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Electrochemical Sensing-Based Internal Temperature Estimation for Lithium-ion Battery

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ABSTRACT

Acquisition of Lithium-ion battery's (LIB) internal temperature is crucial to ensure the safety of the battery system for electric vehicle (EV), yet the immeasurable nature of it renders this goal as challenging. Approaches based on contact sensing and thermal models are widely investigated, but their realizability and effectiveness still beg for further validation. Methods based on electrochemical sensing are receiving more attention due to their attractive features. However, the largest gap lies in the access to the impedance information for on-vehicle application. Using results derived from the passive electrochemical impedance spectroscopy (EIS) with real driving conditions, this paper presents a thorough solution to obtain the internal temperature of LIB. With the accurate high-frequency part of passive EIS at hand, the internal temperature is estimated by employing the regression relationship between temperature and its corresponding EIS landscape. Independent of models and sensors, the proposed scheme uses the mere electrical measurements of LIB and achieves the internal temperature estimation with refreshing rate of 1Hz. This sensorless scheme can meet the real-time requirements of battery management so that precious time for safety countermeasures to act is saved. The proposal in this paper is expected to supplement the battery management techniques with critical inputs to secure the safer use of EV.

Keywords: Lithium-ion battery, Internal temperature estimation, Spectral analysis, Passive EIS

1. INTRODUCTION

In the pursuit of faster charging and longer driving distance, the working conditions of LIB in EVs are deteriorating, and the temperature rise of the battery is becoming more and more fierce. Use of batteries in specific temperature window, with their safety, performance and longevity properly guaranteed, becomes a tough challenge to deal with [1]. For early avoidance of hazardous outcomes, internal temperature acquisition of LIB becomes a central issue in the field of EV battery management.

To measure the internal temperature of LIB in a more direct way, various novel sensors are planted into the battery [2]. The results of this implantation have higher confidence, and are generally used as a reference for internal temperature estimation. As an invasive procedure, the characteristics of the operated battery generally need extra verification by means of X-ray or performance tests [3]. The modified battery has certain loss in insulation, tightness and performance.

Apart from the direct measurement, many model-based approaches are actively discussed in the open literature. The electro-thermal model is closely investigated in related research, mainly based on the equivalent circuit model (ECM). Based on such a model, a joint estimation framework can be established, where the state of charge (SOC) and the state of function (SOF) are additionally estimated [4]. ECM oversimplifies the working principle of LIB, and in order to pursue higher descriptive accuracy, electrochemical model (EM) is adopted. Due to the more explicit physical significance, the description of thermal characteristics becomes more comprehensive, as with the kinetics within LIB [5]. Although EM is prominent among models in accuracy and descriptive ability, it still remains in laboratory due to its complexity. Besides the gap to application, model-based approaches all have a significant number of parameters. Obtaining these parameters accurately is close to impossible, and inaccurate parameters can also cause numerical instability or significant bias in the results.

As a non-invasive and intuitive method, the use of EIS to estimate the internal temperature stands as a promising solution [6]. EIS is frequently discussed and

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practiced in the field of LIB, and its advantages are becoming more and more recognized by researchers. There is a tight relationship between the impedance behavior of LIB and its internal states. In particular, the influence of temperature on impedance is significant, and such relationship is often utilized in the estimation and diagnosis of the internal temperature [7]. Since this correlation is reflected electrically, EIS is expected to provide a faster update rate for the internal temperature estimation, which can satisfy the real-time requirements in battery management. Without the help of sensors and thermal models, EIS is also deemed as sensorless, or called the electrochemical sensing [8].

All of the above EIS-based approaches achieve satisfactory results, but most of them use offline EIS as original input. For a more practical application, a smaller yet efficient EIS measurement scheme is urged. At present, relevant works are carried out, and there are two typical kinds, namely, the active and passive ways to obtain EIS. Active EIS generates a specific broadband current excitation by modifying the on-board controllers, while passive EIS directly uses the current excitation and voltage response in a moving vehicle. Active EIS involves hardware and software modification of power electronics, and requires good coordination between multiple sub-systems, which manifests as difficult. In contrast, the driving condition is more convenient without the generation of excitations.

