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A method for state of energy estimation of lithium-ion batteries at dynamic currents and temperatures

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HIGHLIGHTS

- The state of energy (SOE) is introduced to replace the SOC to determine the residual energy of the battery.
- The energy loss on the internal resistance, electrochemical reactions and decrease of OCV is considered in SOE estimation.
- Temperature and current influence are considered to improve the robustness of SOE estimation.
- The proposed BPNN method is validated under dynamic temperature and current conditions.

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ABSTRACT

The state of energy (SOE) of Li-ion batteries is a critical index for energy optimization and management. In the applied battery system, the fact that the discharge current and the temperature change due to the dynamic load will result in errors in the estimation of the residual energy for the battery. To address this issue, a new method based on the Back-Propagation Neural Network (BPNN) is presented for the SOE estimation. In the proposed approach, in order to take into account the energy loss on the internal resistance, the electrochemical reactions and the decrease of the open-circuit voltage (OCV), the SOE is introduced to replace the state of charge (SOC) to describe the residual energy of the battery. Additionally, the discharge current and temperature are taken as the training inputs of the BPNN to overcome their interference on the SOE estimation. The simulation experiments on $LiFePO_4$ batteries indicate that the proposed method based on the BPNN can estimate the SOE much more reliably and accurately.

1. Introduction

With the improvement of the energy density and the safety performance, Li-ion batteries are widely used in the renewable energy vehicles and energy storage systems, such as electric vehicles, wind power systems, solar power systems, micro-grid and so on. The SOE of the battery [1], which provides the essential basis of energy deployment, load balancing, and security of electricity for the complex energy systems, is a key parameter in the battery system.

Traditionally, the residual energy of the battery is represented by the estimation of the SOC. In recent years, many studies on the SOC estimation can be found in the literature, with the primary methods being the current integral method [2], the electrical model based method [3–7] and the neural network model method [8–10]. The current integral method obtains the SOC estimation through the accumulation of the battery current [2]. The method is easy to implement; however it is an open-loop estimation so that its estimation accuracy becomes poor due to the accumulated error caused by the current measurement noise [7]. As to the electrical model based method, both electrochemical models and equivalent circuit models are established to capture the relationship between the SOC and the OCV of the battery. Then, the Kalman filter methods or the particle filter methods are applied for the SOC estimation based on these battery models. The Kalman filter and particle filter methods are closed-loop, and many algorithms such as extended Kalman filter [5,6,11], unscented Kalman filter [12,13] and unscented particle filter [3,5] are used in the SOC estimation. These methods take the SOC as a state variable, so they can solve the accumulated error of the current integral method by updating the SOC on the basis of the difference between the measured and the prediction value of the terminal voltage. The neural network model methods can describe the dynamic and nonlinear behavior of the battery by means of the multilayer neural networks, and thus

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it could be used to estimate the SOC for Li-ion batteries [8–10]. Some works develop the data-fusion method [14] and the discrete Wavelet method [15,16] for SOC estimation. These approaches have been widely used in the SOC estimation of Li-ion batteries, and most of them have achieved acceptable results.

Nevertheless, with the increasingly widespread application of Li-ion batteries, the functional demand of battery management system appears a more sophisticated and complex trend. Therefore, the disadvantages of using the estimated SOC to represent the battery residual energy become more prominent. Firstly, the SOE is different from the SOC for Li-ion batteries. The SOC defines the ratio of the residual active material to the total original active material inside a Li-ion battery. In this sense, the SOC indicates only the capacity state rather than the energy state on which the battery application conditions is dependent. For a more detailed management of the battery, the discharge efficiency and the residual energy are necessary. There are no more energy information can be got from the estimated SOC since the SOC is only a percentage of the battery capacity. Some works have considered the residual available capacity instead of the SOC to determine the residual energy of the battery [17–20]. Secondly, although there is a positive correlation between the SOE and the SOC, they have no explicit quantitative relationship. The SOC decreases linearly with the discharge current, but the battery energy is the product of the capacity and the OCV of the battery. There are differences between the SOC and the SOE because the energy loss on the internal resistance, the electrochemical reactions and the decrease of the OCV are not considered in the SOC estimation [3–5,21–24]. Thirdly, in the actual battery system, where the discharge current and the temperature usually changes dramatically due to the dynamic load, the performance of the battery becomes poor [25–27]. For SOC estimation, the temperature effect has been considered to build a more accurate battery model [13,28,29]. Xing et al. [28] develop an offline OCV–SOC-temperature table to describe the temperature effect, and pattern recognition based on the Hamming network is presented to check the temperature [29]. However, as to the relation between the SOE and the temperature, it is not adequately addressed in the recent literature. 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. Thus, it is necessary to carry on a more comprehensive analysis on the effect of the discharge current and temperature for getting a more accurate SOE estimation.

