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A new neural network model for the state-of-charge estimation in the battery degradation process

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HIGHLIGHTS

- Predict practicable capacity by cycle life model in the battery degradation process.
- Build a new RBFNN model based on cycle life model to estimate the SOC.
- Evaluate the robustness of new model against varying aging levels and temperatures.
- Assess the robustness of new model against varying loading profiles.
- Analyze the measurement of the battery aging cycles in electric vehicles.

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ABSTRACT

Battery state-of-charge (SOC) is a key parameter of the battery management system in the electric vehicle. To predict the practicable capacity of the battery in the degradation process, the cycle life model is built based on the aging cycle tests of the 6Ah Lithium Ion battery. Combined with the cycle life model, a new Radial Basis Function Neural Network (RBFNN) model is proposed to eliminate the battery degradation's effect on the SOC estimation accuracy of the original trained model. This proposed model is verified through the 6Ah Lithium Ion battery. First, Urban Dynamometer Driving Schedule (UDDS) and Economic Commission of Europe (ECE) cycles are experimented on the batteries under different temperatures and aging levels. Then, the robustness of the new RBFNN model against different aging levels, temperatures and loading profiles is tested with the datasets of the experiments and compared against the conventional neural network model. The simulations show that the new model can improve the accuracy of the SOC estimation effectively and has a good robustness against varying aging cycles, temperatures and loading profiles. Finally, the measurement of actual aging cycles of the battery in electric vehicles is discussed for the SOC estimation.

1. Introduction

As the key parameter of the battery management system, state-of-charge (SOC) can indicate the remaining energy of the battery directly [1]. The accurate SOC estimation is vital for the battery management system to predict the remaining range. Furthermore, it also helps to determine an effective management strategy which can avoid over-charging and over-discharging.

In recent years, the main methods for the SOC estimation include the current integral method [2,3], the open-circuit voltage method [4–6], the equivalent circuit method [7,8], the electrochemical model-based method [9,10], the Kalman filter method [2,11], the extended Kalman filter method [12–16] and artificial neural network models [17–24]. The current integral method is easy to implement, but it may result in the accumulated SOC estimation error. For the open-circuit voltage method, the open-circuit voltage should be measured only after the battery stops some time later, but the running electric vehicle cannot be in the quiescence for a long time. Based on the empirical equation, the equivalent circuit model cannot reflect the dynamic behavior of the battery well because the parameters are generally obtained from the steady state. The electrochemical model-based method may have too complicated mathematical structure to operate or would have to sacrifice its ability of capturing dynamic behavior to achieve a simple structure [9]. The Kalman filter method is a linear filter, but the battery model is nonlinear, so it is easy to generate big estimation error. The extended Kalman filter method is

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sensitive to system parameters and will give unreliable estimation if the nonlinearities of the battery model are severe [16]. As a very nonlinear black box system, the conventional artificial neural network model (CM) does not need accurate formulas to describe the relationship between the battery parameters and the SOC because the relationship can automatically be generated when training the network with the history data (current, voltage and temperature) [23,24]. However, the practicable capacity of the battery will decline when the battery has been used for many times or the temperature becomes severe. The earlier network which is trained based on the history data cannot eliminate the negative effect of the battery degradation on the SOC estimation. To solve the problem, CM should retrain the network with the updated training data [19]. However, the degradation of the battery changes constantly and its process is very complicated, which will bring about several issues including when and how often to retrain the network.

To overcome above defect of CM, the paper proposes a new RBFNN model to estimate the SOC. In this approach, the cycle life model is built to predict the practical capacity based on the aging cycle tests of the 6Ah Lithium Ion battery at different temperatures. As an input parameter of the proposed new model (PM), the predicted capacity of the battery would change in response to the varying temperatures and aging levels, which makes PM suitable for the SOC estimation of the battery in the degradation process.

The paper is organized as follows: in Section 2, the paper carries out the aging cycle tests of the 6Ah Lithium Ion battery at different temperatures and builds the cycle life model to predict the practicable capacity of the battery in the degradation process. In Section 3, Based on the cycle life model, a new RBFNN model is designed for SOC estimation. Meanwhile, the rules of adjusting network parameters are applied to modify network parameters and adjust the network structure with the training data samples. In Section 4, UDDS and ECE datasets of low aging-level battery at different temperatures are collected to train the new model in the variable power discharging experiments, and then the trained network is tested by UDDS and ECE datasets of the battery under different aging levels and temperatures. The estimating performance of PM is evaluated and compared with CM. Finally, the measurement equation is proposed to determine the actual aging cycles of the battery in electric vehicles with the running mileage of the battery.

