Computation-efficient Approach to EIS Feature Extraction for Battery Informatics and Big Data

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Abstract

Electrochemical Impedance Spectroscopy (EIS) has the potential for improved prediction of battery performance and lifespan, but often has costly computation requirements. Current SOC/SOH prediction methods rely on data-driven or model-based matrix approaches. In advancing towards EIS's big data applications, we propose an efficient and unambiguous curve feature extraction method, surpassing traditional ECM fitting.

Keywords

Energy storage, machine learning, impedance, feature extraction, battery informatics

Code metadata

Nr	Code metadata description	Please fill in this column
C1	Current code version	v1
C2	Permanent link to code/repository used for this code version	https://github.com/Powerit-Shock/feature-extraction-paper-2024/
C3	Permanent link to reproducible capsule	N/A
C4	Legal code license	MIT License
C5	Code versioning system used	none

C6	Software code languages, tools and services used	python
C7	Compilation requirements, operating environments and dependencies	N/A
C8	If available, link to developer documentation/manual	https://github.com/Powerit-Shock/feature-extraction-paper-2024/edit/main/README.md
C9	Support email for questions	dshock@powerit.com

1. Introduction

With the burst of production of electric vehicles (EV) and the urgent need to recycle or reuse batteries from EVs[1], it is increasingly important to determine and predict the battery performance and life time. Many efforts have been made to incorporate big data, artificial intelligence (AI) and machine learning into helping the determination and prediction of battery performance [2], [3]. However, most methods for predicting battery performances only collect data from current, voltage, and temperature, which has limited information about the battery impedance or electrochemical properties, resulting in inaccurate predictions [4], [5]. Data fidelity, the mix of various theories and different quality of datasets [6], is another issue that blocks the prevalent application of big data applications in battery. Therefore, it is significant to develop methods to collect features with a computation-efficient, information-rich, and high-fidelity approach.

Electrochemical impedance spectroscopy (EIS) provides information about intrinsic electrochemical behaviors and thus frequently gets adopted in battery research to understand aging or other phenomena. EIS is also combined with machine learning to predict the battery state of charge (SOC) and/or state of health (SOH) [7], [8], [9], [10], [11], [12], [13]. A common way to extract information about electrochemical behaviors from EIS is to fit the Nyquist plot with equivalent circuit models (ECM) [9], [14], [15], [16], [17], [18], [19]. Nevertheless, fitting with ECM requires the selection of a suitable circuit model and manual input of initial values, which is demanding for both user and computation hardware requirements. Besides ECM, some studies apply principal component analysis (PCA) directly on the EIS data or select a few data points

[9], [10], [11], which might lose important information. An efficient way of extracting features from EIS is needed.

In this work, we propose a new method to extract features from EIS Nyquist plots efficiently. Compared to traditional ECM fitting, we extract import curve features from the Nyquist plots that are related to physical parameters in ECM. Our curve feature extraction method would allow extracting important features from the data without initial inputs or complex fitting, which will greatly reduce the computation redundancy and reduce data storage size >100X. This feature extraction tool paves a path to use EIS in big data applications.

1.1 EIS feature extraction method

Nyquist plot of imaginary impedance versus real impedance was analyzed to extract features as shown in Figure 1a and 1b. The raw data was interpolated first. The start of the tail (tailhead) was obtained with smoothing and derivatives or manual input. The intercept with x-axis (intercept), the maximum in y-axis (ymax), corresponding x value of ymax (xofymax) were extracted. The slope of the tail was extracted with linear fitting on the tail. The diameter of the semicircle was calculated with the distance between the intercept and center of the semicircle. The center of the semicircle was obtained by finding the center of curvature with dissection at half max and 0.75 of max. In the case of more than one semicircle at presence in Figure 1b, the connection (shoulder) between two semicircles was found. Shape was the ratio between the differences from center of 0.75 max and that of half max to intercept. Since there is no need for initial inputs or complex curve fitting, this curve feature extraction only takes 0.006s for each computation using Google Collab[20] with NVIDIA Tesla K80 with 12GB of VRAM, which is roughly 200 faster than running an ECM fitting with impedance.py [17] and 8 times faster than PyEIS [16].

