

## Article

# Cross-Condition Lithium-Ion Battery Capacity Multi-Variable Estimation Model Based on Incremental Capacity Curve Features

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## Abstract

Accurate estimation of lithium-ion battery state of health and capacity is critical for intelligent battery management. This study develops a multi-variable cross-condition capacity estimation model based on incremental capacity (IC) curve features. First, the IC curve area is extracted to construct a health indicator. To capture the coupled, non-linear effects of temperature and discharge current on capacity fade, a temperature-zoned modeling framework is implemented. Specifically, first-order linear polynomials are applied for room temperature conditions to prevent overfitting, while second-order polynomials with interaction terms are utilized for high and low temperature conditions to model complex degradation behaviors. Furthermore, to mitigate estimation errors caused by individual battery inconsistency and varying initial states across different operating conditions, the capacity retention rate (CRR) and health indicator retention rate metrics are defined and integrated into the estimation framework. Validation across multiple dynamic operating conditions demonstrates that the optimized CRR-based model achieves an average root mean square error of 0.0261 Ah and a mean absolute percentage error of 2.83%. The proposed temperature-zoned approach provides a robust, data-driven methodology for cross-condition battery health monitoring.

**Keywords:** lithium-ion battery; state of health estimation; incremental capacity analysis; cross-condition estimation; capacity retention rate; temperature-zoned modeling

## 1. Introduction

Advanced energy storage is crucial for global decarbonization. Lithium-ion batteries, featuring high energy density, long cycle life, and specific chemistry-dependent profiles, are the core technology driving transportation electrification and battery energy storage systems (BESS). With accelerating electric vehicle (EV) deployment, managing their entire lifecycle—from primary vehicular use to second-life stationary storage and material recycling—has become vital for achieving a sustainable circular economy [1].

However, during actual application, lithium-ion batteries undergo complex degradation processes, leading to capacity decay and increased internal resistance. In dynamic environments like EVs, wide-ranging temperature fluctuations and variable charge-discharge profiles non-linearly accelerate aging and induce diverse internal degradation mechanisms. To ensure safety, optimize energy management, and maximize lifespan under such varied conditions, a high-accuracy, robust Battery Management System (BMS) is indispensable.



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Accurate State of Health (SOH) estimation is a critical BMS function, quantifying current performance relative to the pristine state. Crucially, precise SOH evaluation is decisive not only for estimating remaining useful life and planning maintenance in active EVs but also as a fundamental prerequisite for the safe, economically viable second-life cascaded utilization of retired batteries [2]. Therefore, achieving robust multi-variable SOH estimation under complex, dynamic operating conditions remains a major technical challenge. Overcoming this bottleneck is essential for improving new energy efficiency and establishing a closed-loop battery economy.

### 1.1. Literature Review

To address the aforementioned challenges in lithium-ion battery SOH estimation, particularly concerning its accuracy and robustness under complex operating conditions, researchers domestically and internationally have conducted extensive and in-depth studies. These studies primarily revolve around different technical approaches. Currently, mainstream lithium-ion battery SOH estimation methods can be broadly classified into the following categories: experimental methods, data-driven methods [3], model-based methods [4], and hybrid methods that combine multiple approaches.

Experimental estimation methods typically combine systematic cycling tests and real-time parameter acquisition with data-driven algorithms to capture electrochemical evolution. Demonstrating this, a rapid assessment technique utilizing specific impedance ratios from Nyquist plots significantly shortened traditional Electrochemical Impedance Spectroscopy (EIS) testing time tenfold, maintaining a low estimation error of 4.46% through second-order polynomial fitting [5]. To further balance accuracy and computational efficiency, hybrid methods integrate the complementary strengths of both model- and data-driven approaches. For instance, estimation robustness across diverse charge-discharge scenarios can be effectively enhanced by fusing internal electrochemical states with external multi-stage voltage-temperature features via machine learning [6]. Furthermore, advanced data-physical fusion frameworks—such as integrating a fractional-order model with a Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) network and Gaussian distribution—have proven to be highly capable of capturing complex battery dynamics, achieving state estimation accuracy within a strict 1% margin [7].

