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A method for state of energy estimation of lithium-ion batteries based on neural network model

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ABSTRACT

The state-of-energy is an important evaluation index for energy optimization and management of power battery systems in electric vehicles. Unlike the state-of-charge which represents the residual energy of the battery in traditional applications, state-of-energy is integral result of battery power, which is the product of current and terminal voltage. On the other hand, like state-of-charge, the state-of-energy has an effect on terminal voltage. Therefore, it is hard to solve the nonlinear problems between state-of-energy and terminal voltage, which will complicate the estimation of a battery's state-of-energy. To address this issue, a method based on wavelet-neural-network-based battery model and particle filter estimator is presented for the state-of-energy estimation. The wavelet-neural-network based battery model is used to simulate the entire dynamic electrical characteristics of batteries. The temperature and discharge rate are also taken into account to improve model accuracy. Besides, in order to suppress the measurement noises of current and voltage, a particle filter estimator is applied to estimate cell state-of-energy. Experimental results on $LiFePO_4$ batteries indicate that the wavelet-neural-network based battery model simulates battery dynamics robustly with high accuracy and the estimation value based on the particle filter estimator converges to the real state-of-energy within an error of ±4%.

1. Introduction

Due to consideration of energy crisis and environment protection, the low-emission and energy saving EV (electric vehicles) have become the developing tendency of the energy transformation. In recent years, various electrochemical energy storage systems have been introduced for EV applications, like NiMH (Nickel/Metal Hydride), Li-ion (Lithium-ion) batteries as well as other types such as ultra-capacitors and fuel cells etc. Li-ion batteries have become widely used power source in EVs for its high power density, high energy density and long lifetime. For instance, Zou et al. [1] proposed a combined SOC (state-of-charge) and SOH (state-of-health) estimation method over the lifespan of a Li-ion battery. Hu et al. [2] presented an integrated method for the capacity estimation and remaining useful life prediction of Li-ion battery. Kang et al. [3] proposed a method to compare the comprehensive properties of different battery systems in terms of a parameter, energy efficiency. Hu et al. [4] discussed an ameliorated sample entropy-based capacity estimator for prognostics and health management of Li-ion batteries in electrified vehicles. Fathabadi et al. [5] presented a novel Li-ion battery pack design including hybrid active-passive thermal management system. In order to maintain optimum battery performance, a BMS (battery management system) is critical for battery system. Therefore, the BMS must know accurate and reliable battery system parameters. The SOC is a critical parameter for power battery systems. It plays a role in representing the residual energy of the battery in traditional applications. Thus, it is used to predict residual driving mileage of EVs. However, with the sophisticated and complex functional demand trend of BMS, the disadvantages of using the estimated SOC to represent the battery residual energy become more prominent [6]. The SOE (State of energy), which provides the essential basis of energy deployment, load balancing and security of electricity for the complex energy systems, is an important evaluation index for energy optimization and management of power battery systems [6].

Traditionally, SOC is used not only to protect battery from been over charged or over discharged, but also to represent the residual energy of battery. Nevertheless, there are several disadvantages of using the estimated SOC to represent the battery residual energy, as

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reviewed by Liu et al. [6]. Firstly, the SOC is defined as the ratio of the residual capacity to the total original capacity of a Li-ion battery, which means that SOC cannot indicate the energy state on which the battery application conditions is dependent. Some works have considered the residual available capacity instead of the SOC to determine the residual energy of battery. For instance, to the determination of the available energy stored in the battery, Waag et al. [7] employed the estimation of battery electromotive force to estimate SOC and capacity of the battery. Hausmann et al. [8] expanded the Peukert equation for battery capacity modeling through inclusion of a temperature dependency. Shen et al. [9] defined the state of available capacity, instead of SOC to denote the battery residual available capacity for lead-acid batteries. Liu et al. [10] proposed an extended Peukert equation to estimate the available capacity of batteries including the temperature effect. Secondly, the battery energy can be regarded as the product of the capacity and the OCV (open circuit voltage) of the battery. Although there is a positive correlation between battery SOE and SOC, they have no explicit quantitative. The SOC decreases linearly with the discharge current, but the battery energy is the product of the capacity and the OCV of the battery. Battery energy change has direct link with its real-time voltage, as a result, it is hard to be accurately calculated. Thirdly, the discharge current and the temperature which usually change dramatically due to the dynamic load in actual battery system will have significant effects on battery performance. Wang et al. [11] measured the electronic conductivity of $LiFePO_4$ and $LiFePO_4$/C at various temperatures to understand the difference of low-temperature electrochemical performance between the carbon-coated and uncoated LiFePO4 cathodes. Yi et al. [12] reported a modeling methodology on the temperature dependence of discharge behavior of a Li-ion battery in low environment temperature. At the same SOC, the SOE may change on account of the fact that the discharge efficiency is dependent on the discharge current and temperature [6]. Thus, it is necessary to take the effect of discharge current and temperature into account for getting a more accurate SOE estimation.