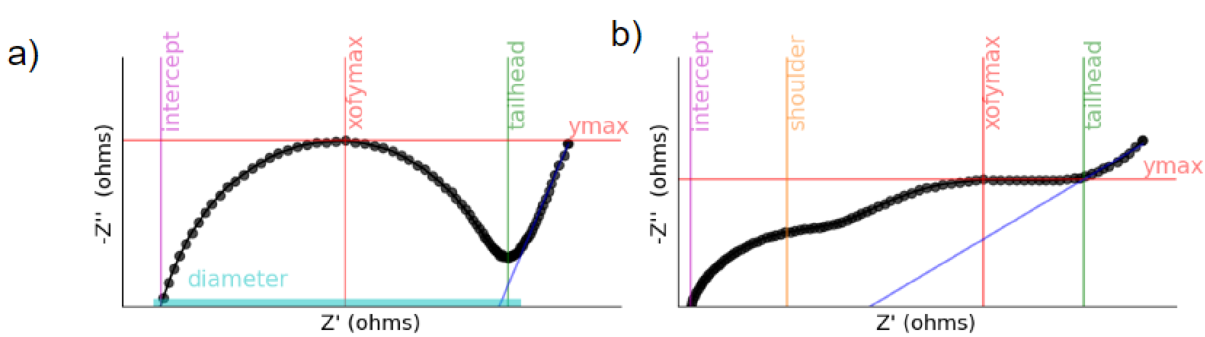

Figure 1: a) and b) Examples of feature extraction for typical EIS Nyquist curves.

