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Feature Extraction from Electrochemical Impedance Spectroscopy for State of Health Estimation of Lithium-Ion Batteries Under Different Temperatures

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Abstract**-- The State of Health (SOH) is a crucial component of battery management systems (BMSs), offering important health information and protection against unsafe usage. In this paper, an accurate model for SOH estimation of Li-ion batteries was developed, which is uniquely characterized by using only the imaginary part of impedance at a specific frequency for precise SOH estimation. Through the identification of the relationship between impedance at a specific frequency and capacity degradation using correlation coefficients , the feature data most closely related to battery aging was selected. Next, the battery aging modeling and SOH estimation were validated on nine batteries across three different temperatures using a Feed-forward Neural Network (FNN). The validation results indicated that the proposed method has a high estimation accuracy, achieving a Mean Absolute Percentage Error (MAPE) of merely 2.05% throughout the entire lifecycle of the battery 45C02 during tests at a temperature of 45°C.**

Index Terms**—State of Health, Capacity Estimation, Electrochemical Impedance Spectroscopy, Machine Learning.**

I. Introduction

The lithium-ion batteries (LIBs) undergo a gradual degradation process due to calendar ageing and cycle ageing. State of Health (SOH) serves as a crucial indicator in this regard, providing a comprehensive reflection of the battery's ageing degree [1]. However, measuring SOH directly by sensors is not possible, and the degradation of LIBs is a complex and changing process [2]. Therefore, accurate SOH estimation becomes imperative for gaining insights into the current level of battery ageing and making informed decisions on the optimal time for battery replacement [3,4]. Among the measurable features of LIBs, such as terminal voltage and charging current, EIS contains relatively sophisticated and high-dimensional information relevant to battery ageing [5-7]. This information, if processed properly, can precisely indicate the degradation of LIBs. However, a typical battery EIS is a frequency-dependent broadband complex parameter, and the measurement is usually in the range from 10^{-3}Hz to 10^{7}Hz [8]. Some information in the EIS can even be misleading. Extracting critical features from EIS and accurately estimating SOH is a major challenge.

In recent years, machine learning has been universally applied in many fields, particularly in tackling the complex problem of battery aging [9]. Recent developments in machine learning [10, 11] have revolutionized the way we model battery degradation, offering precise capacity estimation and health status predictions.

The principal contribution of this work is the extraction of key features related to battery aging from complex and high-dimensional EIS data. The feature proposed in this paper utilizes only the imaginary part of impedance at a single frequency, and it exhibits consistency across various temperature conditions, 25°C, 35°C, and 45°C. Compared to existing feature extraction approaches based on EIS data, the proposed method requires less data input and a broader temperature applicability range, further enhancing the online applicability and generalizability of battery SOH estimation. The methodology of this research is illustrated in Fig. 1.

The paper is structured as follows: Section II introduces the battery dataset. Subsequently, Section III details the feature extraction method and the structure of SOH estimation model. The results and discussion of the SOH estimation are presented in Section IV. Finally, Section V provides the conclusion of this article.

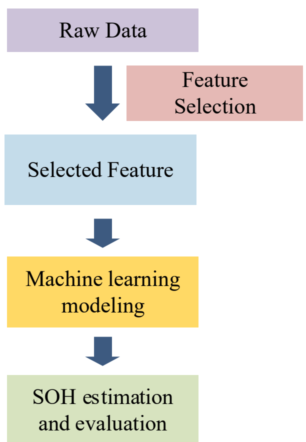

Fig. 1. Pipeline diagram of this paper.

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II. Battery Data Sets

The datasets utilized in this study comprise nine LiCoO2/graphite battery datasets, all sourced from the Cavendish Laboratory at the University of Cambridge [3]. The datasets were obtained at three different temperatures under the same work profile of 1C-rate (45mA) constant current (CC) constant voltage (CV) charging from 3.0V to 4.2V and 2C-rate CC discharging to 3.0V as described in Table I. Included within the datasets are both EIS and capacity data. EIS measurements were conducted at nine different stages of the charge/discharge cycle, spanning a frequency range from 0.02Hz to 20kHz across 60 distinct frequencies, as detailed in Fig. 2. In this paper, we used discharging capacity and EIS data at state IX (0% SOC) to estimate SOH. Cells 25C01-25C04, 35C01, and 45C01 were set as the training dataset, while cells 25C05, 35C02, and 45C02 comprised the testing dataset.

