State-of-Health Estimation of Lithium-ion Battery for Enhanced Electric Vehicle Safety

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***Abstract*—Lithium-ion batteries (LIBs) are considered as the heart of Electric Vehicles (EVs), but their performance degrades over time, affecting vehicle safety and performance. Accurately estimating the battery's State of Health (SOH) is crucial for ensuring optimal battery performance, safety, and longevity. However, current SOH estimation methods are often complex, data-intensive, and unsuitable for real-time embedded use. This project proposes a simple, computationally efficient, and battery management system (BMS)-compatible technique for SOH estimation using voltage-time profiles during constant current charging. The method focuses on extracting two key features — time taken to reach 4.0V and the slope between 3.8V–4.0V during constant current charging of the battery, and applies support vector regression (SVR) function to estimate SOH. The results show accurate prediction with minimal error, validating its real-time suitability for embedded BMSs.**

I. Introduction

The global shift toward Electric Vehicles (EVs) is a critical step in combating climate change and reducing carbon emissions. LIB are the dominant energy storage solution in EVs due to their high energy density and cycle life. However, battery degradation caused by aging, usage cycles, and temperature affects its performance and safety.

SOH estimation allows EV owners and manufacturers to monitor battery condition, optimize usage, and prevent catastrophic failures such as thermal runaway. In literature researchers have developed various SOH estimation techniques

- **Electrochemical model-based methods**: LIB internal behavior is simulated using intricate, physics-based electrochemical models. Ion diffusion, charge transfer, and concentration gradients within the electrodes and electrolyte are examples of electrochemical reactions that are captured by these models. The most widely utilized of these is the pseudo-two-dimensional (P2D) model because of its excellent accuracy in forecasting SOH, temperature, and voltage under a range of operating conditions. But these models' accuracy comes at a price: they require a lot of computing power. They call for the solution of intricate differential equations as well as extremely accurate battery parameters like material characteristics, diffusion coefficients, and reaction rates. Due to restricted processing resources, it is nearly impossible to implement such models in real-time on embedded devices like STM32 [1, 4].
- **Machine Learning-based methods**: Machine learning (ML) techniques have become more and more popular for determining LIB SOH. Without requiring any understanding of battery chemistry, these methods automatically identify patterns using battery data, including voltage, current, temperature, and charge/discharge cycles. For this, algorithms like Gaussian Process Regression (GPR), Random Forests, Support Vector Machines (SVM), and Artificial Neural Networks (ANNs) are frequently employed. The fact that machine learning techniques are data-driven and can handle big datasets gathered from battery usage logs is one of their greatest benefits. They do, however, need a significant amount of labeled training data that covers all battery conditions, including varying temperatures and SOH levels. The process of gathering data can be costly and time-consuming [6, 7].
- **Empirical methods**: For State of Health (SOH) estimates, empirical and model-based approaches are frequently employed because of their ease of use, minimal processing requirements, and compatibility with real-time data. These methods rely on electrical models like the Equivalent Circuit Model (ECM), which replicates the battery using resistor, capacitor, and voltage source combinations, as well as on trends that can be seen. The 2RC model, which accurately depicts the battery voltage response during charging and discharging, is a popular option. Instead of using internal chemical characteristics, these techniques use external data like time, voltage, and current [7, 8].

Based on the extensive literature survey, the key research gaps identified are as follows – most existing methods are either too complex, require internal battery parameters or not compatible with embedded BMS. Hence, there is a need for a simpler, real-time, and externally/empirically measurable method.

To address the aforementioned research gaps, this research study focuses on the development of a simple feature extraction-based SOH estimation technique, which has following advantages:

- Computationally lightweight
- No requirement of internal parameters for the estimation
- Can be implemented on embedded hardware like BMS in EVs

II. Methodology

A. Model Development

Numerous studies concentrate on the modeling aspect of LIBs. a) physics-based models, b) equivalent circuit models, and c) data-driven models are the three main types of LIB models. An equivalent circuit model (ECM) of second order (2-RC) is used in this study to simulate the electrical performance of the battery. The Simulink model of the 2-RC model is displayed in Fig. 1. The model primarily includes a dependent voltage source called open-circuit voltage (V_{OCV}), which represents the LIB cell's no load voltage. It is represented as a nonlinear function of state of charge (SOC). The series resistance (R_{esr}) represents the electrolyte resistance. Two parallel RC branches reflect the LIB cell's activation and concentration polarization events.

