic counting method (or Ah method, Ah stands for Ampere-hour, which is the unit of battery capacity) and OCV-based method.

2.1.1. Ah method

The Ah method is to integrate the discharging current to calculate the remaining charge in the battery, as follows.

$$SOC(k) = SOC(0) - \frac{T}{C_n}\int_0^k (\eta^* i(t) - S_d)dt \tag{1}$$

where $SOC(0)$ is the initial SOC, C_n the nominal capacity of the battery, T is the sampling period, $i(t)$ is the load current at time t, η is coulombic efficiency, and S_d is the self-discharging rate. For LiFePo4 battery used in this experiment, $\eta > 0.994$ under room temperature [11]; according to the manufacturer, the battery self-discharging rate is less than 5% per month. Therefore, $\eta = 1$ and $S_d = 0$ are assumed in this paper.

Based on the on-board measured current signals, it seems