TABLE I
Battery at Various Test Temperatures

Test Temperature	Battery Cells	Cell Chemistry	Work Profile
25°C	25C01 25C02 25C03 25C04 25C05	$LiCoO_2$	Charging: 1C-rate CC-CV Discharging: 2C-rate CC
35°C	35C01 35C02		
45°C	45C01 45C02		

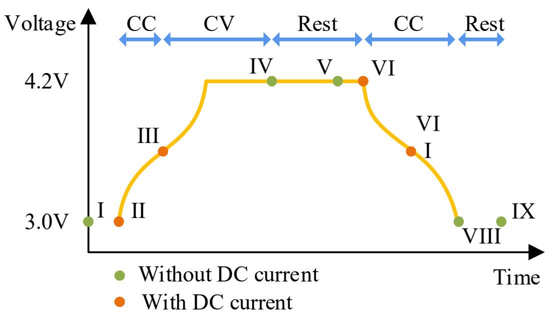


Fig. 2. Nine different charging/discharging states.

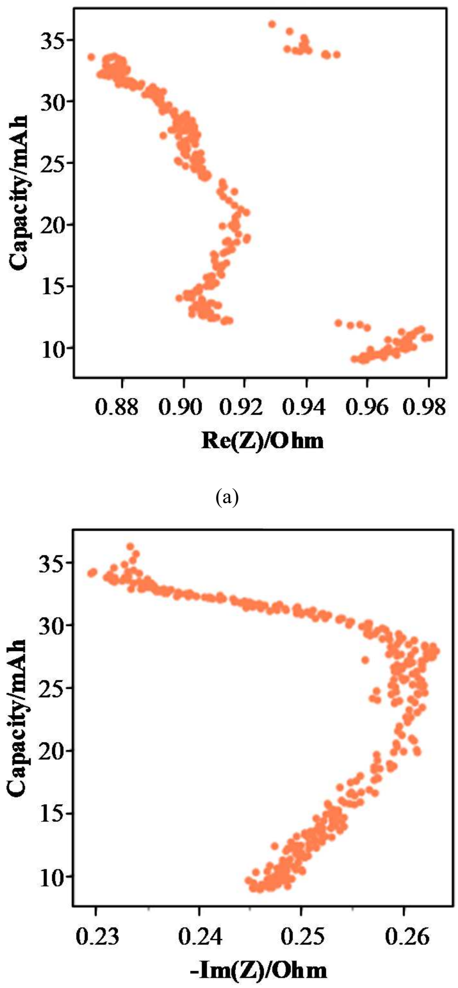
This dataset offers extensive insights into the internal transformations occurring within LIBs. However, within the vast amount of complex and high-dimensional data, only a small portion is significantly related to capacity degradation. The presence of numerous input EIS data complicates the identification of meaningful correlations, potentially diminishing the precision of SOH estimation model. To mitigate this issue, we emphasized the necessity of feature extraction to identify impedance characteristics that strongly correlate with battery degradation, directly impacting the SOH of LIBs. Thus, we introduced an innovative approach for extracting EIS data features, grounded in electrochemical principles, to enhance the accuracy of SOH estimation.

III. Methodology

The methodology of this paper is divided into two main sections: feature extraction and the structure of the SOH estimation model. In the feature extraction section, the method for extracting single-frequency imaginary impedance features using the Spearman correlation coefficient is discussed. The second part provides a detailed explanation of the architecture of the Feed-forward Neural Network (FNN) algorithm used in this study.

A. Feature Extraction Method

To investigate the relationship between the trends in real and imaginary impedance and battery capacity, a plot illustrating this correlation for battery cell 25C01 at 17.8Hz under state IX is presented in Fig. 3. This illustration serves to demonstrate that the correlation between the EIS parameters (both real and imaginary impedance) and battery capacity does not follow a linear trend. Consequently, the use of Pearson's correlation coefficient analysis, which presupposes linearity, is deemed unsuitable for evaluating this particular relationship.



