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Data-Driven Estimation of Internal Resistance of Lithium-IRON Batteries

Abstract: - Battery health prediction is crucial for improving efficiency and longevity, thereby enhancing operational effectiveness. Internal resistance serves as a critical parameter indicative of battery health. This study utilizes Hybrid Pulse Power Characterization (HPPC) tests conducted with CALM CAM72 equipment to assess internal resistance. It proposes a data-driven approach for estimation, employing various regression algorithms such as Linear Regression, Ridge Regression, Lasso Regression, ElasticNet Regression, Decision Tree Regression, RandomForest Regression, GradientBoosting Regression, XGBoost Regression, and LightGBM Regression. The performance of these algorithms is compared to identify the most effective model.

Once the best model is selected, the coefficients from the regression are examined to understand the impact of variables such as State of Charge (SOC), temperature, discharge characteristics, and charging rate (C-rate) on battery health prediction. This analysis aims to provide insights into the factors influencing battery performance, thereby optimizing efficiency and extending battery lifespan. Based on the output of the regression model, an optimal operating range is proposed using data-driven optimization algorithms.

Keywords: Internal resistance modelling, HPPC, Machine Learing, Lithium-Iron-Phosphate, Optimazation

1. Introduction

Lithium-iron batteries (LIBs) are crucial for various applications, including electronics and electric vehicles, where their performance directly impacts efficiency and operational costs. Determining battery health is essential to ensure safe operation and prevent unexpected fire hazards or catastrophic failures. Internal resistance is a key factor in determining battery health, influencing energy efficiency, charging times, and overall lifespan. Traditional methods for assessing internal resistance involve complex measurements and calculations, often lacking scalability and real-time applicability. In contrast, data-driven approaches leverage computational models and machine learning algorithms to predict internal resistance based on operational data.

LIBs, with features such as high specific energy, high power, long life-cycle, low self-discharge rate, and environmental friendliness, have become the preferred power source for electric vehicles. Jie Li et al. (2023) presented a Remaining useful life prediction of lithium-ion batteries via an EIS based deep learning approach with multiple input variables. Ravi Katukam et al. (2014) proposed neural network-based optimization algorithms for engineering system optimization. Recently, there has been growing interest in applying machine learning and deep learning methods to engineering systems such as aircraft, automotive, and batteries. These algorithms utilize sensor data captured from machines to make predictions and optimizations.

Defining a healthy optimal operating range for batteries is challenging due to their complex multi-physics operating environment. Battery performance is influenced by chemical, physical, electrical, mechanical, and environmental conditions. Therefore, a machine learning-based approach is proposed to define optimal parameter ranges for LIBs. Pranav et al. (2013) proposed a simplex tool for optimizing engineering system design within a defined range of parameters. Vineeth Reddy et al. (2016) presented an ant colony optimization algorithm for optimization with multiple parameters.

2. Problem Statement & Solution Approach

Accurately estimating internal resistance is crucial for optimizing battery performance and longevity. Traditional methods often rely on periodic laboratory tests, which are time-consuming and may not fully reflect real-world operational conditions. To address this challenge, a more efficient and scalable approach is needed—one that continuously monitors and predicts internal resistance using readily available operational data. Advanced

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equipment such as the CALM CAM72 can facilitate this continuous monitoring, offering a more comprehensive and timely assessment of battery performance.

2.1. Test Setup & Procedure

The HPPC test setup utilizes the CALM CAM72, a high-precision Coulomb counting system, known for its accuracy in measuring current and voltage variations during battery operation. This setup ensures precise data collection under controlled environmental conditions, minimizing external variables and ensuring reliable results for subsequent analysis.

The experimental platform (as shown in Fig. 1) consists of an environmental chamber for temperature control, batteries, an electronic load, a charger, and a computer for interactive interfacing and data storage. The temperature range of the environmental chamber varies from −40°C to 150°C, with an accuracy of ±0.5°C. The experimental battery is a 72Ah lithium-ion battery (LIB) produced by the China Aviation Lithium Battery Company, with a maximum charging current of 72 A. The recorded data from the experimental platform during the charge and discharge processes include terminal voltage (V), load current (A), discharge capacity (Ah), and temperature (°C). The data collection frequency is 1 Hz.

