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Summary

This is abstract.This section should describe what problem the paper solves, what methods are applied, what results are obtained and summarize them.

This is the second line abstract.And if you look carefully you can see that the spacing within and between paragraphs is different, which facilitates our reading in paragraphs.

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Keywords: Fighting Wildfires; Multi-Objective Optimization; Poisson Distribution; Tabu Search Algorithm; Sensitivity Analysis

Contents

1 Ideal Battery

1.1 Assumptions

To consider an simplist ideal battery model, the following assumptions are made:

- The battery is kept at a constant environment, so the temperature effects are neglected.
- The battery has no energy loss during charging and discharging.
- The battery has infinite cycle life, so the degradation effects are neglected and all the parameters are constant.
- The Open Circuit Voltage (OCV) is only related to the SoC, so we can express the SoC as a functionof U_{OC}:

$$SoC = f(U_{OC}) \tag{1}$$

in which $f(\cdot)$ can be obtained through curve fitting based on experimental data.

- The battery behavior is same for charging and discharging. For smartphones, which mostly use LiCoO$_2$ batteries that has little or no hysteresis, this assumption is reasonable.

1.2 Thevenin Model

A Li-ion battery system can be extremely complex, involving electrochemical, thermal and mechanical processes. However, for system-level studies, an equivalent circuit model is often used to represent the battery behavior. The Thevenin model is a widely used equivalent circuit model that captures the dynamic response of the battery voltage during charge and discharge cycles. The model is described as follows:

The relationship between U_{OC} and other parameters in the Thevenin model can be expressed with Kirchhoff's laws:

$$U_{OC} = U_t + IR_0 + U_1 + U_2 \tag{2}$$

in which U_t is the terminal voltage.

For U_1, U_2 we have:

$$I = C_1 \frac{\mathrm{d}U_1}{\mathrm{d}t} + \frac{U_1}{R_1} = C_2 \frac{\mathrm{d}U_2}{\mathrm{d}t} + \frac{U_2}{R_2} \tag{3}$$

Differentiateing the SoC's definition with respect to time, we get:

$$\frac{\mathrm{d}(SoC)}{\mathrm{d}t} = -\frac{I}{Q_{max}} \tag{4}$$

where Q_{max} is the maximum capacity of the battery.

Combining the above equations, we can derive the complete Thevenin model in matrix form:

$$\frac{\mathrm{d}}{\mathrm{d}t} \begin{bmatrix} SoC \\ U_1 \\ U_2 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -\frac{1}{R_1 C_1} & 0 \\ 0 & 0 & -\frac{1}{R_2 C_2} \end{bmatrix} \begin{bmatrix} SoC \\ U_1 \\ U_2 \end{bmatrix} + \begin{bmatrix} -\frac{1}{Q_{max}} \\ \frac{1}{C_1} \\ \frac{1}{C_2} \end{bmatrix} I \tag{5}$$

where $R_0, R_1, R_2, C_1, C_2, Q_{max}$ are the model parameters that need to be estimated.

1.3   Parameter Estimation

The Hybrid Pulse Power Characterization (HPPC) test is commonly used for this purpose. The test is conducted with steps as follows:

1. The battery is first fully charged to 100% SoC in ways the manufacturer recommends.

2. After resting for a certain period(e.g. 1 hour), the battery is discharged with a constant current pulse (e.g., $0.5C$) for a short duration (e.g., $10s$). The voltage response is recorded.

3. Then discharge the battery to another selected SoC point (e.g., 90%).

4. Repeat steps 2 and 3 until the battery reaches a low SoC point (e.g., 10%) or the maximum discharge limit the manufacturer specifies.

5. If needed, repeat similar steps for charging pulses.

With HPPC data, the model parameters can be estimated through curve fitting techniques. The process are as follows:

- **Estimate R_0**: The instantaneous voltage drop at the start of each pulse can be used to estimate the internal resistance R_0, at which point the capacitive effects are negligible.

$$R_0 = \frac{\Delta U_{instant}}{I_{pulse}} \tag{6}$$

- **Estimate R_1, C_1 and R_2, C_2**: Solve the polarization equation (3), we can get the polarization voltage response:

$$U_{polar} = IR + (U_{init} - IR)e^{-\frac{t}{RC}} \tag{7}$$

where U_{init} is the voltage at the start of the pulse.
Without loss of generality, let $C_1 \leq C_2$, so that the faster electrochemical processes are represented by R_1, C_1 and the slower concentration polarization effects are represented by R_2, C_2. Then substitute them into (2), we have:

$$U_t = U_{OC} - I(R_0 + R_1 + R_2) - (U_{1,init} - IR_1)e^{-\frac{t}{R_1C_1}} - (U_{2,init} - IR_2)e^{-\frac{t}{R_2C_2}} \tag{8}$$

By least squares fitting of (8) to the voltage response data during each pulse, we can estimate the values of R_1, C_1 and R_2, C_2 at different SoC points.
- **Estimate Q_{max}**: The maximum capacity Q_{max} can be estimated by integrating the current over the full discharge cycle:

$$Q_{max} = \int_{t_0}^{t_f} I(t)\mathrm{d}t \tag{9}$$

where t_0 and t_f are the start and end times of the discharge cycle.
Most of the time this value is provided by the manufacturer.

We use a Samsung INR21700 30T 3Ah Li-ion Battery Dataset to demonstrate the parameter estimation process. The fitting result are shown as follows:

1.4 Simulations

1.5 Result