Establishment of an Online Design for Estimation of Available State of Charge and Fault Detection through Simulation of the Equivalent Model of LiMn$_2$O$_4$ Battery

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Abstract. Lithium-ion battery is used as the main energy storage in electric vehicles (EV) because of its large capacity and high power density. The battery management system (BMS) of EVs is important. The traditional BMS simply measures battery voltage and current. Most battery damages are caused by failure of error detection by the sensors or actuators of the battery. Therefore, the system requires accurate fault detection on the battery. An equivalent circuit model should be established precisely to monitor battery charge and open circuit voltage. In this study, equivalent circuit models of LiMn$_2$O$_4$ batteries were implemented in the MATLAB Simulink model to determine voltage and current limit. Simulation results indicate the accurate fault detection of the model.

Introduction

Electric vehicles (EV) are environment friendly because they do not emit harmful gasses or pollutants. Lithium-ion batteries are widely used as energy storage because they exhibit high energy and power density without memory effect [1]. An effective battery management system (BMS) is needed to ensure the safe and efficient operation of battery systems under fleeting and even demanding conditions [2]. The BMS can monitor the status of a battery and detect output current, voltage, and temperature [3]. The primary functions of the BMS include accurate estimation of state of charge (SOC) and identification of key parameters.

The SOC observer with periodic parameter updates outperforms that without real-time parameter renewal [4]. Therefore, real-time determination of battery parameters is essential for credible SOC estimation. Studies have focused on estimation of SOC and the underlying model parameters [5, 6].

One of the most critical steps for developing battery prognostics solutions is to establish a battery model that enables the automaker to simulate battery behavior and interpret battery issues in a form understandable by users and designers.

Battery is a main component that affects the successful operation of EVs [7]. The proper operation of batteries must be ensured when working. To realize this goal, we need a prevention or detection feature in the BMS for the operation of EVs [8].

In this study, a fault detection system is designed to monitor battery parameters. The equivalent model of the battery is established, and fault detection when the battery incurs all possible faults is simulated using MATLAB Simulink.

Analysis and Modeling of Lithium-Ion Battery Parameters

In this study, LiMn$_2$O$_4$ batteries are measured. The LiMn$_2$O$_4$ cathode material exhibits low cost, safe operation, and low-temperature properties. However, the material is unstable and easily decomposes. This material is mainly used in large and medium-type batteries, such as power batteries.

Table 1 shows some basic parameters of the experimental battery.
Table 1. Basic parameters of the experimental battery.

| Parameter                        | Value     |
|----------------------------------|-----------|
| Rated capacity [Ah]              | 30        |
| Nominal voltage [V]              | 3.6       |
| Internal impedance [mΩ]          | 1.12      |
| Cutoff voltage [V]               | 4.25      |
| Minimum discharge voltage [V]    | 2.4       |
| Maximum discharge current [A]    | 120 [4C]  |
| Fast-charge current [A]          | 60 [2C]   |
| Working temperature [°C]         | −20–55    |
| Cycle life                       | ≥1500     |

This study used a Thevenin model with first-order RC circuit. As shown in Figure 1, the circuit is mainly composed of three parts including open-circuit voltage $U_{OC}$, internal resistance, and equivalent capacitances. The internal resistances include ohmic resistance $R_O$ and polarization resistance $R_p$. The equivalent capacitance $C_p$ is used to describe transient responses during charging and discharging. $U_p$ is the voltage across $C_p$, and $I$ is the charging current. The electrical behavior of the Thevenin model can be expressed by Equations (1) and (2).

$$U_L = U_{OC} + IR_O + U_p. \quad (1)$$

$$\dot{U}_p = \frac{I}{C_p} - \frac{U_p}{R_pC_p}. \quad (2)$$

The output can be obtained from the state space models and includes SOC, Open Circuit Voltage (OCV), $U_d$ (voltage difference between the terminal voltage and voltage OCV), and $U_p$.

In this study, modeling parameters must be determined first. In the experiment, the battery is charged and discharged several times by pulse current, and voltage data are recorded.