Data-driven methods bypass complex electrochemical mechanisms by leveraging historical operation data and machine learning algorithms to directly map external measurement signals to SOH [3]. In recent applications, fusing partial incremental capacity (IC) with artificial neural networks (ANN) has proven highly effective for simultaneously estimating SOH and Remaining Useful Life (RUL) with minimal error [8]. Similarly, adaptive estimation frameworks have been successfully developed by pairing online alternating current (AC) impedance with ANN [9]. Advanced optimization techniques also play a crucial role; for example, integrating Gaussian process regression (GPR) with multi-island genetic algorithms [10] or directly accounting for internal resistance changes [11] ensures highly accurate state estimations. Furthermore, cross-domain data-driven techniques—such as coupling multi-stage feature extraction with Particle Swarm Optimization-Bidirectional LSTM (PSO-BiLSTM) networks from renewable energy forecasting—provide valuable insights for processing complex time-series features in battery health monitoring [12].

Model-based methods attempt to describe the battery's internal electrochemical behavior or external electrical characteristics by establishing internal models, thereby reflecting SOH through changes in model parameters or states [4]. These approaches can typically be divided into physical models and mathematical or empirical models [13]. Physical models, such as electrochemical models (ECM), are built upon a comprehensive understanding of

internal electrochemical reactions and transport processes. To track SOH changes dynamically, these models are frequently combined with nonlinear state estimators or adaptive filtering techniques, particularly Kalman filtering (KF) [14] and particle filters (PF) [15]. Recent advancements in this domain have demonstrated that integrating improved or genetic particle filtering algorithms can yield superior estimation accuracy compared to traditional PF frameworks [16,17]. Similarly, coupling the Thevenin equivalent circuit model with KF has proven highly effective for online state tracking [18]. Furthermore, the foundation of model-based SOH estimation has been significantly broadened by related structural research. This includes investigations into the impact of Hybrid Pulse Power Characterization (HPPC) parameters on equivalent circuit performance [19], the development of model-driven, health-aware fast charging strategies [20], and the introduction of novel architectures like electrochemical reduced-order models [21] and the BattX equivalent circuit model [22].

Another prominent branch of model-based methods utilizes mathematical or empirical models [13]. Rather than simulating complex internal electrochemistry, these approaches extract Health Indicators (HIs) from empirical charge-discharge data. Differential Voltage Analysis (DVA) and Incremental Capacity Analysis (ICA) achieve this by performing differential or integral transformations on voltage-capacity curves to amplify internal phase transitions. These techniques have been widely deployed to estimate SOH and analyze aging mechanisms. For instance, diverse DVA-based algorithms have been developed to enhance calculation accuracy and online applicability across various battery chemistries like lithium iron phosphate (LFP) and nickel manganese cobalt (NMC) [23–26]. Similarly, ICA methods have been extensively utilized to identify specific degradation stages [27,28], extract constant-voltage charging features [29], evaluate different filtering reconstructions [30], and develop temperature-robust regression models [31].

Despite their proven effectiveness under controlled laboratory conditions, these methods face significant challenges in dynamic practical applications. Specifically, IC curve features and the derived HIs are notoriously sensitive to external operating conditions, particularly ambient temperature and discharge current. This acute sensitivity dictates that most existing SOH estimation models heavily depend on stable operating profiles, severely limiting their accuracy under complex, variable conditions.

Consequently, achieving robust SOH estimation across dynamic environments remains a critical bottleneck. While recent studies have begun acknowledging condition variations, they predominantly focus on isolated dimensions. For example, several SOH models have explored temperature variations but failed to systematically investigate the simultaneous impact of dynamic discharge currents [32–34]. Conversely, other research has quantified how higher discharge currents accelerate capacity degradation, but this analysis was strictly restricted to a single room-temperature condition [35]. In reality, environmental temperature, charge/discharge currents, and cutoff voltages collectively and significantly dictate the battery's SOH [36]. The complex, non-linear coupled influence of both temperature and discharge current on capacity fade has not been comprehensively analyzed within a unified modeling framework. Quantifying these multi-variable coupling relationships under dynamically changing conditions forms the most pressing challenge for developing highly robust, real-world SOH estimation models.