Fig 1: HPPC Test Setup

Battery resistance tests were conducted using the HPPC method proposed by our research group (Wei et al., 2019) to measure the internal resistance of the battery. The sample voltage and current response of the HPPC method is shown in Fig. 2. This method added a capacity replenishment and resupply stage, which helps avoid capacity loss during the charge-discharge pulse compared to traditional HPPC methods. The HPPC method not only accurately calculates the SOC of the battery at each stage but also completes tests with different rates in each charging and discharging pulse experiment.

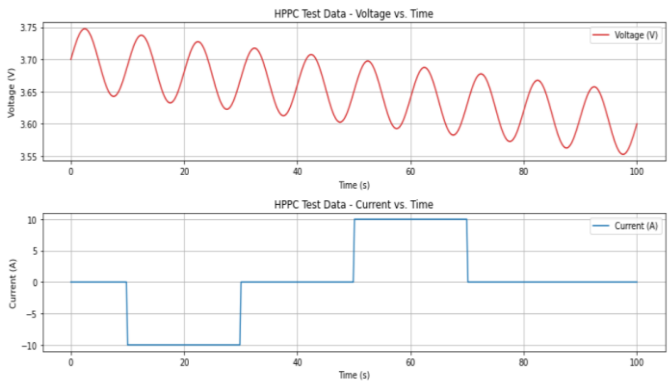


Fig 2: Sample HPPC Test Data (Voltage vs. Time & Current vs. Time)

The experimental batteries were tested at different temperatures (5°C, 15°C, 25°C, 35°C, 45°C, and 55°C), SOC levels (95%, 90%, … , 10%), and discharge rates (0.5C & 1C). The voltages and currents under various temperatures, SOCs, and discharge rates were recorded. The experimental flow chart is displayed in Fig. 3, and the experimental sequence is as follows:

1. The battery was charged with constant current-constant voltage (CC-CV) until fully charged at the ambient temperature of 25°C.
2. The battery was rested for 1 hour.
3. The initial temperature of the environmental chamber was set to 5°C.
4. The battery was discharged at a constant current (1C) until its SOC decreased by 10%, followed by a 1-hour rest period.
5. The battery was discharged at a 0.5C rate for 10 seconds, then rested for 40 seconds.
6. Subsequently, the battery was charged at a 0.5C rate for 10 seconds and then rested for 40 seconds to compensate for capacity loss.

The above test was repeated with an increment of 0.5C per cycle until the maximum discharge rate reached 1C. Discharge currents and voltage data were recorded under all discharge rates. After Test 4, the battery was discharged at a constant current rate of 0.5C until the SOC decreased by 10%. When the SOC was greater than or equal to 10%, the previous step was repeated; when the SOC was less than 10%, the next step, the temperature cycle test, was conducted. In this test, the ambient temperature was increased by 10°C.

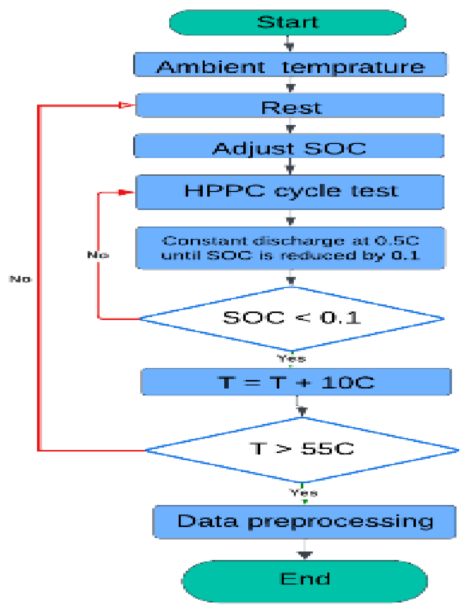


Fig 3: HPPC Test Flowchart

3. Data Set Description

Data collected during HPPC tests using CALM CAM72 include time-stamped measurements of current, voltage, and temperature. Preprocessing involves noise reduction and calibration to ensure data accuracy and consistency. The dataset covers a diverse range of operational scenarios to capture variability in internal resistance under different conditions, thereby enhancing the robustness of the estimation model.

