Electrochemical impedance spectroscopy-based safety diagnosis for large capacity lithium-ion batteries.

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ABSTRACT

It is essential to monitor the lithium-ion battery's (LiB) temperature for its optimal functioning, health, and safety during usage. The interior temperature influences the battery capacity and power characteristics, which is a significant aging accelerator. Lithium plating and growth in the solid electrolyte interphase (SEI) are a couple of the impacts of aging. LiBs are the most used type of battery in the current EV world, thus, preventing SEI growth and stopping the Lib from reaching unsafe temperatures is necessary to encourage its practical application. However, battery temperature is never monitored at a single-cell level due to cost and space. Electrochemical impedance spectroscopy (EIS) is proven to have a high correlation with the internal temperature of the battery, thus EIS diagnostic can be used for the detection of high-temperature LiBs. Therefore, this study uses K-nearest neighbor (K-NN) regression based on EIS data of 70Ah pouch cells to detect the early abnormal change in cells' temperature. Our model obtained a validation accuracy of 97.8% and a test accuracy of 89.3%.

1. Introduction

EIS is frequently employed in aging, modeling, and SoC/SoH estimation research, as well as the extraction of kinetic and transport features in electrode materials. In our previous paper, we studied the optimal frequency for EIS diagnostics of nickel, manganese cobalt (NMC) 70Ah pouch batteries [1]. In the study, we concluded the frequency that is most sensitive to temperature only and independent of another battery state of charge (SoC). The data used in this paper is the resulting experimental EIS data of 10 same cells at this frequency (i.e., 10Hz). When the internal temperature of the battery reaches temperatures close to 60°C the solid electrolyte interphase (SEI) growth occurs and if not stopped can lead to SEI decomposition or cathode discharge [2]. Therefore, Monitoring the battery's internal temperature and controlling it before reaching the rapid aging and degradation levels of temperature between 45°C to 60°C is crucial to minimize aging for the battery state of health (SoH) and also prevents reaching the temperatures with the risk of safety hazards. EIS inspections can be used to sense the internal temperature of LiBs, however, this system is limited by EIS limitations, though EIS allows for good characterization of a single cell it changes significantly from one cell to another, especially in the presence of manufacturing deviations. Fig. 1 shows how data for a single temperature can differ from one battery to another making class identification challenging. The goal of this paper is to classify the 70Ah NMC pouch battery temperature by zones of 5°C using the EIS magnitude and phase data at 10 Hz to detect abnormal temperature changes from the rest of the batteries at a cell level with means of the K-NN regression.

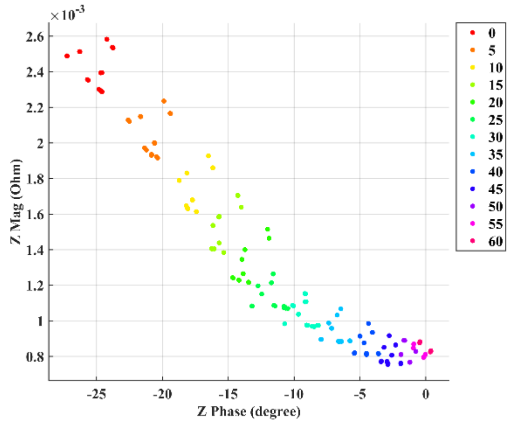

Fig. 1 10 Hz EIS data repartition according to temperature

2. K- nearest neighbor

K-NN is an effective technique for classifying data in pattern recognition. When used for regression, k-NN calculates a weighted average of the responses from the k closest training points, $\mathbf{x}_{(1)}, \mathbf{x}_{(2)}, \cdots, \mathbf{x}_{(k)}$, to estimate the response of a testing point, $\mathbf{x}_t$. A kernel function is frequently utilized to determine each neighbor's weight based on how close they are to the testing point. Let $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2 \cdots, \mathbf{x}_M\}$ be a training data set made up of M training points with N characteristics each. The weighted Euclidean distance is expressed as:

$$d(\mathbf{x}_t,\mathbf{x}_i) = \sqrt{\sum_{n=1}^{N} w_n (x_{t,n} - x_{i,n})^2} \qquad (1)$$

can be used to determine how close each training point $\mathbf{x}_i$ is to the testing point $\mathbf{x}_t$. N stands for the number of features, $x_{t,n}$ and $x_{i,n}$ are the nth feature values of the testing point $\mathbf{x}_t$ and the training point $\mathbf{x}_i$, respectively.