In recent years, many researches have been devoted to developing improved methods for SOC estimation. Ng et al. [13] proposed a smart estimation method based on coulomb counting. The electrical model based methods established battery models to capture the relationship between the SOC and the OCV of the battery, then the adaptive filters, such as Kalman filter [14] and particle filter, for instance, dual-particle-filter presented in Liu et al. [15], unscented particle filter proposed in Zhong et al. [16] and He et al. [17]. Charkhgard et al. [18] presented a method for SOC estimation of Li-Ion batteries using neural networks and the EKF (extended Kalman filter). Some works developed the fuzzy logic method [19] and support vector machines [20] for SOC estimation. Most of these methods have been widely used and made acceptable achievements in different applications. Adopting same methods as SOC estimations, an assortment of techniques have previously been reported to measure or estimate the SOE of the cells. Among them, Stockar et al. [21], Mamadou et al. [22] and Kermani et al. [23] presented the definition of SOE and the algorithms to follow-up the SOE based on direct power integral method which used power integral to estimate the SOE. However, this method had a significant estimation error because of the measurement noises of current and terminal voltage of the battery. Liu et al. [6] has proposed an improved direct SOE estimation method at dynamic current and temperature conditions based on BPNN (back-propagation neural network). In the input layer, the battery terminal voltage, the current and the temperature are taken as the input parameters, and the output layer is the estimated SOE. However, this method is an open-loop estimation so that its estimation accuracy becomes poor due to the incorrect measurements. Wang et al. [24] has proposed a joint estimator for SOC and SOE to overcome the disadvantages of power integral method. However, the SOE estimation accuracy depends on the SOC estimation accuracy in this developed method. Zhang et al. [25] proposed a novel model-based joint estimation approach to improve the estimation accuracy and reliability for battery SOE and power capability, and the battery model takes SOE as a state variable. However, it has not taken the influence of temperature and discharge rate on total available energy into account, while the total available energy is a critical parameter directly limit the pack performance through "capacity fade". Unlike SOC, SOE is integral result of battery power, which is the product of current and terminal voltage. On the other hand, like SOC, SOE has an effect on terminal voltage. Therefore, it is hard to solve the nonlinear problems between SOE and terminal voltage, which will complicate the estimation of a battery's SOE. Therefore, there is need to establish a battery state space model that takes SOE as a state variable. Once this model is established, the adaptive filter algorithms used in SOC estimation will be available for SOE estimation for getting more accurate SOE estimation.

In this paper, a WNN (wavelet neural network) -based battery state-space model and PF (particle filter) estimator is carried out to improve the battery modeling and SOE estimation. It is organized as follows. A clear scheme of battery test bench, the definition of SOE and some battery test data analysis for Li-ion batteries are given in Section 2. The test results are used to analyze some influencing factors of the SOE estimation, such as OCV, discharge current and temperature. In Section 3, a state-space model of the SOE that takes into account the effect of the discharge current and temperature is established. Then, parameters of the WNN-based battery model are identified by the experimental data of $LiFePO_4$ batteries. In Section 4, the PF method based on the proposed model is applied to estimate the SOE. In Section 5, simulations and comparison tests based on the proposed model and real battery data will be presented to verify the superiority of the proposed algorithm.

2. Experimental

As an application case, $LiFePO_4$ batteries are chosen to verify the proposed approach. Section 2.1 gives a brief introduction for the test bench. In order to analyze the characteristics of SOE, the definition of SOE is first given in Section 2.2.1. Then, the test data analysis is given in Section 2.2.2.

2.1. Test bench

Experimental studies are conducted on $LiFePO_4$ batteries with a rated capacity of 9 Ah (produced by Hefei Guoxuan High-Tech Power Energy CO., Ltd. of China). The parameters of the battery are given in Table 1. In order to acquire experimental data such as current, voltage and temperature, a battery test bench has been established. The configuration of the test bench is drawn in Fig. 1, which consists of a battery test system NEWWARE BTS4000, a BMS, a CAN communication unit, a programmable temperature chamber, a computer to program and store experimental data and some test cells. The NEWWARE BTS4000 is responsible for loading the

Table 1
Battery parameters of $LiFePO_4$.

Parameter	Value
Rated capacity	9 A h
Low cutoff voltage	2.0 V
Upper limit voltage	3.65 V
Operating temperature	$-20^{\circ} \sim 60\,^{\circ}$C

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