Variables:

- Voltage (V)
- Current (A)
- CDS Temperature1 (°C)
- Capacity (Ah)
- Global Charge Capacity (Ah)
- Global Discharge Capacity (Ah)

- Global State of Charge (SOC) (%)
- Charge Capacity (Ah)
- Discharge Capacity (Ah)
- Charge Energy (Wh)
- Discharge Energy (Wh)

These variables are crucial for analysing battery performance and predicting internal resistance based on the HPPC test data.

3.1 Data Collection

The study utilizes HPPC tests conducted with CALM CAM72 equipment to collect data. These tests provide detailed insights into the battery's performance under different conditions, as tabulated in Figure 4.

	Voltage(V)	Current(A)	CDS Temperature	Capacity(Ah)	Global charge Capacity(Ah)	Global discharge Capacity(Ah)	Global Soc(%)	Charge Capacity(Ah)	Discharge Capacity(Ah)	Charge Energy(Wh)	Discharge Energy(Wh)
0	3.252799	-37.597656	14.7	0.004000	0.000000	3.763366	94.993527	0.000000	0.004000	0.000000	0.013018
1	3.250953	-37.578434	14.7	0.006266	0.000000	3.765632	94.990512	0.000000	0.006266	0.000000	0.020388
2	3.249569	-37.582279	14.7	0.008531	0.000000	3.767897	94.987499	0.000000	0.008531	0.000000	0.027751
3	3.248493	-37.597656	14.7	0.010787	0.000000	3.770153	94.984498	0.000000	0.010787	0.000000	0.035081
4	3.247570	-37.578434	14.7	0.013043	0.000000	3.772409	94.981497	0.000000	0.013043	0.000000	0.042408

Fig. 4: Data Collection from the Test Setup

Figure 5 appears to be from a Hybrid Pulse Power Characterization (HPPC) test, which is commonly used to evaluate battery performance, particularly in terms of power and energy capabilities under different load conditions. Here's a breakdown of what the graph shows:

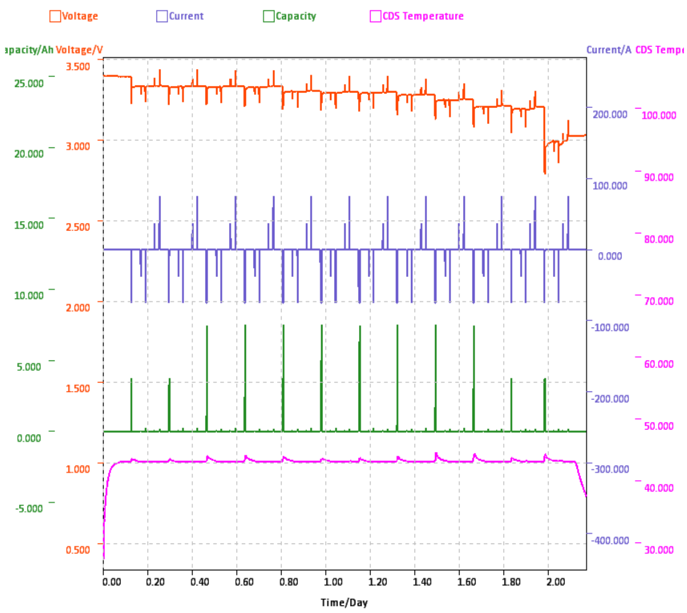


Fig. 5: Variation of Test Parameters

The horizontal axis represents time in days, spanning from 0 to 2.50 days, indicating that the HPPC test was conducted over a period of two days.

The vertical axis (Left Side, multiple scales):

- Voltage: Represented by the orange line, with a scale ranging from 0 to 3.5V, showing the battery's voltage behaviour during the test.

- Current: Represented by the blue line, with a scale ranging from 72A to -72A (charge to discharge), indicating the current flow during the test.
- Capacity (Ah): Represented by the green line.
- Temperature (°C): Represented by the pink line, with a scale ranging from 5°C to 100°C, showing the temperature changes during the test.