(a)

(b)

Fig. 3. The non-linear correlation between the battery EIS and capacity: (a) real impedance vs. capacity, (b) imaginary impedance vs. capacity.

To accurately capture this non-linear dynamics, the Spearman's rank correlation coefficient is utilized, offering a robust metric for clarifying the relationship between impedance and capacity. This coefficient ranges from +1, indicating a positive correlation, to -1, signifying a negative correlation, with values near the extremes (i.e., close to +1 or -1) denoting stronger correlations. Fig. 4 illustrates Spearman's coefficient for various battery cells, revealing an absence of a uniform correlation within the extensive frequency spectrum of EIS (covering 60 different frequencies from 0.02Hz to 20004.45Hz). However, a distinct frequency band from 0.41976Hz to 2.73547Hz in the imaginary impedance domain consistently exhibits a significant negative correlation with battery capacity. This finding suggests that an increase in imaginary impedance within this frequency range is associated with capacity degradation, highlighting a specific area of focus for battery health assessment.

To pinpoint the frequency within this range that most closely correlates with capacity degradation, we conducted standard deviation analyses. These analyses identified that the frequency of 1.07Hz not only demonstrates a high Spearman's coefficient but also features the lowest standard deviation. This combination suggests a robust and consistent link to capacity degradation.

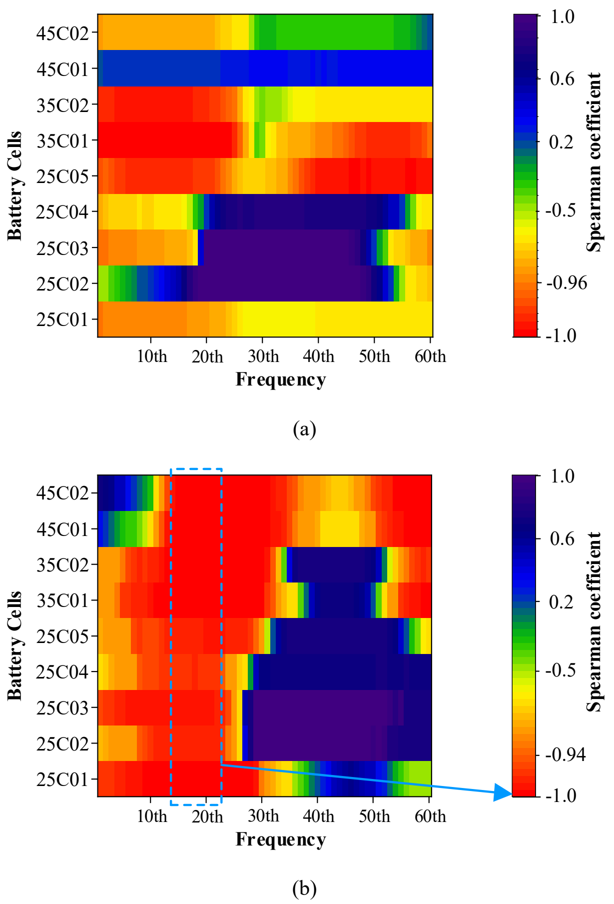


Fig. 4. Heatmap of Spearman coefficients for nine battery cells across 60 distinct frequencies: (a) the correlation between real impedance and capacity, and (b) the correlation between imaginary impedance and capacity.

B. Model structure

After identifying the frequency that exhibits the strongest correlation between impedance and capacity, the imaginary component at 1.07Hz was selected for SOH estimation. Subsequently, a FNN was utilized to establish the battery aging model, distinguished by its strong regression abilities and adeptness at identifying complex non-linear patterns in datasets.

A three-layer FNN architecture was developed, as shown in Fig. 5, incorporating the Leaky Rectified Linear Unit (Leaky ReLU) as its activation function. This choice offers a significant improvement over the conventional ReLU by allowing a minor, positive slope for negative input values, effectively preventing neurons from becoming inactive during training. Leaky ReLU maintains several benefits of its predecessor, such as computational efficiency and the avoidance of gradient saturation, while simultaneously overcoming its primary drawback.