In this paper, passive EIS is used to estimate the internal temperature of LIB. Through the specially designed road test, the current excitation of the real vehicle is obtained, and the impedance spectrum is calculated with the excitation. With passive EIS, the internal temperature of the battery is estimated with relatively high real-time performance. This paper completes the whole process from fast EIS acquisition to internal temperature estimation, which can provide references for more effective safety and thermal management of the battery system.

2. METHODS

2.1 Experimental

The acquisition of passive EIS depends on the real conditions from the driving. In order to ease the acquisition and verification, real current excitation on high voltage (HV) network on EV is collected with high precision. By applying the equivalent current excitation to single cell, the voltage response can be obtained, which enables the spectral investigation for a variety of batteries in different states with a given working condition. For these purposes, separate vehicle tests and cell tests are designed.

Vehicle Test The vehicle under test is a GAC Aion Y model. Vehicle tests involve multiple conditions in and around the city. Due to a higher typicality, this paper chooses the city driving conditions in the evening rush-hours for further analysis. The current pulsations on the HV DC bus of EV are recorded in real time during driving. High bandwidth Hall current clamp is selected as the sensor front-end. The data acquisition device digitalizes the output of the sensor, and transmits it to the computer for recording. The current measurements are normalized with the capacity of the battery system on vehicle, and the current curve in C-rate is obtained. A positive value denotes charging.

Cell Test With the current excitation at hand, the cell tests under different states are carried out. Because of the high bandwidth of the excitation, test with traditional charging equipment could introduce great spectral losses. In this paper, a modified electrochemical testbench is used to cover the excitation generation with a bandwidth greater than 2MHz. The batteries under test are placed in a climate chamber and the tests are initiated after the thermal equilibrium is reached at the target temperature. The operation of the battery in actual driving is uniformly simulated, and the current, voltage and surface temperature of the batteries are constantly recorded during the test. Such a test configuration restores the excitation in the real driving and achieves comparability at sample level.

2.2 Passive EIS Acquisition

This paper presents the passive EIS acquisition process as shown in Fig.1.

There are 3 steps to acquire the passive EIS. Length of the analysis window is T_{ana} in second, corresponding to $f_s \cdot T_{ana}$ samples, where f_s is the sampling rate in Hertz. To improve the utilization of the data, samples in the window are updated with a certain overlap ratio of k. The update is carried out in a first-in-first-out fashion by removing the oldest $M = (1-k)\, f_s T_{ana}$ samples and adding the same amount of the latest samples each time.

In the spectral analysis, the typical windowing and fast Fourier transform (FFT) are performed to obtain the original spectrum of current and voltage. Windowing effectively reduces the leakage error of FFT, but often ignores the information at both ends of the window, so the overlap ratio k is necessary. The value of k is generally between 1/2 and 2/3. The smaller k is, the larger the computation of passive EIS is, and the higher the update rate is. Since the current waveform in driving is more of