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1.2 Usage and examples

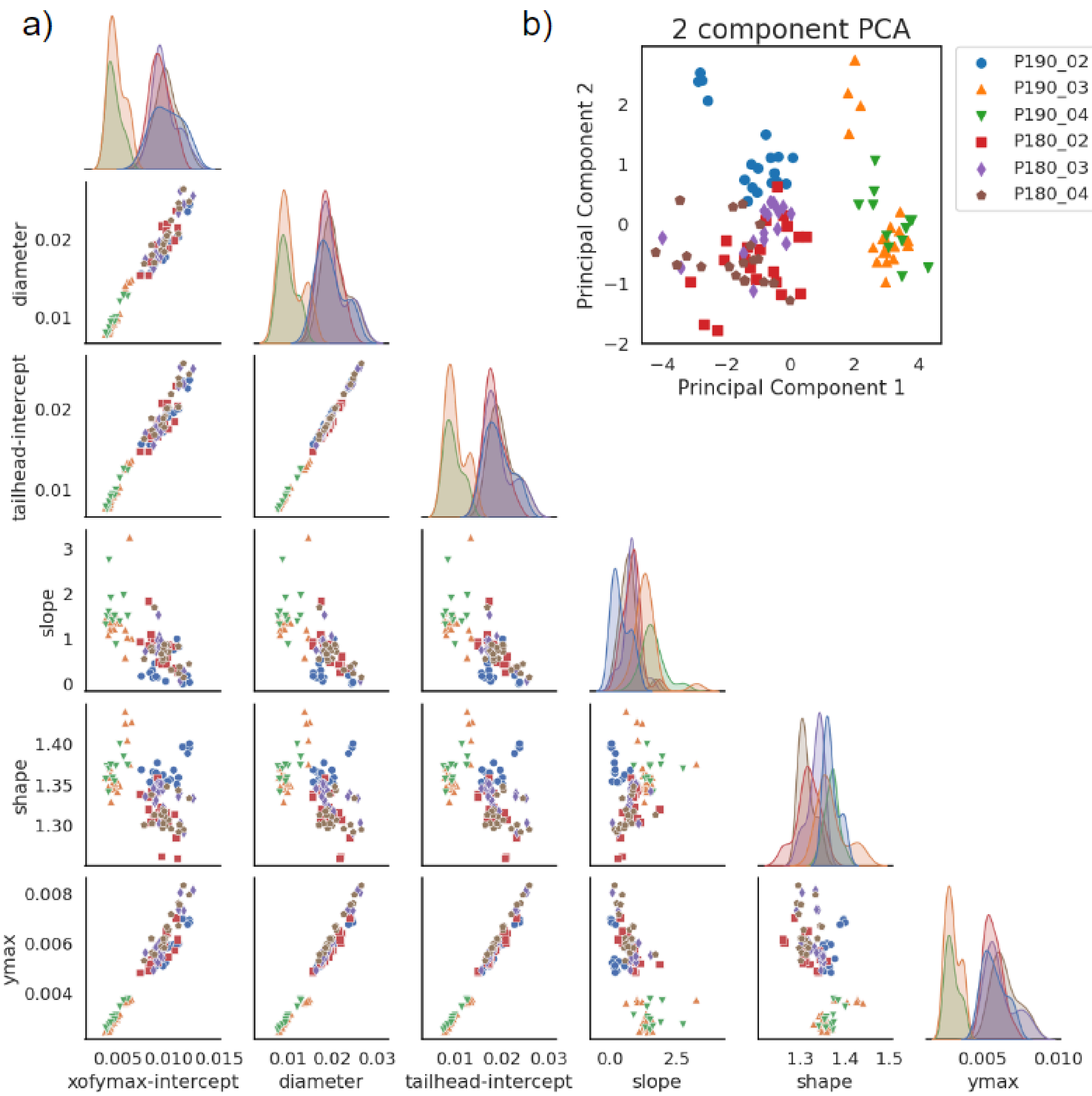

Figure 2: a) EIS Features of charging the and discharging the Ryobi pack of five 18650 cells in series and measuring individual cells with potentiostat. b) Plot of principal components for EIS features.

Three of 5s1p 3600mAh and 18V battery pack P180 (RBL1805) and three of 5s1p 2000mAh and 18V P190 (ONE+ P190) were tested for the feature extraction.There were five 18650 cells in series in each of the pack. The Ryobi pack was charged with model P135 class 2 battery charger from Ryobi and discharged with Ryobi (P21081VNM) leaf blower for 10-20 minutes to partially or fully discharge the battery packs. The cells in the battery pack were tested with potentiostat individually. This process was repeated four times, EIS of the individual cells from the batter packs at discharged states were collected after resting the pack for at least one hour to cool down to 25 °C. Admiral Instruments (Squidstat Plus) was used to measure the EIS. The EIS was taken between 1MHz and 0.1 Hz with 10 mV excitation amplitude and 10 steps per decade. As shown in Figure 2a, some features were processed again with subtraction to compensate for the series resistance change due to electrical connection variations. There are some correlations between certain features such as diameter and trailhead-intercept. Hence the features were further scaled and analyzed with PCA. In Figure 2b of the two principal components with larged mean squared errors, it is shown that the packs from the same brand have the same trend. This example demonstrates the feasibility of using EIS and curve feature extraction to differentiate behaviors from different battery branding: P180-2, 3 and 4 are aggregated in the lower region for principal component 1 and 2 while P190-2 ,3, and 4 are spread more linearly in the upper region. This result of similar branding of battery packs showing similar trend in PCA of this computationally efficient feature extraction proves that the curve feature extraction of EIS Nyquist plots has the potential to be used in machine learning or other big data applications.

2. Impact overview

Unlike other EIS analysis tools, this curve feature extraction tool has the additional advantage of being chemistry-agnostic and does not require manual input of initial values or selection of ECM for fitting to get features. For scientists familiar with electrochemistry, it lifts the burden to manually inspect and guess initial values for each curve. This tool also invites programmers and data scientists to use EIS data by removing the prerequisite of electrochemical knowledge. Most importantly, this method eliminates the ambiguity that traditional ECM fitting is faced with when selecting different models and initial values, which allow observing battery behaviors from a pure data-driven perspective.

Since there is no complex curve fitting in this tool, the computation is extremely efficient. It frees the computation power from going through complex optimization. This computation-efficient method provides the chance to generate features from batches of EIS data. The generated features can be directly used for machine learning. This method simplifies the process to use EIS data for machine learning studies or applications, making it possible to use EIS, such an information-rich measurement to predict battery performances, in big data applications.

Besides collecting EIS with advanced potentiostats in the lab environment, there are chips in development allowing testing EIS in portable devices or incorporating into BMS [21]. The need for computational efficient algorithms like the one covered here will be critical for these portable EIS enabled devices/technologies to be successful in the marketplace. Incorporating EIS on battery packs in EVs could generate more than thousands of EIS data that need analysis. With this software tool, users would be able to generate features and conduct analysis efficiently either through cloud-based systems or with the software integrated into regular maintenance routines.

3. Limitations and Future Development

This software only analyzes the features from EIS Nyquist plots. Future work will incorporate modeling Bode plots of impedance and frequency as a function of frequency. We are aware that there could be different unique curve shapes so we plan to make the codes accommodate all shapes.

For next development, we plan to integrate this EIS feature extraction method with typical data from BMS including current, voltage, and temperature. Experiments to capture SOC/SOH information together with EIS will help develop the feature extraction for prediction of SOC/SOH.

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Declaration of Competing Interest

Xueying Li Quinn, Dan Shaw, Yujia Liang and David Shock have a patent pending for the feature extraction method.

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