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An adaptive remaining energy prediction approach for lithium-ion batteries in electric vehicles

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HIGHLIGHTS

- An adaptive SoE estimation approach is established.
- A data-driven model is established for SoE estimation.
- The forgetting factor RLS method is employed for parameter identification.
- Dynamic current and temperature profiles are performed on the $LiFePO_4$ cells.

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ABSTRACT

With the growing number of electric vehicle (EV) applications, the function of the battery management system (BMS) becomes more sophisticated. The accuracy of remaining energy estimation is critical for energy optimization and management in EVs. Therefore the state-of-energy (SoE) is defined to indicate the remaining available energy of the batteries. Considering that there are inevitable accumulated errors caused by current and voltage integral method, an adaptive SoE estimator is first established in this paper. In order to establish a reasonable battery equivalent model, based on the experimental data of the $LiFePO_4$ battery, a data-driven model is established to describe the relationship between the open-circuit voltage (OCV) and the SoE. What is more, the forgetting factor recursive least-square (RLS) method is used for parameter identification to get accurate model parameters. Finally, in order to analyze the robustness and the accuracy of the proposed approach, different types of dynamic current profiles are conducted on the lithium-ion batteries and the performances are calculated and compared. The results indicate that the proposed approach has robust and accurate SoE estimation results under dynamic working conditions.

1. Introduction

With the growing concerns on the depletion of energy resources and global warming problems caused by conventional internal combustion engine vehicles, electric vehicles (EVs) have drawn more of people's attentions. The battery is the key to the development of EVs. Lithium-ion batteries as featured by high energy density, low self-discharge rate and long cycle life have found wide applications in the area of EV power supply systems [1]. A lithium-ion battery is a high-energy battery in which Li + embeds into and escapes from positive and negative materials when charging and discharging. The positive electrode materials of lithium-ion batteries are intercalation compounds of lithium-ion, commonly $LiCoO_2$, $LiNiO_2$, $LiMn_2O_4$, $LiFePO_4$, $LiNi_xCo_yMn_{(1-x-y)}O_2$, and so on. The negative electrode materials are commonly Li_xC_6, TiS_2, V_2O_5, and so on. There is a recent trend in lithium-ion battery research community gearing toward high rate materials that can charge/discharge at very fast rates [2]. The lithium-ion battery is a strong nonlinear and time variability system for its complicated electrochemical process. The estimation of cell state parameters, such as the state-of-charge (SoC) and state-of-energy (SoE), plays an important role in ensuring vehicle stability and reliability.

The SoC reflects the residual capacity of a battery and is defined as the ratio of the remaining capacity to the total capacity as:

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$$SoC(t) = SoC(t_0) + \eta_c \int_{t_0}^{t} i(\tau)\mathrm{d}\tau / C_N \quad (1)$$

where $SoC(t)$ is the SoC value at time t, $SoC(t_0)$ is the SoC value at initial time t_0, $i(\tau)$ is the current at time τ and C_N represents the total capacity of the battery. η_c denotes the coulombic efficiency of battery. In this sense, exact energy information cannot be known from the estimation of SoC since it is a percentage of the battery capacity. The SoE is defined to indicate the remaining available energy of the batteries. The SoE can be expressed as the following equation:

$$SoE(t) = SoE(t_0) + \eta_e \int_{t_0}^{t} P(\tau)\mathrm{d}\tau / E_N \quad (2)$$

where $SoE(t)$ is the SoE value at time t, $SoE(t_0)$ is the SoE value at initial time t_0, $P(\tau)$ represents the power at time τ and E_N represents the nominal energy of the battery. η_e denotes the energy efficiency of battery.

Compared with the SoC which varies linearly with the charge/discharge current, the SoE is nonlinear with the current because of the consideration of energy loss on the internal resistance, the electrochemical reactions and the decrease of the OCV [3–6]. For a more complete and applicable BMS, the estimation of SoE is more meaningful to predict the remaining driving range (RDR) of the EVs and can indicate the actual available energy of the batteries.