To enhance the model's generalization capabilities and reduce the likelihood of overfitting, a dropout strategy was adopted. This technique selectively "drops" a portion of neurons and their connections during training, forcing the network to learn more diverse and generalized patterns. This addition not only strengthens the model's predictive reliability but also ensures its robustness across various battery cells.

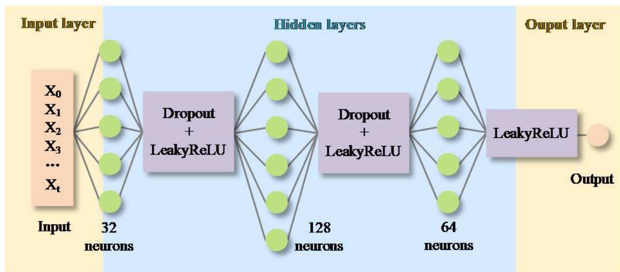


Fig. 5. Model structure.

IV. Results and Discussion

Based on the analysis and calculations detailed previously, we employed imaginary impedance at 1.07Hz as the optimal feature for estimating SOH of battery cells under three different temperature settings: 25°C, 35°C and 45°C. The training dataset include cells 25C01 to 25C04, 35C01, and 45C01, while cells 25C05, 35C02, and 45C02 were set as the testing dataset. Both datasets contain battery data from three different temperature conditions. The results in Fig. 6 demonstrated that FNN can effectively capture the degradation trend of different LIBs through the selected EIS feature. Specifically, Figures 6(a), 6(b), and 6(c) present the SOH estimation results for 25C05, 35C02, and 45C02, respectively. Table II summarizes the SOH estimation evaluation results, which are analyzed across four key metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2). Metrics for cell 25C05 show an RMSE of 1.13, an MAE of 0.92, a MAPE of 2.91%, and an R^2 of

0.78. For battery cell 35C02, we note an RMSE of 1.21, an MAE of 0.97, a MAPE of 3.3%, and an R^2 of 0.82. Importantly, cell 45C02's analysis reveals an RMSE of 0.74, an MAE of 0.68, a MAPE of 2.05%, and an R^2 of 0.93, indicating a relatively higher accuracy in SOH estimation. The experimental results showed that both the feature extraction method and FNN are feasible and effective for SOH estimation across varied temperature settings.