During pulse charging and discharging, in addition to changes caused by $R_O$, $U_L$ varies because of the polarization effect [9]. The equivalent circuit of the polarization effect is expressed by the $R_pC_p$ parallel circuit. In the analysis of the polarization effect of lithium battery, continuous values of various parameters of the battery can be obtained using the interpolation algorithm in MATLAB because the polarization parameters are determined from a different SOC. The parameters obtained when the SOC is 50% are shown in Table 2. The experimental temperature was maintained at 25 °C. The polarization parameters under different SOCs were then measured.

Table 2. Polarization parameters in charging state.

| SOC [%] | $C_p$ [F] | $R_p$ [mΩ] |
|---------|-----------|------------|
| 50      | 956.4     | 10.5       |

Figure 1. Thevenin Equivalent Circuit Model.
Design of Fault Detection System

Fault detection determines faults present in a system and time of detection and identify malfunctions in real time as soon and as surely as possible [10].

Figure 2 shows the block diagram of the designed system. By measuring various parameters, including the current voltage and temperature of the battery, the system provides information on the state of the battery and detects the error.

Figure 2. Block diagram of the fault detection system.

Simulation was performed in MATLAB Simulink to determine the working conditions of the system. To simplify the simulation process, we assume a constant temperature of 25 °C and a SOC of 50%.

Figure 3 shows the fault detection system comprising two inputs, namely, current and voltage, which are related to battery modeling based on Thevenin’s equivalent circuit models. Battery modeling employs parameters R0, Rp, and Cp to measure the outputs SOC, OCV, and Vd. The output is detected, and the result is recorded in real time. This research focuses on simulation of four outputs (overcurrent, overvoltage, SOC, and OCV fault detection) to determine the condition of the battery especially under fault condition. When the input voltage and current are given, the system can detect errors at the first attempt.

Figure 3. Simulink model of simulation.
Current and voltage data are directly obtained from sensor readings on the battery. Based on the characteristics of the battery, the voltage must have a maximum value of 4.25 V and a minimum value of 2.4 V to ensure the safety of the battery. The safe current range of the battery should be between 120 A and 80 A.

The SOC of this model is calculated by Coulomb counting method. We determine the SOC to be 100% when the voltage reaches the highest maximum value of 4.25 V or 0% for the minimum threshold voltage of 2.4 V. OCV is obtained by model simulation according to Equations (1) and (2). The reasonable range is within 2.4 V and 4.25 V. The simulation results are shown in the following section.

**Simulation Results and Analysis**

Voltage and current are added as inputs to the fault detection modeling system to simulate the error status of the battery. Current and voltage signals are assigned with some special values to simulate the error state of the battery pack.

![Figure 4](image)

Figure 4. (a) Input current and (b) current fault detection.

Figure 4(a) shows the input current curve. The output detection is considered to be under the safe condition when the current is still in the operation area. As shown in Figure 4(b), when the current reaches 80 A, it causes a fault, and the current detection module output takes a value of 1. If no error occurs, then the detector remains 0.

Figure 5(a) shows the input voltage curve. The voltage varies from 1.4 V to 4.9 V. When the voltage becomes greater than 4.25 V or less than 2.4 V, the detector output value is 1, indicating that the battery is overvoltage or undervoltage.

![Figure 5](image)

Figure 5. (a) Input voltage and (b) voltage fault detection.
The OCV has a maximum value of 4.25 V and a minimum value of 2.4 V, which are obtained based on the experimental data on the battery before Simulink modeling and fault detection on the battery. Figure 6 shows the simulation results.

The SOC of this model is calculated by Coulomb counting method. As shown in Figure 7, a fault is formed even if the SOC is equal to 1 and has a maximum value of 100% SOC. Hence, when the SOC fault detector reaches a value of 1, the battery is fully charged or simply runs out of electricity.

Conclusion

In this study, the equivalent model of the battery is established, and parameters used in the simulation of LiMn$_2$O$_4$ battery are determined experimentally. Fault detection simulation of voltage and current OCV and SOC are conducted using the given voltage and current values. The detected error can be sent to the user and the manufacturer; as such, the user can grasp the situation of the vehicle in time and the manufacturer can determine the shortcomings of the product from the large amount of data. Furthermore, we hope that the BMS can deal with the error in the first time that it detects a fault. For example, the power supply can be cut off in time when overvoltage or overcurrent fault occurs.

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