### *1.2. Motivation and Original Contribution*

To address the aforementioned challenges in lithium-ion battery SOH and capacity estimation under complex multi-variable operating conditions, particularly the sensitivity of feature-based methods to condition variations, the lack of sufficient analysis and modeling of temperature and discharge current coupled effects in existing work, and the

difficulties in handling cross-condition estimation and battery inconsistency, this study proposes the following layered modeling and optimization strategy, aiming to provide a systematic solution capable of achieving high-accuracy and robust capacity estimation under complex conditions:

- (1) **Temperature Zone Modeling based on Capacity Fade Rate per Cycle (CFRPC) Indicator:** To overcome the problem that single models find it difficult to effectively capture the differences in battery capacity fade characteristics across different temperature zones (as shown by the dominant role of temperature in the quantitative analysis in Section 3.3), this study quantitatively analyzes the influence rules of temperature based on the CFRPC indicator and proposes and constructs a differentiated estimation model framework based on temperature zones to enhance the model's adaptability to temperature variations and estimation accuracy.
- (2) **Quadratic Polynomial Representation of Discharge Current Nonlinearity and Interaction:** To address the complex nonlinearity of discharge current's influence on capacity fade and its interaction with HI under dynamic conditions (as shown in the analysis in Section 3.3), and to overcome the limitations of traditional linear models or single current parameter models, this study adopts a quadratic polynomial to represent the nonlinear relationship between discharge current and battery capacity or model parameters, and introduces interaction terms to capture the coupled effects of current and aging state more accurately.
- (3) **CRR-HIRR Association Model to Handle Cross-Condition and Battery Inconsistency:** To effectively solve the estimation deviation caused by battery inconsistency and inconsistent initial states across different operating conditions on cross-condition estimation (as demonstrated in the validation in Section 4.3), this study innovatively proposes the concept of Capacity Retention Rate (CRR) and constructs an association model between CRR and HI Retention Rate (HIRR) based on IC features. This strategy, by normalizing different initial states and individual differences using relative indicators, is a key innovation for improving model cross-condition estimation robustness and handling battery pack inconsistency.

In summary, the layered modeling and CRR-HIRR optimization integrated approach proposed in this study, by using CFRPC analysis to guide temperature zone modeling, employing quadratic polynomials to capture current nonlinearity, and constructing the CRR-HIRR association model to solve cross-condition and inconsistency problems, forms a systematic, high-accuracy, and robust capacity estimation method for complex operating conditions. This holds not only significant theoretical research value but also provides a promising solution for reliable health management in BMS in practical applications.

### 1.3. Configuration of This Study

The remainder of this paper is organized as follows: Section 2 introduces the experimental dataset, the HI extraction method, and the definitions of evaluation metrics (RMSE, MAPE, and NRMSE). It also proposes the Capacity Retention Rate (CRR) and HI Retention Rate (HIRR) concepts alongside a preliminary single-variable model analysis. Section 3 quantitatively investigates the battery capacity fade characteristics under multi-condition tests, emphasizing the dominant role of temperature using the CFRPC indicator. Section 4 details the construction and comprehensive validation of the multi-variable capacity estimation framework, which integrates Temperature-Zoned Modeling (TZM) and quadratic polynomials to achieve robust cross-condition estimation. Finally, Section 5 summarizes the conclusions. The overall flowchart of the proposed method is illustrated in Figure 1.