Fig. 6: This bar graph visually highlights the most and least variable aspects of the battery's performance during the HPPC test, which helps in assessing the overall robustness and behaviour of the battery under dynamic conditions.

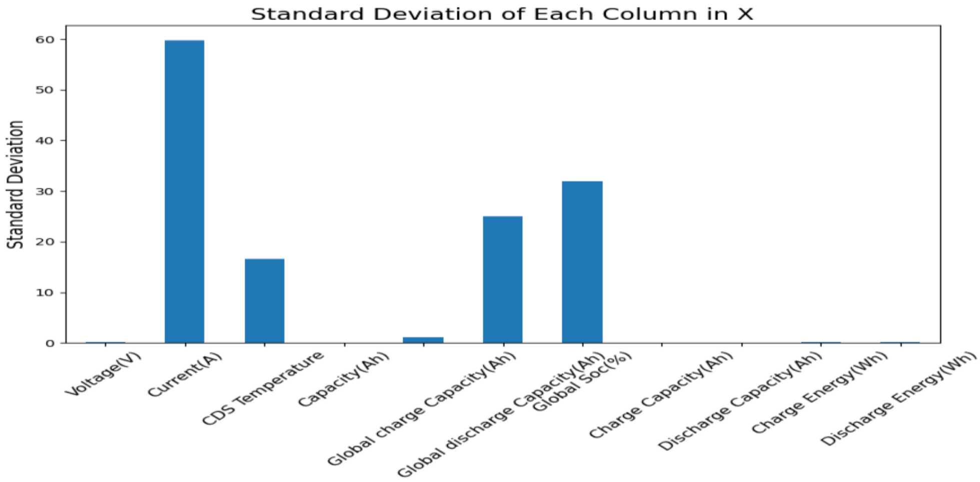


Fig 6: Variation of Standard Deviation

The high standard deviation in current reflects the intentional variability in the test, where the current was rapidly pulsed to simulate real-world battery use.

The moderate standard deviation in temperature suggests that the battery experienced notable temperature changes, but these were controlled and not extreme. The low standard deviations in voltage, capacity, SoC, and energy indicate that the battery maintained consistent performance in these parameters, which is a positive indicator of the battery's stability and reliability during the test.

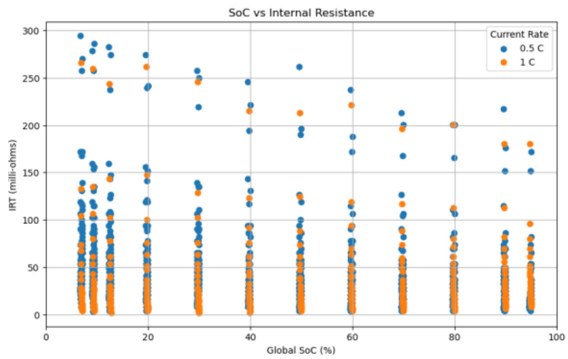
3.2 Machine Learning Algorithms

The machine learning algorithms used in this study for estimating internal resistance each have unique strengths and were selected based on their ability to handle specific characteristics of the data, such as linearity, feature interactions, or high dimensionality. By comparing these methods, the study aims to determine the most effective approach for estimating internal resistance in this specific application. The algorithms used include:

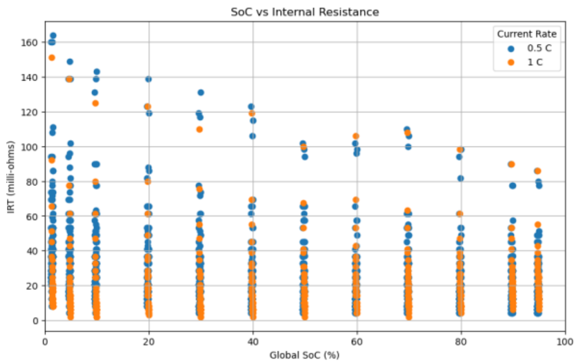
- Ridge Regression
- Lasso Regression
- ElasticNet Regression
- Decision Tree Regression
- Random Forest Regression
- Gradient Boosting Regression
- XGBoost Regression
- LightGBM Regression