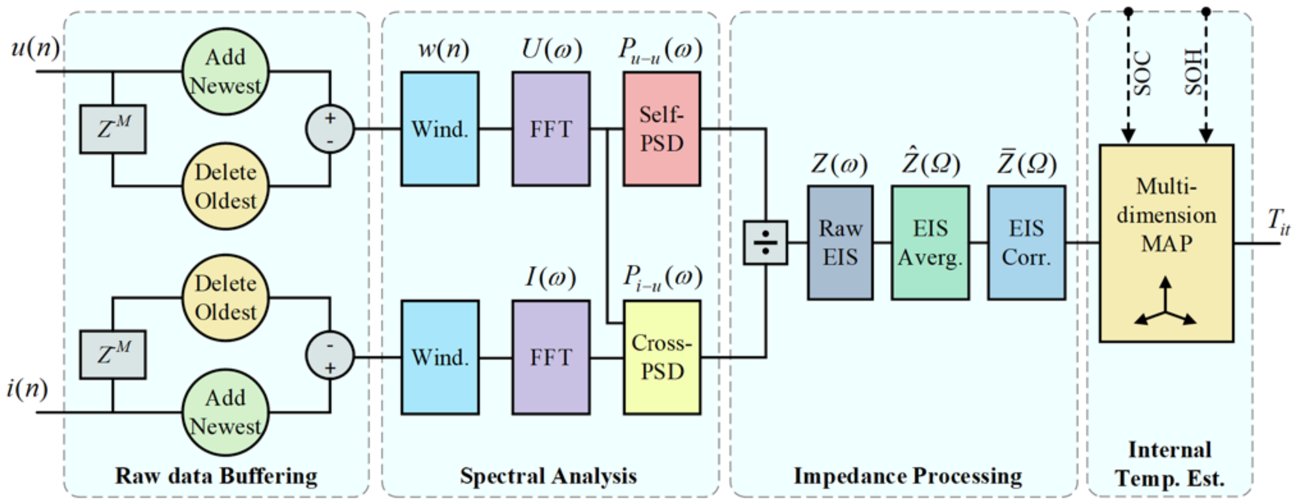

Fig.1 Procedures for acquiring passive EIS and internal temperature

a random signal in nature, a common sinusoidal window function is chosen.

After performing FFT, spectrum $U(\omega)$ and $I(\omega)$ are obtained, where ω is the angular velocity. Since the excitation and response of the battery are generally polluted by the noises, it is necessary to use the power spectrum-based method for processing. If the response signal-to-noise-ratio (SNR) is low, the H1 estimator is generally used to calculate the impedance, while if the excitation SNR is low, the H2 estimator could yield better results. After quantitative evaluation, both SNRs in cell test are at a relatively high level, while that of voltage is even higher. Therefore, H2 estimator is selected for the processing in this paper.

The raw impedances are calculated using Formula (1), which is the H2 estimator.

$$Z(\omega) = P_{u-u}(\omega) / P_{i-u}(\omega) \tag{1}$$

where, P_{u-u} is the self-spectrum density of voltage and P_{i-u} is the cross-spectral density of voltage and current.

Due to the low quality of excitation, the original impedances obtained from driving conditions are far from perfect results as offline EIS, because the power of the random excitation is spread over a wide frequency range, causing inferior SNRs for individual frequencies. This result cannot be utilized effectively and needs to be averaged with a radius Δ around a specific frequency Ω, as in Equation (2).

$$\bar{Z}(\Omega) = \frac{\sum_{(\Omega-\Delta)T_{ana}/2\pi}^{(\Omega+\Delta)T_{ana}/2\pi} \pi Z(\omega)}{\Delta T_{ana}} \tag{2}$$

The impedances of continuous frequencies can also be obtained using formula (2) to gather more clues about the kinetics of LIB.

2.3 Inductance correction

An inductive feature at high frequencies exists for both the offline and the passive EIS, which causes shift of impedance at mid- and high-frequency areas. The removal of inductance by distribution of relaxation time (DRT) transform is a feasible scheme [9]. DRT is a post-processing method for EIS, which can convert the impedances into a form similar to the spectrum. Resolving of DRT requires a specific kernel and solving configuration. Main body of the DRT kernel is generally a number of RC entries in series. The solving of DRT generally relies on the nonlinear fittings in the least square family, and its optimization objective generally incorporates regularization to increase the smoothness of the result.

By solving the DRT of the kernel, the optimal solution of inductance can be obtained at the same time. The inductance correction of EIS can be realized by bringing the distribution function back into the kernel free of inductance. Inductance-corrected passive EIS can be used for subsequent diagnosis of the battery states. Offline EIS tests are also carried out in this paper, and the inductance correction of these data is also performed.

2.4 Estimation of internal temperature

EIS reflects the rapidly varying reactions and kinetics inside a LIB. Such characteristics are specific not only to the chemistry, but also to the battery states. Under different conditions, EIS shows a fickle nature preventing the hidden relationships from being discovered. Although the literatures in Chapter I provide good state estimations by using impedance of a specific frequency or range, these frequencies are inherently contingent. For different batteries or other conditions, their effectiveness could topple. It is viable to characterize the state of the battery with limited inputs, but the reliability could be sacrificed and the underlying principles oversimplified. Since there is not yet a universal impedance model to approximate the EIS under a variety of conditions, the necessary engineering treatment still finds useful. This paper presents an engineering-oriented approach as shown in Fig.1, that is, using the offline EIS at different SOCs and temperatures to form a multidimensional map, and the internal temperature is determined by looking-up tables. Offline EIS are measured after the batteries are fully settled and can be viewed as a snapshot in a specific state. It is assumed that the EIS of a working LIB only moves along the multidimensional surface represented by the map.