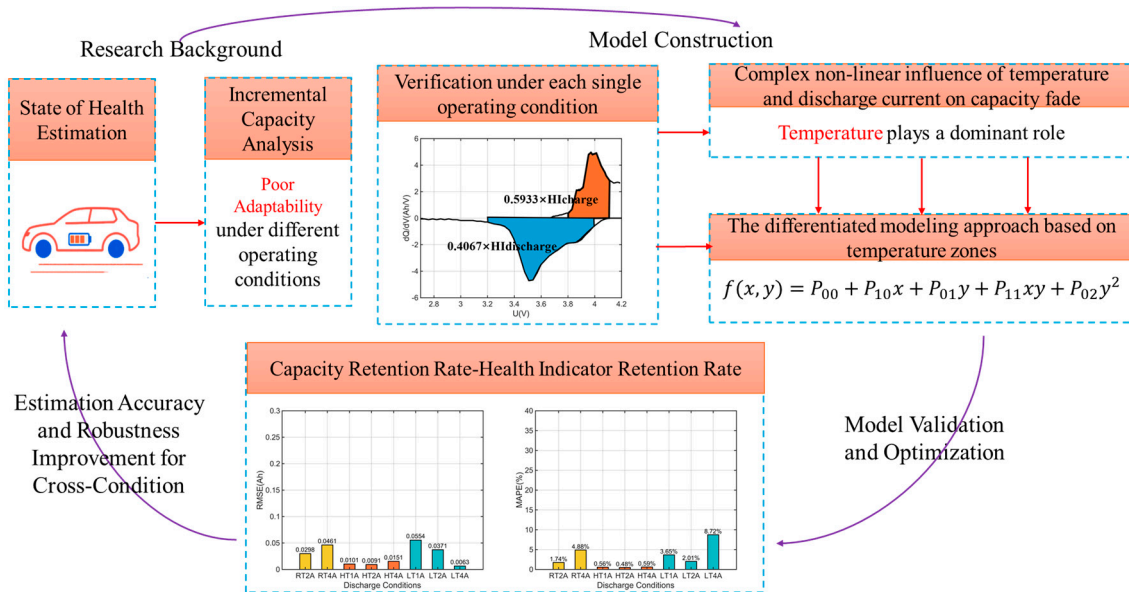


**Figure 1.** Overview of proposed method for battery capacity multi-variable estimation.

## 2. Experimental Description and Health Feature Construction Method

### 2.1. Data Description

This study uses 18650-type NCA lithium-ion batteries from the public dataset of the National Aeronautics and Space Administration (NASA) Prognostics Center of Excellence (PCoE) [37]. The general information and specifications of the batteries are summarized in Table A1. The experimental data were obtained from cycling tests conducted under three different temperature zones: Room Temperature (RT) (24 °C), High Temperature (HT) (44 °C), and Low Temperature (LT) (4 °C). A complete cycle includes a charging phase immediately followed by a discharging phase. The charging phase for all battery sets was conducted in Constant Current (CC) mode at 1.5 A until the battery voltage reached 4.2 V, then switched to Constant Voltage (CV) mode, continuing until the charging current dropped to 20 mA. The discharging phase for each battery set was conducted at varying temperatures and discharge current magnitudes in CC mode until the cell voltage dropped to its respective cut-off voltage. The experiment involved repeatedly cycling the batteries until they reached their End of Life (EOL) standard, generally defined as a 30% decay in rated capacity from 2 Ah to 1.4 Ah. (Note: For batteries #38, #39, and #40, the EOL standard was set as a 20% decay from 2 Ah to 1.6 Ah due to the original dataset setup).

Specifically, this difference in EOL thresholds implies that the raw data spans different portions of the degradation trajectory. Cells cycled to a 20% capacity loss primarily reflect the earlier, often more linear aging phase, whereas those cycled to a 30% loss capture deeper, non-linear degradation behaviors. Consequently, directly comparing absolute capacity estimation models across these cells may introduce statistical bias. This comparability challenge directly motivates the introduction of the relative normalization strategy (CRR and HIRR) detailed in Section 2.5, which is designed to decouple the estimation process from inconsistent absolute EOL standards.

To construct robust cross-condition estimation models and reflect real-world battery operations, this study specifically selected battery data containing multi-stage sequences with continuous condition changes during a cell's life, rather than relying solely on fixed-condition data. Crucially, to rigorously evaluate the model's cross-condition generalization capability and explicitly prevent any potential data leakage, a strict "independent-cell" train/test split strategy was implemented. Models were fitted exclusively using data from the training cells (#5, #38, #29, and #42). The subsequent cross-condition assessments were

performed entirely on unseen, independent validation cells (#7, #40, #31, and #43). By evaluating the models on these independent validation cells as they undergo dynamic phase transitions (e.g., cell #43 shifting sequentially from 2 A to 4 A, and then to 1 A at 4 °C), strict separation for cross-condition assessment is guaranteed. The explicit mapping of cells, cycle segments, operating conditions, and their respective roles (Training vs. Validation) is thoroughly detailed in Table 1.