4. Results and Discussion

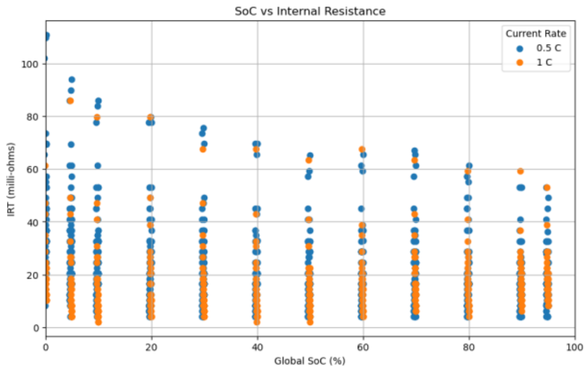
The graphs in Fig. 7 illustrates the relationship between the Global State of Charge (SoC%) and Internal Resistance (IRT in milliohms) for a battery at various ambient temperatures: 5°C, 15°C, 25°C, 35°C, 45°C, and 55°C. The data points are plotted for two different current rates: 0.5C (blue dots) and 1C (orange dots).



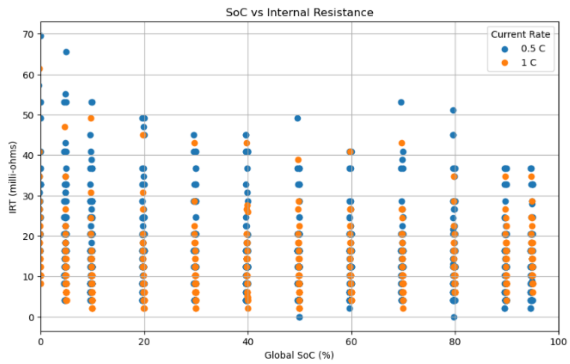
(a) 5°C Internal resistance



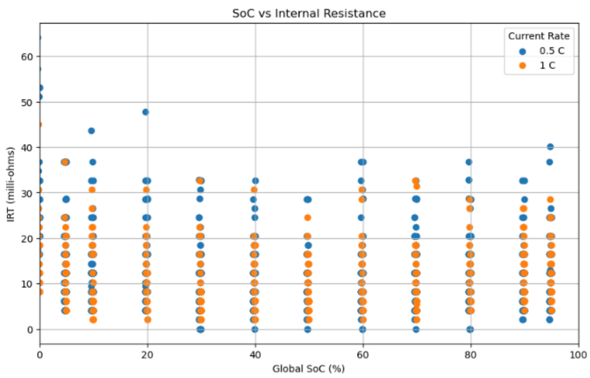
(b) 15°C Internal resistance



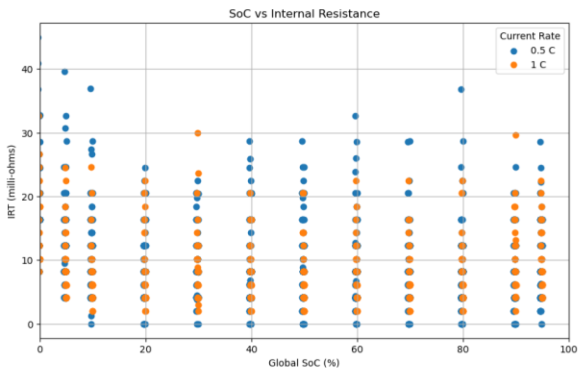
(c) 25°C Internal resistance



(d) 35°C Internal resistance



(e) 45°C Internal resistance



(f) 55°C Internal resistance

Fig 7: Internal resistance at different discharge rates

The graph shows that as the ambient temperature of the battery gradually increases (from 5°C to 55°C), the discharge resistance in each SoC state decreases, indicating a negative correlation between temperature and discharge resistance. The fluctuation in internal resistance with SoC is more pronounced at lower temperatures (5°C) compared to room temperature (25°C) or higher temperatures (55°C).