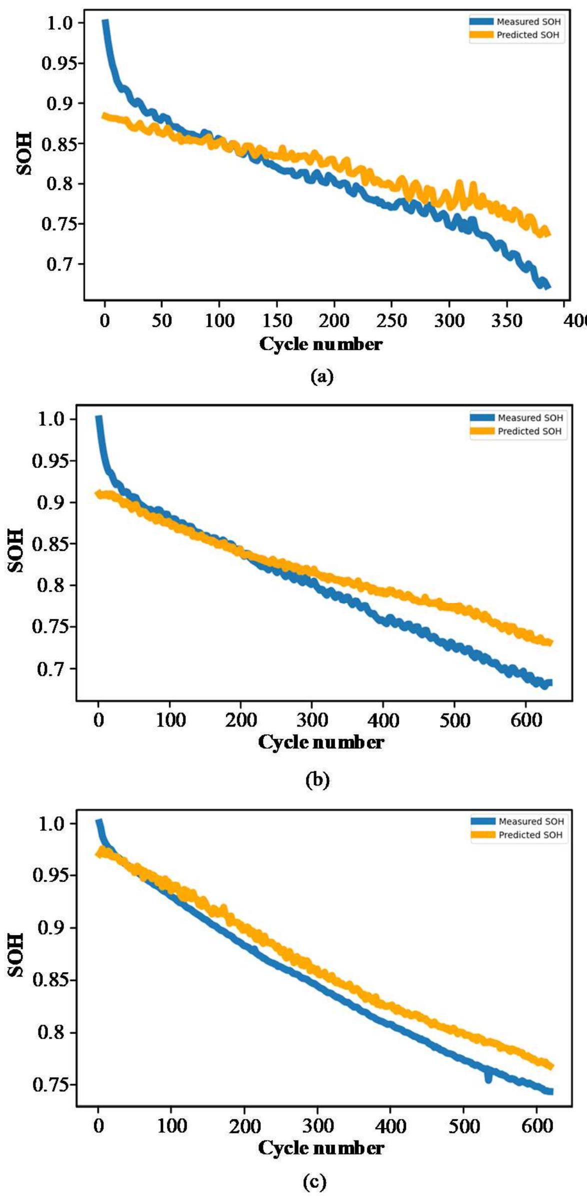


Fig. 6. Estimation of the battery SOH using the imaginary impedance at 1.07Hz: (a) Battery 25C05; (b) Battery 35C02; (c) Battery 45C02.

TABLE II
PERFORMANCE METRICS FOR THE SOH ESTIMATION

Battery Cells	RMSE	MAE	MAPE(%)	R^2
25C05	1.13	0.92	2.91	0.78
35C02	1.21	0.97	3.30	0.82
45C02	0.74	0.68	2.05	0.93

To further highlight the superiority of the proposed feature extraction method, we compared the results of this study with those in existing literature [8] that used different feature extraction methods for SOH estimation on the same datasets. The outcomes in Table III clearly indicated that the approach proposed in this study yields improved results in RMSE, MAE, MAPE, and the R^2 when using Neural Networks (NN) as the modeling algorithm.

TABLE III
COMPARISON BETWEEN THE PROPOSED METHOD AND EXISTING LITERATURE

Battery Cells	RMSE	MAE	MAPE(%)	R^2
35C02	1.21	0.97	3.30	0.82
[8]	1.51	1.46	4.57	0.73

The feature extraction method presented in this study, along with the validation results, clearly indicates that using the imaginary impedance at 1.07Hz as the feature input for SOH estimation can lead to accurate results. To clarify the marked correlation between this frequency range and battery degradation, an EIS plot is provided in Fig. 7. According to references [1,12,13], an EIS spectrum can be categorized into three areas: high-frequency, mid-frequency, and low-frequency regions. It has been noted that 1.07Hz is situated within the mid-frequency area, which, as reported in studies [1, 14], is significantly connected to critical electrochemical behaviors such as changes in electrochemical reaction kinetics, constraints in lithium-ion diffusion, and the formation of the Solid Electrolyte Interphase (SEI) layer.

The results obtained in this study suggest that the battery degradation process under the operational conditions analyzed is primarily influenced by these three electrochemical changes. The approach proposed herein provides a fresh dimension for exploring battery degradation. Future studies should focus on extending the verification of these insights, thus enhancing our understanding of the mechanisms of battery aging and contributing to the development of more robust BMSs

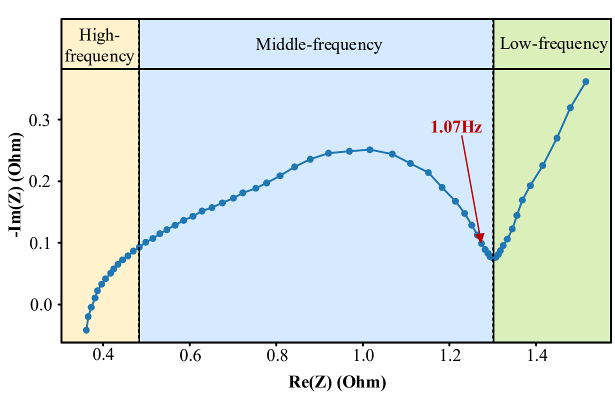


Fig. 7. EIS curve divided by three frequency regions.