**Table 1.** The detailed description of each operating condition of the battery data set [37].

| Temperature | Operating Condition | Training Data (Cell ID & Cycle Segments) | Validation Data (Cell ID & Cycle Segments) | Cut Off Voltages |
|-------------|---------------------|------------------------------------------|--------------------------------------------|------------------|
| RT (24 °C)  | RT2A                | #5 (cycles 1–166)                        | #7 (cycles 1–166)                          | 2.7 V, 2.2 V     |
|             | RT4A                | #38 (cycles 1–11)                        | #40 (cycles 1–11)                          | 2.2 V, 2.7 V     |
| HT (44 °C)  | HT1A                | #38 (cycles 12–38)                       | #40 (cycles 12–38)                         | 2.7 V, 2.2 V     |
|             | HT2A                | #38 (cycles 39–44)                       | #40 (cycles 39–44)                         | 2.2 V, 2.7 V     |
|             | HT4A                | #29 (cycles 1–39)                        | #31 (cycles 1–39)                          | 2.0 V, 2.5 V     |
| LT (4 °C)   | LT1A                | #42 (cycles 87–111)                      | #43 (cycles 87–111)                        | 2.0 V, 2.2 V     |
|             | LT2A                | #42 (cycles 1–40)                        | #43 (cycles 1–40)                          | 2.0 V, 2.2 V     |
|             | LT4A                | #42 (cycles 41–86)                       | #43 (cycles 41–86)                         | 2.0 V, 2.2 V     |

## 2.2. Health Feature Construction Method

This study constructs health features for evaluating battery SOH based on the analysis of IC curves. The IC curve is the differential curve of battery capacity with respect to voltage. It can amplify voltage plateau characteristics during battery charge and discharge processes, which are related to phase transitions and reaction kinetics of the electrode materials internally, and its change with aging can sensitively reflect the battery's internal state. Building upon our previous work [38], to ensure methodological reproducibility and inherently suppress measurement noise without relying on direct numerical differentiation, we applied a robust voltage-binning accumulation method. Specifically, the reference voltage sequences were set with a step size ( $\Delta V$ ) of 10 mV for the charging phase (3.4–4.2 V) and 30 mV for the discharging phase (2.7–4.2 V), optimized to balance noise reduction and feature retention. A moving average filter with a window size of 3 was subsequently applied to smooth the generated IC sequences.

Given that the shape and features of the IC curve can sensitively reflect internal electrochemical changes, the area enclosed by the curve and the voltage axis reflects the total charge that the battery can store or release within a specific voltage range. As the battery ages, loss of active material and increase in resistance lead to a gradual decrease in this area, thus it generally has a good correlation with the battery's available capacity. In this study, the HI is defined as the integrated area under the IC curve. To capture the primary degradation mechanisms while excluding edge noise, the integration voltage intervals were strictly set to 3.8–4.1 V for charging and 3.21–3.99 V for discharging. This area-based method integrates the overall information of the curve and offers better robustness to noise or partial peak disappearance compared to methods relying solely on peak features.

Furthermore, in analyzing battery HIs for EVs, it is necessary to consider that EV usage in practice includes both charging and discharging phases. Using IC features from only one phase may not fully reflect the battery's SOH or may not be closely related to actual operating conditions. Therefore, a fused health indicator ( $HI_{\text{fusion}}$ ) was constructed. Based on statistical analyses of the New European Driving Cycle (NEDC) and the China New Energy Vehicle Big Data Research Report [39,40], the charge-to-discharge capacity ratio

in typical household EV usage is approximately 0.5933 to 0.4067 (excluding regenerative braking). Thus, the weighted fusion formula is explicitly defined as follows:

$$HI_{\text{fusion}} = 0.5933 \times HI_{\text{charge}} + 0.4067 \times HI_{\text{discharge}},$$

Using data from representative batteries (such as #5, #29, #38, #42), health features were constructed according to the above method, and the relationship between the fused weighted HI and battery capacity under different operating conditions is shown in Figure 2.

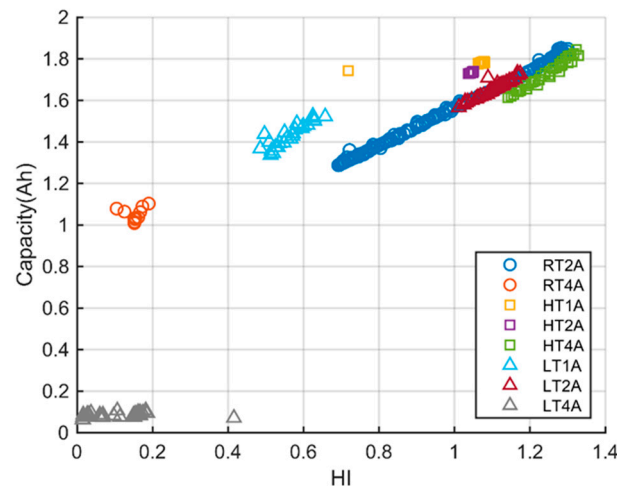


**Figure 2.** The relationship between HI and capacity under different operating conditions.

### 2.3. Single-Variable Model Construction and Preliminary Validation

In previous research [38], it was found that under a specific single constant operating condition (e.g., RT2A), a single-variable association model constructed based on IC curve HI and battery capacity could achieve good capacity estimation performance. However, to systematically investigate the universality and potential limitations of this simplified modeling method under more extensive and diverse constant operating conditions, thereby providing a basis for constructing more complex models, this study adopts the same modeling approach and model form. For each independent operating condition segment listed in Table 1, a battery capacity estimation model based on HI as the single independent variable was constructed and preliminarily validated.

