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High Accuracy internal temperature estimation of high-capacity lithium-ion batteries across various SOC and SOH using electrochemical impedance spectroscopy

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ABSTRACT

Temperature represents a significant obstacle to the fast charging capability of batteries. This study presents the internal temperature estimation of commercially available high-capacity pouch lithium-ion batteries across various states of charge (SOC) and state of health (SOH) using features extracted via electrochemical impedance measurements. Sensitivity analysis in conjunction with Pearson correlation coefficient (PCC) analysis is conducted on the electrochemical impedance spectroscopy (EIS) data, and the phase part of the EIS is used to create a temperature model that is highly sensitive to temperature and independent of the SOC and SOH, hence increasing the general applicability of the estimation in the battery's entire life span. The model demonstrates a high accuracy with RMSE less than 0.8 ℃ in predicting the internal temperature.

1. Introduction

Lithium-ion batteries (LIBs) have gained widespread attention and have become the dominant power source in their applications in the automotive industry. Customer demands for fast charging/discharge at higher rates, especially for high-capacity LIBs, can result in potential thermal issues. Despite their increasing market penetration, the widespread adoption of electric mobilities continues to face technological bottlenecks associated with thermal issues in LIBs [1]. This study uses EIS measurements to present the internal temperature estimation of high-capacity pouch lithium-ion batteries across various SOCs and SOHs. This method uses features independent of both SOC and SOH, increasing the accuracy and general applicability of the estimation of the internal temperature.

2. Temperature estimation methodology

Owing to the influence of temperature on electrochemical reactions occurring within batteries, EIS undergoes variation with fluctuations in battery temperature. The EIS-based state of temperature (SOT) estimation is often based on the temperature dependency on the battery impedance [2]. Because battery impedance is influenced by the SOC and SOH of the battery, uncertainties are likely to affect SOT estimation, potentially resulting in heightened estimation errors. Hence, it is crucial to thoroughly examine the EIS outcomes and identify an ideal frequency or frequency range wherein specific impedance characteristics are sensitive to battery temperature while remaining unaffected by battery SOC and SOH. A 70 Ah pouch nickel manganese cobalt oxide (NMC) is used for analysis in this study. The EIS temperature was measured from 0 to 60 ℃ with a 5 percent increment. The SOC-EIS test was performed at 20% intervals, from 100% to 0%. Each EIS was taken after 3 hours of rest for the battery to reach electrical equilibrium. The battery was cycled at a rate of 0.1 C (7 A). EIS was measured every 50 cycles to obtain the SOH data.

2.1 EIS temperature analysis

The reduction in temperature corresponds to an increase in the magnitude of the impedance spectra, indicating an electrochemical action, as shown in Fig. 1(a). The resulting EIS data was meticulously analyzed to identify a single frequency point that fulfills three criteria: (1) Demonstrates a strong correlation with temperature. (2) Remains unaffected by battery SOC and SOH variations, ensuring temperature prediction regardless of charge level or degradation state. (3) Exhibits high sensitivity to temperature changes. The sensitivity of the phase and magnitude components to temperature is shown in Fig. 1(b) and (c), respectively.

2.2 Identifying optimal frequency for SOT estimation

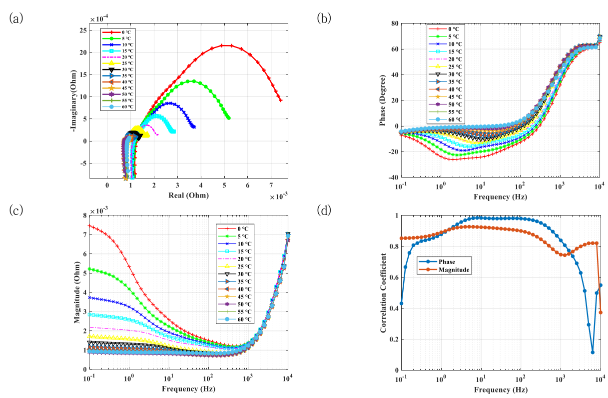

Fig. 1: (a) EIS Nyquist plots with various temperatures, (b) Phase change with temperature, (c) Magnitude change with temperature, (d) PCC of Phase and Magnitude components of the EIS with temperature

The PCC in Eq. (1) is used to evaluate the relationship between the EIS parameters and temperatures ranging from 0 to 60 ℃.