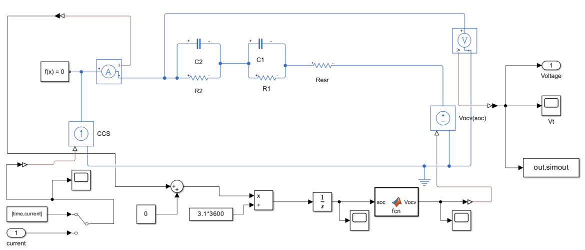

Fig. 1. Second-order equivalent circuit model of a lithium-ion battery cell

B. Model Parameter Estimation

To make the circuit model behave as a real LIB, it is essential to identify the model parameters. For this purpose, parameter estimation was performed using an experimental pulse cycling method, as illustrated in Fig. 2. A LIB is cycled with a pulse current of 1C-rate with pulse width of 6 minutes and rest duration of 2 hours. Next, with the help of least-square estimation technique, the model parameters are identified, the detail description of the method is presented in [9].

The estimated parameter values are as follows:

- $R_{\text{esr}} = 0.0414\ \Omega$
- $R_1 = 0.0292\ \Omega$
- $R_2 = 0.0154\ \Omega$
- $C_1 = 1.0984 \times 10^3$ F
- $C_2 = 3.8849 \times 10^4$ F

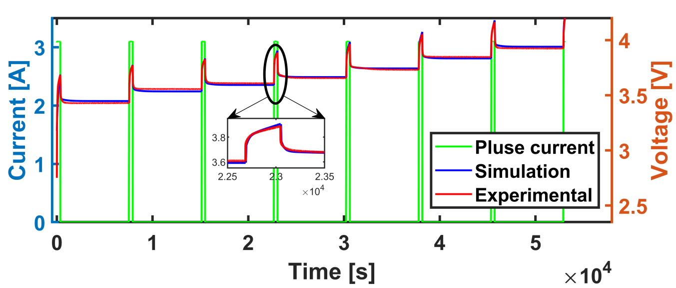

Fig. 2. Pulse current (1C-rate) and voltage profiles of LIBs

After the complete model development of the LIB, the battery is excited with a constant current charging profile of C/2-rate. The resulted voltage-time data was obtained at 100% State of Health (SOH) of the battery, as shown in Fig. 3.

However, it was observed from [3] that as SOH decreases, the voltage-time curve shifts upward, and the battery reaches its upper cutoff voltage in shorter time, as depicted in Fig. 4.

This study observers the changes in the voltage vs. time profiles of LIBs at different SOH levels (shown in Fig. 4),

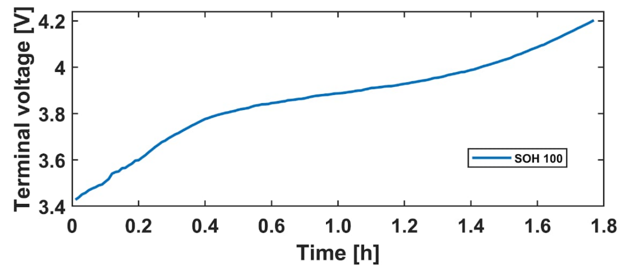

Fig. 3. Voltage-Time profile during constant current charging at 100% SOH of LIB

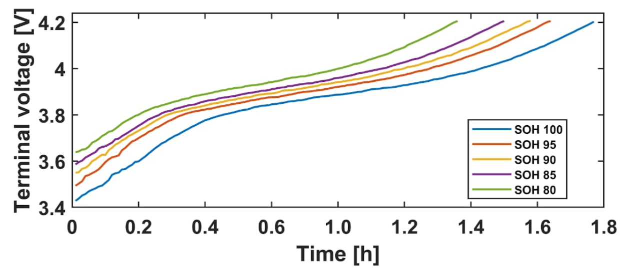

Fig. 4. Voltage-time profiles during constant current charging at different SOH Levels of LIBs [3]

and estimate the SOH of a LIB with unknown voltage vs. time profile with the help of feature extraction.