A systematic evaluation was conducted for the estimation model constructed under each single operating condition, quantifying the model's performance. Model fitting quality was evaluated using the Sum of Squared Errors (SSE) and the Coefficient of Determination ( $R^2$ ). A lower SSE indicates minimal residual deviation between actual and predicted values, whereas an  $R^2$  approaching 1 signifies that the model robustly explains the data variance. The model's parameters and goodness of fit metrics are presented in Table 2. Furthermore, the fitting results and corresponding capacity estimation errors are visually presented in Figure 2 and Figure 3, respectively.

Through analysis of the model's performance shown in Figures 3 and 4, it can be seen that under most single constant operating conditions, the single-variable model based on HI can estimate battery capacity to some extent, which preliminarily indicates that HI is effective as a health feature. However, the model shows significant variability and limitations when applied to all conditions. For example, under RT4A conditions, the model's estimation error (the RMSE value, as shown in Figure 4) is significantly higher than under other conditions (e.g., RT2A), which strongly suggests the limited generalization ability of this simplified modeling method when current or temperature and other conditions change significantly, indicating a need for modification or improvement. It is worth noting that

the Mean Absolute Percentage Error (MAPE) value under LT4A conditions is abnormally high at 25%. This is primarily attributed to the error amplification effect caused by the battery's actual available capacity being at an extremely low level under this condition, the maximum capacity in this condition is only 0.1065 Ah, far below the rated capacity of 2 Ah, approaching the set 5% rated capacity threshold. When the true capacity value is in the low range and approaches zero, a small absolute estimation deviation can lead to the relative error metric fluctuating by orders of magnitude. This is essentially a statistical metric distortion caused by dynamic range compression of low-range data, but it also reflects the challenging nature of estimation under this condition.

**Table 2.** The model parameters and goodness of fit for each single operating condition.

| Condition | $f(x,y) = P_{00} + P_{10}x$ |          | Goodness of Fit |         |          |
|-----------|-----------------------------|----------|-----------------|---------|----------|
|           | $P_{00}$                    | $P_{10}$ | SSE             | $R^2$   | RMSE     |
| RT2A      | 0.657                       | 0.9093   | 0.01409         | 0.9976  | 0.009269 |
| RT4A      | 1.018                       | 0.2038   | 0.009497        | 0.02201 | 0.03248  |
| HT1A      | 1.661                       | 0.1117   | 0.000197        | 0.8846  | 0.002807 |
| HT2A      | 0.9973                      | 0.7043   | 0.00002894      | 0.7345  | 0.00269  |
| HT4A      | 0.2704                      | 1.172    | 0.006116        | 0.9616  | 0.01286  |
| LT1A      | 0.8178                      | 1.091    | 0.01612         | 0.7998  | 0.02648  |
| LT2A      | 0.613                       | 0.9453   | 0.005733        | 0.9234  | 0.01245  |
| LT4A      | 0.08031                     | 0.03328  | 0.004216        | 0.06623 | 0.009789 |

