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A novel approach of battery pack state of health estimation using artificial intelligence optimization algorithm

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HIGHLIGHTS

- A novel battery pack SOH definition is proposed.
- A PSO-GA estimator is applied in parameters identification.
- The accuracy and robustness of the method is verified by different profiles.
- The influential battery pack SOH factors are performed.

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ABSTRACT

An accurate battery pack state of health (SOH) estimation is important to characterize the dynamic responses of battery pack and ensure the battery work with safety and reliability. However, the different performances in battery discharge/charge characteristics and working conditions in battery pack make the battery pack SOH estimation difficult. In this paper, the battery pack SOH is defined as the change of battery pack maximum energy storage. It contains all the cells' information including battery capacity, the relationship between state of charge (SOC) and open circuit voltage (OCV), and battery inconsistency. To predict the battery pack SOH, the method of particle swarm optimization-genetic algorithm is applied in battery pack model parameters identification. Based on the results, a particle filter is employed in battery SOC and OCV estimation to avoid the noise influence occurring in battery terminal voltage measurement and current drift. Moreover, a recursive least square method is used to update cells' capacity. Finally, the proposed method is verified by the profiles of New European Driving Cycle and dynamic test profiles. The experimental results indicate that the proposed method can estimate the battery states with high accuracy for actual operation. In addition, the factors affecting the change of SOH is analyzed.

1. Introduction

Due to the energy crisis, more and more people pay great attention to the field of new sources of energy [1]. The lithium-ion battery, which has the features of high energy density, low self-discharge and long service life, has been widely used in distribution energy storage systems and electric vehicles [2]. Meanwhile, the new material [3] is also applied in lithium-ion battery to ensure the battery work with high performance and stability [4]- [5]. In general, the battery pack is composed of hundreds and thousands of single cells to meet the demand of high voltage plateau and energy storage. However, the characteristics of batteries will be different after the battery using for a long time due to a change of battery health. Therefore, the battery management systems (BMS) [6] are developed to measure the battery real time states and predict the battery health state to make the battery work with safety and high efficiency.

There are many methods on battery state of health (SOH) estimation, which can be divided into three categories: the first category is based on battery capacity. Han et al. [7] proposed a method of genetic algorithm (GA) to identify the battery capacity in battery cycle life model under two different test temperatures. Wu et al. [8] proposed a novel SOH estimation method using group method of data handling. Ouyang et al. [9] used a novel capacity degradation model that can simulate the degradation dynamics under varying working conditions for large-format lithium-ion batteries. The experimental results based on accelerated aging test verified the proposed model can capture the degradation behavior well. Kim et al. [10] used the approach of an adaptive discrete-time sliding-mode observer (ADSMO) for terminal

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and open circuit voltage (OCV) estimation, and the maximum capacity of the cell was estimated to predict battery SOH. A smart battery coulomb counting method [11] was employed in SOH estimation by predicting battery maximum releasable capacity. Besides, the methods of Gaussian process (GP) [12] regression, support vector regression [13], slope analysis [14], multi-time-scale observer [15] and the least square method [16] were also used in battery SOH estimation. The second category is based on battery impedance: Eddahech et al. [17] proposed models of a simple and linear-recursive battery state of charge (SOC) and voltage, and the parameters of battery impedance model parameters were identified by a recursive least squared algorithm. A special purpose model [18] deduced from an equivalent circuit was also proposed in the battery SOH estimation by monitoring the increase of the internal resistance. Zenati et al. [19] analyzed the battery aging performance under different SOC and temperature, and the electrochemical impedance spectroscopy (EIS) test results were applied to estimate SOH. Eddahech et al. [20] used the approach of recurrent neural networks (RNN) to predict the battery SOH by modeling a high-energy-density lithium-ion cell based on EIS measurement. Yuan et al. [21] presented an offline SOH estimation based on charge transfer resistance for high-power lithium-ion batteries. The method of the mean entropy and relevance vector machine [22] was also used in battery resistance estimation to predict SOH. The final category is based on battery charge/discharge curve. Guo et al. [23] provided an adaptive transformation of charging curves at different stages of life to estimate SOH by analyzing the battery capacity fade. Feng et al. [24] used the method of probability density function for predicting the SOH by analyzing the battery charge/discharge curve.

These methods can estimate the battery SOH with high accuracy. Unfortunately, most of these methods are only applied in single cell and not suitable for battery pack. In general, the battery pack consists of a lot of single cells. The differences in cells' characteristics and working temperature make the method of battery pack SOH different from single cell. Besides, the appearance of cells uniformity makes the way of SOH estimation difficult. Moreover, above mentioned methods are also limited by the computational ability of BMS and not easy to be employed in real application. To realize the battery SOH estimation with high accuracy, a novel definition of battery SOH is proposed to reflect the changes of battery characteristics.