At low temperatures, the fluctuation in internal resistance exhibits typical nonlinear characteristics. The increase in internal resistance as the temperature drops from 15°C to 5°C is much larger than the decrease observed when the temperature drops from 55°C to 35°C. Moreover, when the SoC is at 10%, the internal resistance is 280 mΩ at 5°C, whereas it is 38 mΩ at 55°C. The deviation between these two measured values is approximately 242 mΩ, highlighting the significant impact of temperature on internal resistance.

The dots representing internal resistance at 5°C and 25°C follow a similar trend with varying SoC values. When the SoC increases from 10% to 50%, the internal resistance decreases by 30 to 40 mΩ. However, when the SoC increases from 50% to 100%, the internal resistance decreases by nearly 10 to 20 mΩ. The discharge resistance trends are consistent at 35°C, 45°C, and 55°C. The discharge internal resistance curve is stable, with fluctuations of only 5 to 10 mΩ at 35°C and higher temperatures (45°C and 55°C). At these higher temperatures, SoC has little effect on internal resistance, whereas SoC has a greater influence on internal resistance at lower temperatures. This is because SoC affects the resistance value of the battery by influencing the disassembly and embedding speed of lithium ions in the anode and cathode, as well as the viscosity of the electrolyte (Ahmed et al., 2015).

The effect of temperature in cold conditions, such as at 5°C ambient temperature, generally increases the internal resistance of the battery. At colder temperatures, the viscosity of the electrolyte increases, reducing ionic mobility and thereby increasing resistance. This effect is particularly evident at lower SoC levels, where resistance is highest.

At an elevated temperature of 55°C, the internal resistance is relatively low compared to what might be expected at lower temperatures. High temperatures typically increase ionic mobility, leading to lower internal resistance. However, the scatter and fluctuations observed indicate that despite the overall lower resistance, high temperatures can cause instability, potentially leading to occasional higher resistance values. This may be due to thermal stress affecting the electrode materials and electrolyte conductivity.

The performance of these algorithms is compared using metrics such as Mean Squared Error (MSE) to identify the most effective model for predicting internal resistance. Figure 8, shows the Mean Squared Error (MSE) of various regression algorithms, with the y-axis representing the MSE values and the x-axis listing different algorithms. Linear Regression and Ridge Regression have relatively high MSE values, indicated by bars of similar height. This suggests that both linear models do not perform well on this dataset. Lasso Regression and Elastic Net Regression, which are regularization techniques, also show high MSE values, similar to or slightly higher than Linear and Ridge Regression. This indicates that these methods do not significantly improve upon the basic linear model, possibly due to the nature of the dataset.

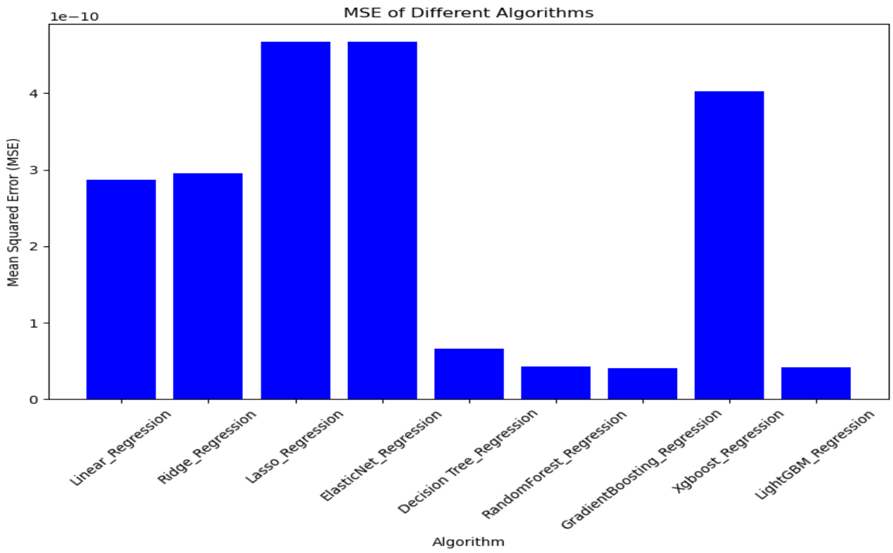


Fig 8: Relative comparison of regression algorithms based on mean square error

On the other hand, Decision Tree Regression, Random Forest Regression, Gradient Boosting Regression, and LightGBM Regression show significantly lower MSE values, with LightGBM and Random Forest performing the best among them. This suggests that tree-based models are well-suited for this dataset, likely due to their ability to handle non-linear relationships and interactions between features. XGBoost has a relatively higher MSE compared to other tree-based methods but still outperforms the linear models. This indicates that while XGBoost performs moderately well, it is not as effective as other boosting techniques like LightGBM.