3. MATERIAL AND METHODS

The excitation condition used in this paper is shown in Fig.2(a).

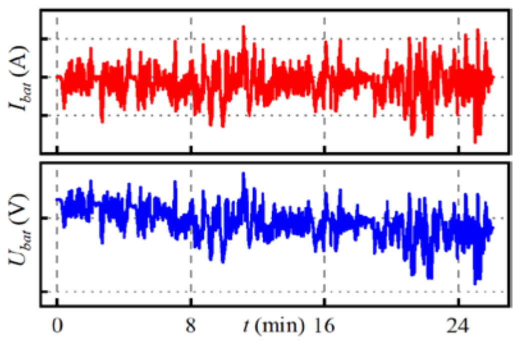

Fig.2 Driving condition used in this paper

Fig.2(b) shows the corresponding voltage response tested at 25℃. The battery used is Panasonic NCR18650BD with a rated capacity of 3.2Ah and chemistry of NCM. It can be seen that the current fluctuates around zero, while the voltage gradually decreases over time. The SOC at the beginning of the test is 55%, and the shift in SOC after the test is -1.26%. The maximum rise in surface temperature is 0.23℃. The same driving condition in Fig.2(a) is also replayed at 10℃ and 40℃. Three groups of excitation and response data are obtained, and the passive EIS results are shown in Fig.3 by using the processing flow in Fig.1.

Fig.3(a)-(c) show the transition of passive EIS over time at 10℃, 25℃ and 40℃ respectively. Batteries are tested from 55 %SOC. The extracted passive EIS ranges from 0.3Hz to 3kHz. The length of analysis window for the passive EIS is $T_{ana} = 60\text{s}$, and the overlap ratio is 2/3, implying each result will be output every 30s. The influence of temperature on passive EIS is very significant. It can be seen that the impedances of the middle and high frequencies remain basically unchanged, while those of low frequencies fluctuate with time. Since the SOC and temperature changes are mild, this fluctuation mainly comes from the time-variance associated with the current [10]. Fig.3(d)-(f) show the reference EIS along with the first and last sample of passive EIS. It can be seen that the passive EIS are in good acceptance with the reference, especially at high frequencies. Based on this, consecutive high-frequency impedances are picked as the input of internal temperature estimation in this paper.

Fig.4 shows the reference EIS of different temperatures at 55 %SOC, with an interval of 2℃.

It can be seen that the impedance curve shifts regularly. Such EIS results are suitable for the characterization of the internal temperature with high resolution. For the estimation of the internal temperature, its regression relationship with reference EIS is extracted. The frequency range of the passive EIS used for internal temperature estimation in this paper is