III. SOH Estimation Based on Feature Extraction

This section presents two main extracted features based on which the SOH estimation techniques is developed, and then it shows the algorithm.

A. Data Collection

Known charging profile data (voltage vs. time) for SOH levels of 100%, 95%, 90%, 85%, and 80% were extracted from [3], and shown in Fig. 4.

Two key features were analyzed, as it is illustrated in Fig. 5:

1) T_{4V}: Time taken to reach 4.0 V during constant current (C/2-rate) charging.
2) Slope: Rate of change of voltage with respect to time in the region between 3.8 V and 4.0 V.

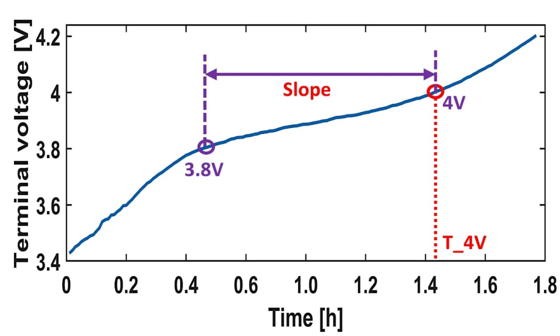

Fig. 5. Representation of Feature Extraction

The known extracted features were arranged into MATLAB arrays for training, as shown below:

```
X = [0.002571 1.44 ; % SOH 100%
    0.002678 1.26 ; % SOH 95%
    0.002812 1.17 ; % SOH 90%
    0.002902 1.10 ; % SOH 85%
    0.003298 0.94 ]; % SOH 80%

Y = [100; 95; 90; 85; 80];
```

Here, each row in matrix X represents a pair of features: *Slope* and T_{4V}, while vector Y contains the corresponding SOH values.

B. MATLAB Code Development

A complete MATLAB script was developed to automate the following tasks:

- Feature extraction from all known voltage-time datasets
- Training the Support Vector Regression (SVR) model
- Predicting SOH for an unknown voltage-time dataset

IV. Key Steps from the Code

A. Feature Extraction Loop for Known Profiles

```
for i = 1:length(soh_levels)
  % Extract slope and T_4v from each voltage-
      time profile
  X = [X; slope, T_4v];
  Y = [Y; soh_levels(i)];
end
```

B. Train SVR Model

```
mdl = fitrsvm(X, Y, 'KernelFunction', 'rbf', '
    Standardize', true);
```

C. Predict SOH of Unknown Profile

```
predicted_soh = predict(mdl, [slope_u, T_4v_u
    ]);
```

This approach enabled SOH estimation without relying on internal model parameters such as resistors and capacitors, making it simpler and more suitable for integration into BMS.

V. Results Obtained

The developed regression model was tested with unknown test cases. The results are presented in Table I.

TABLE I
SVR Model Prediction Results

Case	Slope (V/s)	T_{4V} (h)	Predicted SOH (%)	Actual SOH (%)	Abs. Error (%)
CASE 1	0.002919	1.14	88.06	87–89	1.22, 1.06
CASE 2	0.002654	1.36	99.10	98–100	1.12, 0.90

The absolute percentage error remained under 1.2%, indicating strong predictive accuracy of the SVR model using just two features: the slope and the time taken to reach 4.0V during constant current charging.

VI. Conclusion

The proposed method is simple, accurate, and suitable for real-time implementation. It requires only voltage-time data, eliminating the need for internal battery parameters. This approach is also compatible with embedded BMS in electric vehicles (EVs).

VII. Future Scope

- Testing with real experimental charging data.
- Extending the method to include temperature compensation.
- Deployment in an STM32-based plug-and-play IoT system.

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