5. Optimization

The optimization section focuses on identifying the optimal operating parameters for lithium-ion batteries based on the data-driven models developed in the study. This involves using the best-performing regression model to determine the ideal values for various battery parameters to enhance performance and longevity.

Data collected during HPPC tests include time-stamped measurements of current, voltage, and temperature. Preprocessing steps involve noise reduction and calibration to ensure data accuracy and consistency. Using the best regression model, the study estimates the optimal values for key parameters that minimize internal resistance and enhance battery health. These optimal values are derived from the regression model's coefficients and their impact on battery performance.

Based on the output of the regression model, an optimal operating range for lithium-ion batteries is proposed. Data-driven optimization algorithms are employed to define this range, considering the complex interplay of different operational parameters.

The study presents the following optimal values for battery parameters:

Parameter	Optimal Value
Voltage (V)	3.260
Current (A)	0.999
CDS Temperature (°C)	28.681
Capacity (Ah)	0.080
Global Charge Capacity (Ah)	1.813
Global Discharge Capacity (Ah)	42.790
Global SOC (%)	45.488
Charge Capacity (Ah)	0.039
Discharge Capacity (Ah)	0.041
Charge Energy (Wh)	0.133
Discharge Energy (Wh)	0.128

Interpretation:

- **Voltage:** The optimal voltage is found to be around 3.26V. Maintaining this voltage level helps in reducing internal resistance and improving efficiency.
- **Current:** The optimal current is approximately -1A. This indicates the ideal current draw for maintaining battery health.
- **Temperature:** The optimal temperature for the battery's operation is around 28.68°C. Operating within this temperature range helps in minimizing resistance and enhancing battery life.

Capacity and Energy Metrics: These values indicate the optimal charge and discharge capacities and energy levels for the battery, which contribute to maintaining its health and performance

6. Conclusion

When analysing HPPC test data for internal resistance, it is critical to consider factors such as SoC (State of Charge), temperature, aging, and pulse characteristics. Understanding these influences helps optimize battery performance, lifespan, and safety, particularly in applications that demand high power and fast response, such as electric vehicles and energy storage systems.

The analysis of MSE (Mean Squared Error) across different algorithms reveals that when dealing with similar datasets, it is advisable to start with tree-based algorithms, with a focus on LightGBM or Gradient Boosting techniques, to capture complex relationships and achieve lower prediction errors. Linear models and regularization techniques may be reserved for cases with more straightforward, linear patterns or as baseline comparisons.

The optimization process identifies the most effective operating conditions for lithium-ion batteries. By using data-driven models and regression analysis, the study provides a robust framework for optimizing battery performance. This approach ensures scalability and real-time applicability, offering significant improvements in battery efficiency and lifespan.

Understanding how internal resistance varies with SoC and current rates at different temperatures is crucial for designing battery management systems. Higher internal resistance at low temperatures can lead to reduced efficiency, increased heat generation, and potential performance issues, especially in applications where consistent power delivery is critical. The Optimal Operating Range suggests that the battery exhibits lower and more stable internal resistance values at middle SoC ranges (40%–70%), particularly at higher current rates (1 C). Operating the battery within these ranges can enhance performance and reduce internal losses. While higher temperatures generally reduce internal resistance due to increased ionic mobility, they can also introduce variability and instability, which might affect battery longevity. Therefore, care should be taken when operating at 55°C.

Understanding these internal resistance characteristics is crucial for developing battery management systems (BMS) that can optimize charging and discharging processes, prevent overheating, and maintain battery health, especially in high-temperature environments.

Future Work: Suggest areas for future research, such as advanced materials to lower internal resistance, improved thermal management techniques, and more sophisticated diagnostic tools for real-time internal resistance monitoring.

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