2. The new model using RBFNN

2.1. The cycle life model of the Lithium Ion battery

The Lithium Ion battery always degrades with the time in real operations. And the degradation can be manifested as the capacity loss. The capacity loss is partly due to the loss of the recyclable Li-ions caused by many factors, such as cathode structure degradation, side reactions, passivation form and lithium plating at the anode [25]. The above factors change greatly under different temperatures and aging levels of the battery [26]. So it is significant for the battery management system to study the effect of the temperature and aging level on the capacity loss, which equals the difference between the nominal capacity and the practical capacity.

According to the battery test specification of national 863 high technology projects [27], the aging cycle test of the battery is a process which consists of the constant current charge, constant voltage charge and constant current discharge. In the paper, the aging cycle test of the 6Ah Lithium Ion battery (the selected battery was 6Ah $LiMn_2O_4$ type, which was developed by WESTECH INDUSTRY&TRADING CO., LIMITED) is accomplished respectively at 10 °C, 25 °C and 40 °C. The process of the aging cycle test is showed in Fig. 1. During the whole process, the practicable capacity of the battery is measured every 25 aging cycles. One aging cycle is showed in Fig. 2.

The results of the aging cycle tests at different temperatures are showed in Fig. 3. As the age cycles of the battery increase, the cell polarization will exist in the Lithium Ion battery and the amount of recyclable Li-ions in the anode will become less, which could cause capacity fade. As for the phenomenon that the practical capacity of

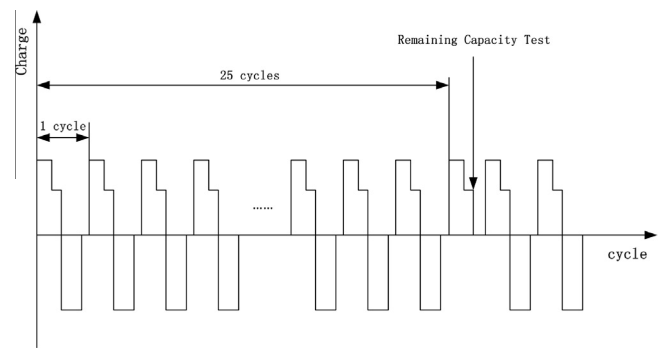

Fig. 1. The aging cycle test of the 6Ah Lithium Ion battery.

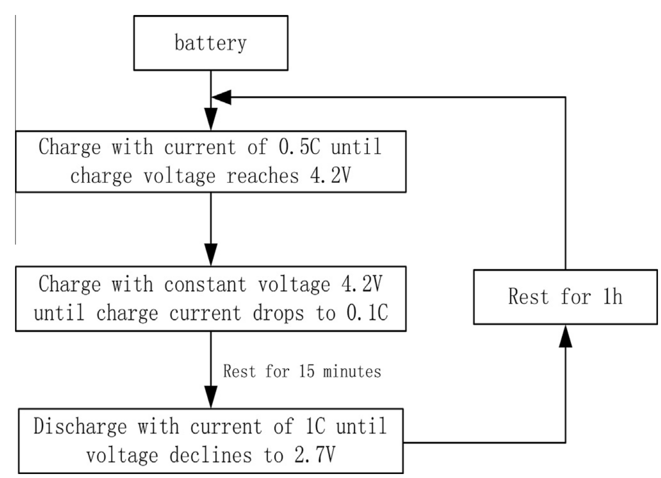

Fig. 2. The schedule of one aging cycle.

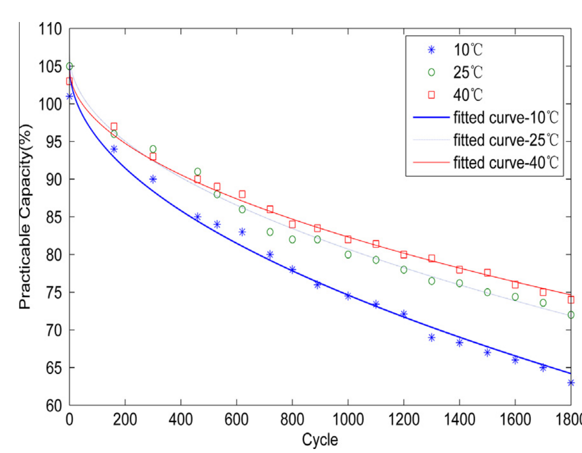

Fig. 3. Practicable capacity of the 6Ah Lithium Ion battery in the degradation process.