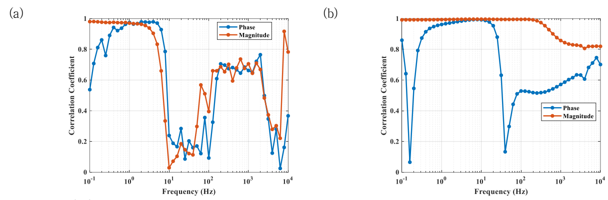

Fig. 2: (a) Correlation of Phase and Magnitude components of the EIS with SOC, (b) Correlation of Phase and Magnitude components of the EIS with SOH

$$R = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{1}$$

where x and y are random variables. The variables x_i, and y_i represent i-indexed individual sample values with means given as $\bar{x}$ and $\bar{y}$, respectively. The variable n represents the size of the tested data.

Examining the correlation between phase and temperature across all the measured frequencies reveals that frequencies within the range of 5Hz to 160Hz exhibit PCC values exceeding 0.97. Similarly, frequencies ranging from 1.5 Hz to 80 Hz demonstrate correlation coefficients greater than 0.90 for magnitude and temperature correlation. The correlation results are shown in Fig.1(d). The correlation of the phase and magnitude components and SOC at various stages of battery degradation is conducted as shown in Fig. 2 (a). The results generally depict that SOC has a relatively lower impact on the magnitude and phase parts of the EIS measurements at frequencies between 100 Hz and 10 Hz. Further correlation analysis is performed to ascertain the correlation of the EIS components with the battery aging. From Fig. 2 (b), the magnitude component of the EIS is highly dependent on the battery SOH at all frequencies, while the phase shows a correlation of less than 0.15 at 40 Hz frequency. With these analyses done, the phase component at 40 Hz was chosen as the optimal frequency to predict the temperature. The magnitude component was ignored because of its high dependence on the SOH.

$$T_{est} = a\varphi + b \tag{2}$$

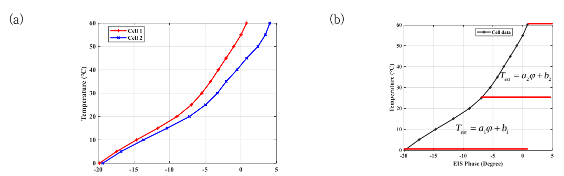

Fig. 3:(a) The change of the EIS phase with temperature change of the two cells, (b) Double linear regression model

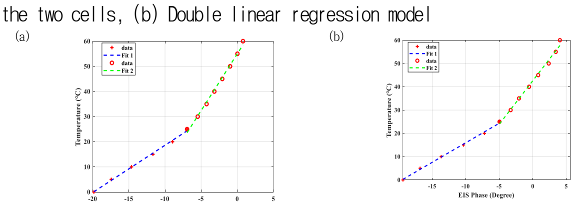

Fig. 4; (a) Double linear fitting of cell 1 (b) Double linear Double linear fitting of cell 2

2.3 Temperature Estimation Model

The change of the EIS phase with temperature change is shown in Fig. 3 (a). The temperature curve has two different gradients. Two different fits allow us to capture different parts of the data more accurately (0 to 25 ℃ and 25 to 60 ℃) as shown in Fig. 3 (b). A linear regression model is used to relate the phase component at 40 Hz to the temperature in Eq. 2., where T_{est} represents the estimated temperature, φ indicates the phase component and a and b denotes the gradient and intercept, respectively.

3. Results and discussions

Two different cells were examined to confirm the temperature estimation's accuracy. The predictions of the temperature of the cells resulted in a good root mean square error of less than 0.8 ℃. The linear fitting results of the phase part of the impedance at 40 Hz are shown in Fig.4. The calibration coefficient of each cell is shown in Table 1. Where a_1 and a_2 are the gradients and b_1 and b_2 are the intercepts of the first and second fitting, respectively.

Table 1. Model coefficients and performance

Cell No.	a_1	b_1	a_2	b_2	RMSE(℃)
1	1.88	37.38	4.51	54.94	0.64
2	1.67	32.70	3.73	42.55	0.76

4. Conclusions

This work presented a temperature estimation method considering the impact of battery SOC and SOH utilizing EIS. It is deduced that the phase component of the EIS at 40 Hz is best for temperature estimation. The model estimates the temperature with an RMSE of less than 0.8 ℃. Future work will develop a temperature model during the battery operation.

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