In this paper, to determine the energy loss on the internal resistance, the electrochemical reactions and the decrease of the OCV, the SOE instead of the SOC is introduced to represent the residual energy of Li-ion batteries, and a BPNN method is proposed to improve the SOE estimation at dynamic currents and temperatures. In Section 2, we give a clear definition of the SOE for Li-ion batteries. Battery tests with various currents at different temperatures are carried out to analyze their effect on the SOE in Section 3. In Section 4, a BPNN battery model is established to take into account the effect of the OCV, discharge current and temperature. And then, parameters of the BPNN battery model are identified by the experimental data of $LiFePO_4$ batteries. In Section 5, simulations based on the BPNN algorithm are used to verify the accuracy of the estimation of the battery SOE.

2. SOE

The SOE provides the information of the remaining available energy of Li-ion batteries [30,31], so it is a critical parameter for energy optimization and management for the battery system. In this paper, the SOE is defined as:

$$SOE(t) = E_c - E_d(t) \tag{1}$$

where $SOE(t)$ is the remaining energy of the battery at time t, E_c is the total energy of the battery and $E_d(t)$ is the discharged energy of the battery until time t. Generally, the SOE reaches its maximum after it is fully charged, and the SOE is zero when the battery is discharged to its low cutoff voltage.

The study of Li-ion batteries indicates that the energy, which is consumed during the discharge process, is mainly composed of the output electric energy, the energy consumed on the internal resistance heating and the energy consumed on the electrochemical reactions. The output electric energy is used to meet the load, and it is usually expressed by the SOC in previous studies. The internal resistance will heat the battery during the discharge process, so it expends the battery energy. The electrochemical reactions inside the battery also cause the energy consumption.

The available energy of Li-ion batteries changes with the battery temperature. Specifically, the available energy decreases significantly at low temperatures. Under high discharge currents, a Li-ion battery may demonstrate empty conditions via the low cutoff voltage. However, the battery still has energy that may be utilized at lower discharge currents. This characteristic can bring great difficulties to the estimation accuracy of the SOE.

3. Experiments

3.1. Test bench

In order to acquire experimental data of Li-ion batteries, a test bench is built, as shown in Fig. 1. The test bench is composed of a battery test system NEWARE BTS4000, a battery management system (BMS), a CAN communication unit, a host computer for online experiment control and a programmable temperature chamber. The NEWWARE BTS4000 is used to load the battery with a maximum voltage of 5 V and a maximum current of 100 A, and its voltage and current measurement accuracy is ±0.1%. The experimental data such as current, voltage, temperature, accumulative ampere-hours (Ah) and Watt-hours (Wh) are measured by the NEWWARE BTS4000 and recorded by the host computer. The BMS

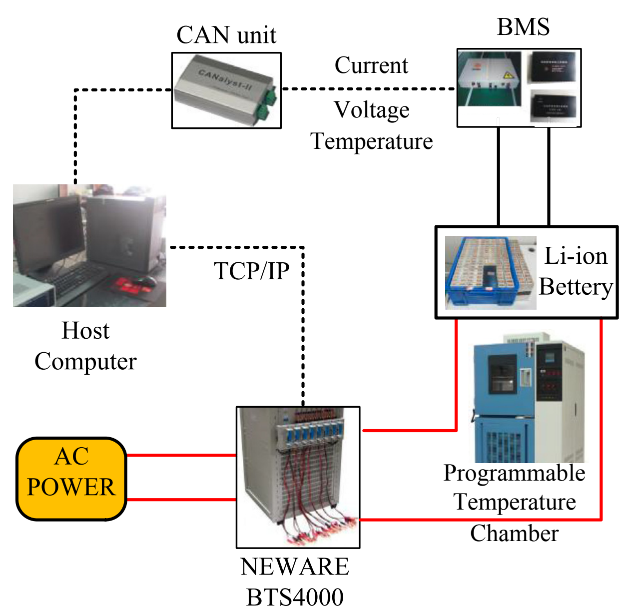

Fig. 1. Configuration of the battery test bench.