In this paper, the battery pack SOH is defined as the change of battery pack maximum energy storage. It contains all the cells' information including battery capacity, the relationship between SOC and OCV, and battery inconsistency. Furthermore, battery pack maximum energy storage can reflect the driving mileage of battery system more directly than SOC. To estimate the battery SOH with high accuracy, the method of particle swarm optimization-genetic algorithm (PSO-GA) is applied in identifying the battery parameters. Then, the method of particle filter (PF) is employed in battery SOC and OCV estimation to avoid the influence of measurement noise and current drift. Moreover, the method of recursive least square (RLS) is used to update the battery capacity based on the accuracy estimation of battery SOC. Finally, the proposed method is verified by the profiles of the New European Driving Cycle (NEDC) [25] and dynamic profiles.

This paper is organized as follows. In section 2, the definition of battery pack SOH is proposed. In section 3, the battery pack model is introduced. Besides, the proposed method is also presented in this section. Section 4 describes the test bench and analyzes the experimental results. Section 5 gives the conclusions.

2. The definition of battery pack state of health

2.1. Battery pack remaining discharge energy

The battery pack remaining discharge energy is the battery discharge cumulative energy from the current state to the state that one of the cells in the battery pack reaches the lower cutoff voltage [26]- [27]. For a steady battery pack, the battery pack remaining discharge energy can be formulated as follows:

$$E_{PRDE} = \sum_{i=1}^{n} \int_{SOC_{t_1}^{i}}^{SOC_t^{i}} C^i U_{OCV}^{i}(SOC)\mathrm{d}SOC \tag{1}$$

where E_{PRDE} is the battery pack remaining discharge energy, C^i is the maximum available capacity of the ith battery, n is the number of cells in the battery pack connected in series, SOC_t^i is the SOC of the ith cell at time t, and $SOC_{t_1}^i$ is the SOC of the ith battery at time t_1 when one of the cells in the battery pack reaches the lower cutoff voltage. U_{OCV}^i is the OCV of the ith series cell.

2.2. Battery pack maximum charge energy

The battery pack maximum charge energy can be defined as the charge energy form the battery pack current state to the state that the cell in the battery pack reaches the upper cutoff voltage as shown in Eq. (2).

$$E_{PMCE} = \sum_{i=1}^{n} \int_{SOC_t^{i}}^{SOC_{t2}^{i}} C^i U_{OCV}^{i}(SOC)\mathrm{d}SOC \tag{2}$$

where E_{PMCE} is the battery pack maximum charge energy, and $SOC_{t_2}^i$ is the SOC of the ith battery at time t_2 when one of the cells in the battery pack reaches the upper cutoff voltage.

2.3. Battery pack state of health

Based on above analysis, the battery pack maximum energy storage can be expressed as the sum of the remaining discharge energy and the maximum charge energy shown as follows:

$$E_{PMES} = E_{PMCE} + E_{PRDE} \tag{3}$$

where E_{PMES} is the battery pack maximum energy storage.

The battery pack state of health can be defined in Eq (4).

$$SOH = \frac{E_{PMSE,bat}}{E_{PMSE,0}} \tag{4}$$

where SOH is the battery pack state of health, $E_{PMES,bat}$ is the battery pack present maximum energy storage, $E_{PMES,0}$ is the battery pack maximum energy storage when the battery is fresh.

3. Battery pack model and parameters identification

3.1. Battery pack model

As shown in Eqs. (1)–(3), to acquire the battery pack energy storage, SOC and battery maximum available capacity are needed. However, the battery discharge/charge characteristics are nonlinear due to the complex physical and chemical reactions, which make the battery SOC and capacity estimation difficult. Therefore, a battery pack model is needed to reflect the battery characteristics. There exits many methods in battery modeling [1,28-30]. A common used model [30] among them is shown in Fig. 1, which contains n open circuit voltages U_{OCV}^i, n resistors R_o^i and n RC networks.

The electrical behavior of battery pack model can be described as:

$$\begin{cases} \dot{U}_p^i = -\frac{1}{R_p^i C_p^i} U_p^i - \frac{1}{C_p^i} I_b \\ U_t^i = U_{OCV}^i + R_o^i I_b - U_p^i \end{cases} \quad (i = 1,2,\ldots,n) \tag{5}$$

where U_t^i is the ith series cell terminal voltage, U_p^i represents the terminal voltage of RC network, R_o^i is the ith series cell electrical resistance, U_{OCV}^i is the OCV of the ith series cell, n is the number of battery in the battery pack connected in series. The OCV can be achieved based on the combined electrochemical model [31] as shown in Eq. (6).