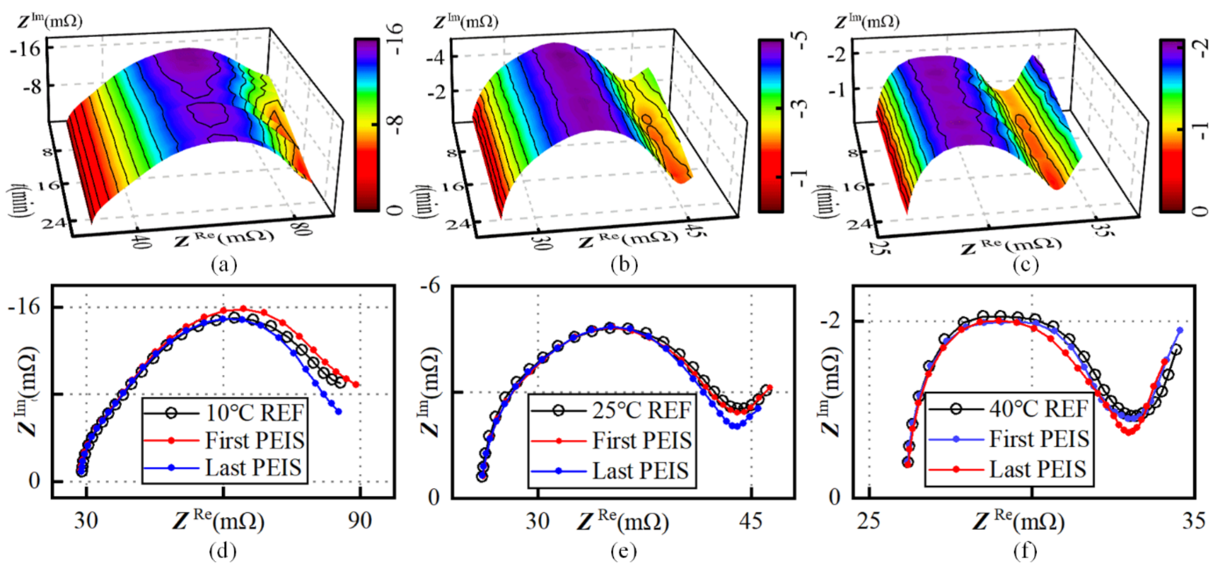

Fig.3 Passive EIS results

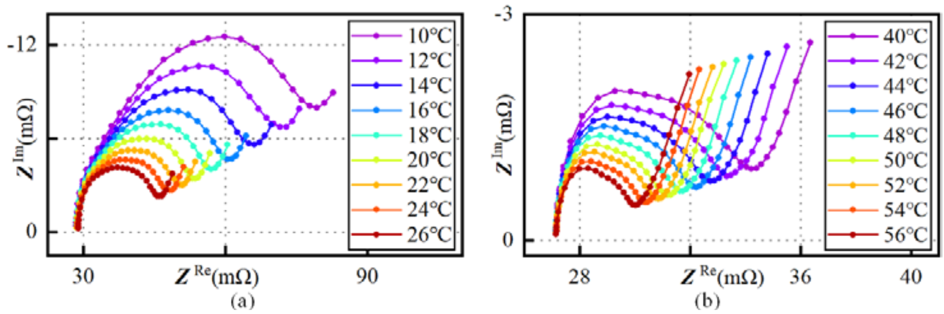

Fig.4 Reference EIS at different temperatures

100~2kHz. Commonly used regression methods include linear, Gaussian process regression (GPR) and support vector machine (SVM), and both linear and GPR can achieve good regression. In this paper, linear regression is used to estimate the internal temperature of LIB.

Since the real driving conditions fail to arouse obvious temperature rise, a high-current condition is specially designed by intercepting and mixing different driving conditions. Two cell tests are carried out at 10℃ and 40℃. The corresponding current and voltage time series are obtained by applying such condition. Passive EIS is calculated according to the process shown in Fig.1. The length of the analysis window is 3s and the overlap is 2/3, that is, each passive EIS sample can be expected every second. The passive EIS results in Fig.5 can be obtained by analyzing the entire time series. These passive EIS are all processed with inductance correction.

Reference EIS of 10℃ and 20℃ are given in Fig.5(a), and those of 40℃ and 50℃ are shown in Fig.5(b). It can be seen that the passive EIS gradually moves from the vicinity of the reference EIS at lower temperature to that at higher temperature, and this shift is mainly caused by the internal temperature change, so that the internal temperature can be simply inferred. Using the linear regression mentioned above, it is possible to calculate the internal temperature from the passive EIS, and the results are shown in Fig.5(c) and (d). The change of surface temperature 'SURF' and estimated internal temperature 'INTT' over time are given, both of which rise rapidly at the beginning and reach stabilization after a certain time. Due to the existence of excitation, the internal temperature is always higher than the surface, and a fixed difference is maintained after equilibrium, which is consistent with the actual situation. There are fluctuations in the internal temperature estimations, but this is not entirely due to the measurement errors from passive EIS. By analyzing particular fluctuations, especially the step-down pulses, it can be found that they have a strong correlation with current zero-crossing, suggesting that the internal temperature derived from passive EIS reflects a more meticulous internal heat production and absorption process. The fluctuations are more drastic at high temperatures, because the voltage SNR drops significantly. The internal temperature estimation given in this paper is a result reflected by the electrical characteristics rather than the heat transfer, thus a near instantaneous temperature sensing can be achieved.