V. CONCLUSIONS

In this paper, we introduced a feature extraction technique based on correlation coefficients for estimating the SOH of LIBs. We focus on utilizing only the imaginary part of the EIS at 1.07Hz to set as feature. Subsequently, a FNN algorithm is employed to model the non-linear relationship between impedance and capacity, thereby establishing an SOH estimation model. This approach outlines the methodology for accurately estimating battery health under three distinct temperatures. Using only single-frequency imaginary impedance data can significantly reduce the memory demands of the BMS and streamline the SOH estimation process. This strategy is not only resource-efficient but also paves the way for further simplification in battery health diagnostics. Detailed findings and extended research on this topic will be shared in our subsequent publications. Our approach illustrates consistent effectiveness across the entire lifecycle of LIBs, as evidenced by precise estimation metrics for the battery cell 45C02, including an RMSE of 0.74, an MAE of 0.68, an MAPE of 2.05%, and an R^2 of 0.93. The innovative feature selection strategy, coupled with the application of FNN, offers valuable insights for advancing industrial practices in battery management and health assessment.

REFERENCES

[1] X. Hu, L. Xu, X. Lin, M. Pecht, "Battery Lifetime Prognostics," *Joule*, 4 (2020) 310-346.

[2] Y. Zhang, T. Wik, J. Bergström, M. Pecht, C. Zou, "A machine learning-based framework for online prediction of battery ageing trajectory and lifetime using histogram data," *J. Power Sources*, 526 (2022) 0378-7753.

[3] Y. Zhang, Q. Tang, Y. Zhang, et al, Identifying degradation patterns of lithium ion batteries from impedance spectroscopy using machine learning. *Nat Commun* 11, 1706 (2020).

[4] Y. Jiang, Y. Chen, F. Yang, W. Peng, "State of health estimation of lithium-ion battery with automatic feature extraction and self-attention learning mechanism," *J. Power Sources*, 556 (2023) 0378-7753.

[5] S. Kim, Y. Choi, J. Choi, "Impedance-based capacity estimation for lithium-ion batteries using generative adversarial network," *Appl. Energy*, 308 (2022) 0306-2619.

[6] J. Obregon, Y. Han, C. Ho, D. Mouraliraman, C. Lee, J. Jung, "Convolutional autoencoder-based SOH estimation of lithium-ion batteries using electrochemical impedance spectroscopy," *J. Energy Storage*, 60 (2023) 2352-152X.

[7] B. Jiang, J. Zhu, X. Wang, X. Wei, W. Shang, H. Dai, "A comparative study of different features extracted from electrochemical impedance spectroscopy in state of health estimation for lithium-ion batteries," *Appl. Energy*, 322 (2022) 0306-2619.

[8] K. Luo, H. Zheng, Z. Shi, "A simple feature extraction method for estimating the whole life cycle state of health of lithium-ion batteries using transformer-based neural network," *J. Power Sources*, 576 (2023) 0378-7753.

[9] S. Fu, S. Tao, H. Fan, et al. "Data-driven capacity estimation for lithium-ion batteries with feature matching based transfer learning method." *Appl. Energy*, 353 (2024) 121991.

[10] D. Zhang, Z. Wang, P. Liu, et al. "A multi-step fast charging-based battery capacity estimation framework of real-world electric vehicles," *Energy*, 294 (2024) 130773.

[11] X. Bian, Z. Wei, W. Li, J. Pou, D. U. Sauer and L. Liu, "State-of-Health Estimation of Lithium-Ion Batteries by Fusing an Open Circuit Voltage Model and Incremental Capacity Analysis," *IEEE Trans. Power Electron.*, 37 (2022) 2226-2236.

[12] Y. Che, X. Hu, X. Lin, J. Guo and R. Teodorescu, "Health prognostics for lithium-ion batteries: mechanisms, methods, and prospects," *Energy Environ. Sci.,* 2 (2023) 338-371.

[13] Z. Ning, P. Venugopal, G. Rietveld and T. B. Soeiro, "Data-Driven Methods for Robust Battery Capacity Estimation based on Electrochemical Impedance Spectroscopy," *2023 25th European Conference on Power Electronics and Applications (EPE'23 ECCE Europe)*, Aalborg, Denmark, 2023, 1-8.

[14] W. Hu, Y. Peng, Y. Wei, Y. Yang, "Application of Electrochemical Impedance Spectroscopy to Degradation and Aging Research of Lithium-Ion Batteries," *J. Phys. Chem. C*, 127 (2023) 4465-4495.