In recent years, large numbers of estimation approaches of battery state have been proposed in literature, such as the coulomb counting method [7], the OCV based approach [8,9], nonlinear observer method [10,11], the fuzzy logic method [12], the neural network model method [13] and the model based algorithm [14]. In real system, the estimation error increases conspicuously due to the accumulated error introduced by current or voltage drift of sensors. A small error on the predicted voltage will lead to a larger deviation in SoC due to that lithium-ion batteries have a relatively flat voltage curve over the SoC. Therefore model-based estimation methods such as the extended Kalman filter (EKF) [15–19], unscented Kalman filter (UKF) [20], particle filter (PF) [21–23] and unscented particle filter (UPF) [24,25] have been attracted more of people's attention. The model-based estimator can precisely estimate the voltage and adjust the gain according to the terminal voltage error between the measured values and the estimated values timely. The core content of this method used for state estimation is to establish a reasonable battery model and the performance is highly dependent on the prediction precision of the battery model. In order to get accurate SoE estimation results, an accurate battery model is desperately needed. The most commonly used battery models can be divided into three types, the electrochemical models, the neural network models and the equivalent circuit models. The electrochemical model based on the electrochemical mechanism of the battery can accurately reflect the characteristics of the battery. The current commonly used electrochemical models for battery state estimation include the shepherd model [26], the Unnewehr universal Model [26], the Nernst model [18] and the combined Model [18]. The neural network model can simulate the high nonlinearity of lithium-ion batteries, but requires a large number of training samples [13]. Based on the dynamic characteristics and working principles of the battery, the equivalent circuit model is developed by using resistors, capacitors, and voltage sources to form a circuit network [27].

The term SoE is employed to represent the percentage of present remaining energy with the nominal total energy. In Ref. [3] Wang et al. used a combined electrochemical model and proposed a method for joint estimation of both SoC and SoE. Liu et al. [6] developed a neural network model for SoE estimation which considered the OCV, the discharge current and the temperature. He et al. [28] proposed a Gaussian model which is adaptive for both $LiFePO_4$ and $LiMn_2O_4$ batteries. The simulation result agrees well with the experimental result.

In this study, an adaptive SoE estimator is proposed. Based on the experimental data of the $LiFePO_4$ battery, a data-driven model is established to describe the relationship between the OCV and the SoE. What is more, the forgetting factor recursive RLS method is used for parameter identification to get accurate model parameters. This paper is organized as follows: In Section 2, a data-driven model for SoE estimation is first proposed. Then the forgetting factor RLS method is introduced for on-line parameter identification to get accurate model parameters. In Section 3, the algorithm and the implementation of the adaptive SoE estimator is proposed. In Section 4, different types of dynamic profiles are conducted on the lithium-ion batteries to verify the accuracy of the proposed method. The results show that accurate and robust SoE estimation results can be obtained by the proposed method. Finally, the conclusions of this work are given in Section 5.

2. Battery model

2.1. Battery model description

It is difficult to obtain an completely accurate model to describe the relationship between the terminal voltage and varied dynamic loads, since the lithium-ion battery is a very complex electrochemical system with physical and chemical processes. The equivalent circuit model has been widely used in various types of modeling and simulation for its high accuracy. Depending on different applications and the required accuracy, different types of cell models have been developed in literature. Among which, the Thevenin equivalent circuit model is an effective model to represent the battery's dynamics.

As shown in Fig. 1, the Thevenin equivalent circuit model includes an open-circuit voltage U_{ocv} which is used to represent the voltage source and describe the static character of the cell, a serial resistance R_o which is used to describe the cell ohmic internal resistance, a RC network which describes the cell polarization effect is composed by a polarization resistance R_p and a polarization capacitance C_p. Based on the electric circuit analysis, the electrical behavior of the cell model can be expressed as:

$$\dot{U}_p = -U_p / C_p R_p + i / C_p \quad (3)$$

$$U_t = U_{ocv} - U_p - iR_o \quad (4)$$

where i represents the load current (negative for charge, positive for discharge), U_{ocv} represents the open-circuit voltage, U_t represents the terminal voltage, U_p represents the polarization voltage

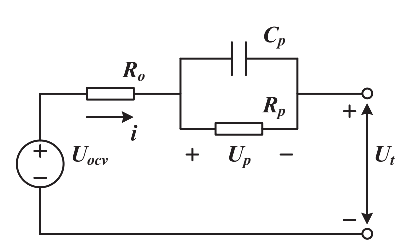

Fig. 1. Battery equivalent circuit model.