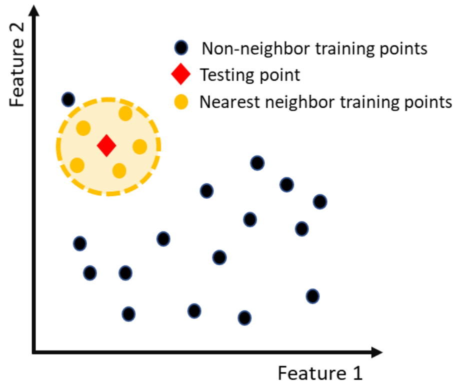

Fig. 2 K-NN in a two-dimensional feature space

The concept is illustrated in Fig. 2 for a two-dimensional feature space (N=2), where the NN training data are the five (k=5) points with the closest Euclidean distances to our test point.

3. Simulation Results and analysis

Fig. 3 shows our data results of the K-NN training and validation steps. 8 cells were used at this step, with 4 cross-validation steps. Cross-validation is used to avoid overfitting of the data. The model achieved an overall 97% validation accuracy with a total validation cost of 6 (6 false predictions). Fig. 3 (a) shows the correct and incorrect predictions at each zone, while Fig. 3 (b) shows the true classes compared to the predicted ones. In the blue squares the number of the correct position and in the brown squares the number of the incorrect estimations. 3 false predictions occurred at 25°C and 3 at 40°C. very low and very high temperatures were predicted with 100% accuracy.

After the validation, we tested our model on 2 newly introduced cell data. The regression model test accuracy was 89.3%, with 6 errors in classifying the temperatures of the new cells. Fig. 4 shows the true values compared to the predicted values for the test cell results. 3 false predictions occurred at 30°C, and a single false estimation at each of the temperatures 45°C, 50°C, and 55°C. The impedance values at really high temperatures are very close making difficult to classify, however, the model's safety is not endangered by these errors as the predictions show a high-temperature class.

4. Conclusion

In this study, we used single frequency impedance data at 10Hz and k-NN regression to classify temperature at the cell level. The work enables early identification of the unusually heated cell, enabling the diagnosis of likely defective cells.

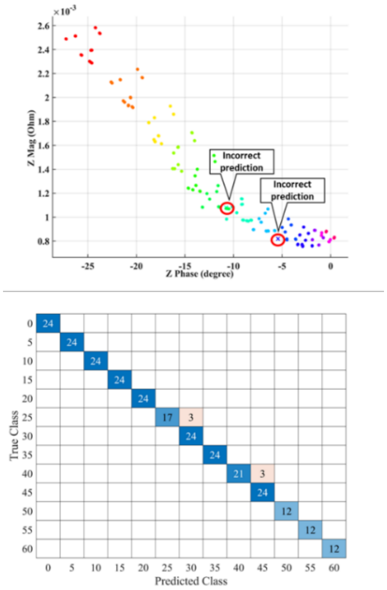

Fig. 3 Top: Classification results during validation, Bottom: validation predicted vs true class.

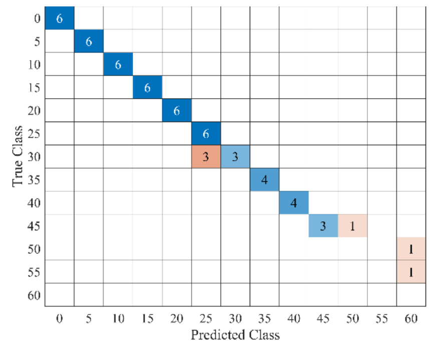

Fig. 4 Test cell true vs predicted classes.

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References

[1] EZAHEDI Salah Eddine, Seongyun Park, Changsoo Lee, Jonghoon Kim. (2022). Optimal frequency selection for EIS-based internal temperature estimation of high capacity pouch cell. Power Electronics Conference, 416-417.

[2] A. Jinasena et al., "Online Internal Temperature Sensors in Lithium-Ion Batteries: State-of-the-Art and Future Trends," Frontiers in Chemical Engineering, vol. 4, Feb. 2022, doi: 10.3389/fceng.2022. 804704.