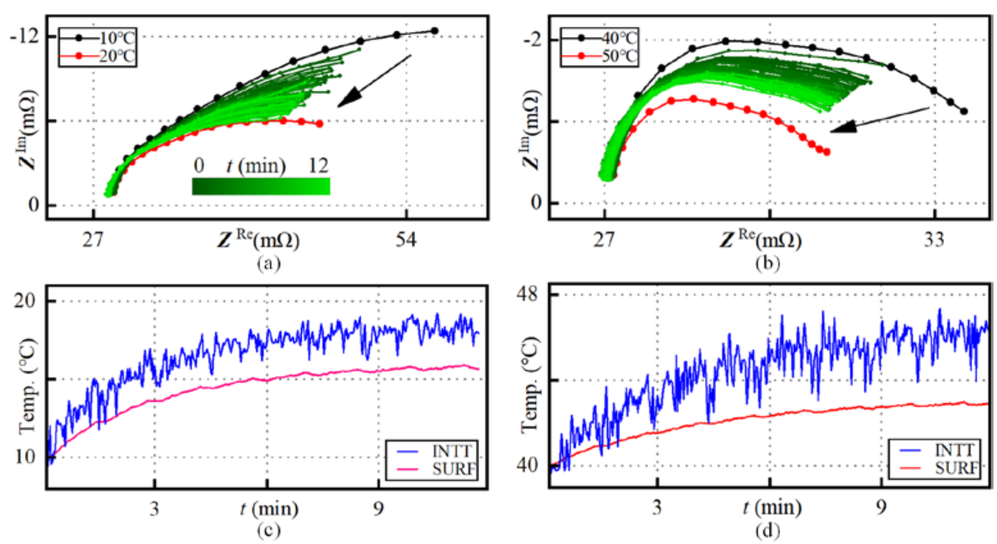

Fig.4 Reference EIS at different temperatures

The internal temperature estimated in this paper reflects more of the temperature accompanying the electrochemical processes of LIB, or the average temperature of internal reaction, which is closer to the working principle of the battery and is one of the better temperature characterizations that are accessible. The estimation period of one second is much shorter than the thermal time constant of LIB, which can better meet the needs of battery management, not only achieve more effective thermal management and prolong life-cycle, but also provide a strong basis for safety diagnosis and avoid hazards.

4. CONCLUSIONS

Safety concerns are persistent constraints on the wide deployment of EVs. By obtaining the internal temperature of LIB faster, thermal runaway is expected to be avoided, hence the catastrophic consequences. Current battery management techniques need extra high-quality inputs to achieve better risk control and isolation. The estimation of internal temperature based on electrochemical sensing is investigated frequently. Although it demonstrates high effectiveness and feasibility, there is still a barrier to on-vehicle applications, namely the timely acquisition of EIS.

In order to achieve a more feasible access to internal temperature, an estimation strategy based on passive EIS is designed in this paper. The time-domain current data for passive EIS is obtained by arranging real vehicle tests. Through the modification of electrochemical testing system, the excitation is reproduced with high precision, and the corresponding time series under different conditions are collected. Using the designed processing flow, acceptable passive EIS results are obtained. Due to the higher accuracy and smaller analysis window, high-frequency passive EIS is chosen for internal temperature estimation. By analyzing offline EIS at different temperatures and SOCs, the linear regression between internal temperature and impedance is extracted. With the help of this relationship and the constantly updated passive EIS, the internal temperature is conveniently calculated and compared to the surface temperature. Without complex algorithms and models, this idea is friendly for on-vehicle applications. The internal temperature estimation in this paper also achieves a faster update rate, so its timely usage for earlier decisions on safety controls can be available. This paper realizes the full process from passive EIS acquisition to internal temperature estimation, which provides a valuable reference for relevant vehicle applications.

DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

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