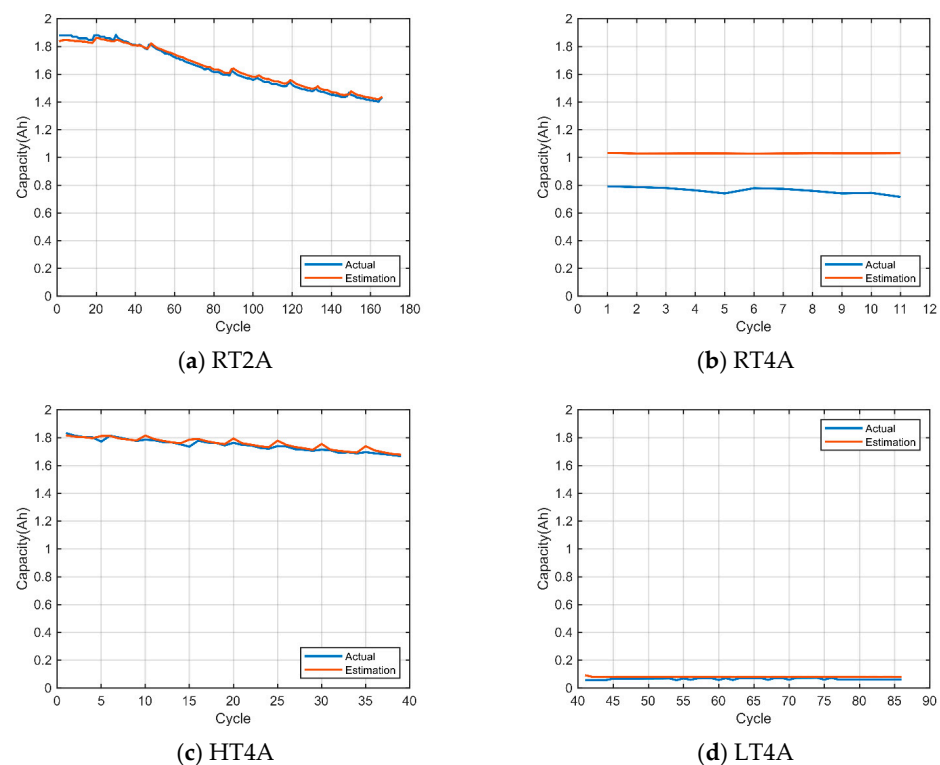


**Figure 3.** The capacity estimation results under each single operating condition.

Overall, although it is conceptually feasible to construct estimation models for different single operating conditions using the single-variable method based on HI, and they possess certain estimation capability under some conditions, the phenomenon of large estimation errors occurring under specific conditions such as RT4A or LT4A clearly indicates that this simplified single-variable modeling method is insufficient to meet the requirements for accuracy and robustness of battery capacity estimation under complex and variable actual

operating conditions. This finding strongly demonstrates the necessity of considering more operating condition variables and their interactions in the battery capacity estimation model to achieve high-accuracy capacity estimation across different conditions, laying the foundation for subsequent research.

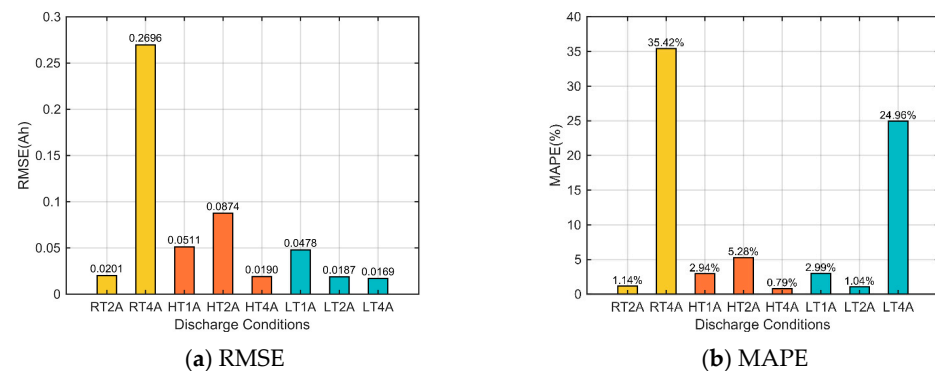


**Figure 4.** The capacity estimation errors under each single operating condition.

#### 2.4. Generalized Temperature-Zoned Modeling Framework

Building upon the critical limitations identified in the single-variable analysis above, it is evident that relying solely on HI is insufficient to capture the complex, highly coupled capacity fade dynamics under variable conditions. To address the significant estimation errors observed in extreme scenarios, this study proposes a comprehensive multi-variable approach: the Temperature-Zoned Modeling Framework.

The core principle of this framework is to explicitly incorporate the discharge current (denoted as  $y$ ) alongside the Health Indicator (denoted as  $x$ ) to estimate the battery capacity, while adaptively adjusting the model's complexity based on the specific temperature zone. To accommodate the varying degrees of non-linearity caused by temperature-current interactions, a generalized polynomial model is defined as follows:

$$f(x, y) = P_{00} + P_{10}x + P_{01}y + P_{11}xy + P_{02}y^2,$$

where  $f(x, y)$  represents the estimated health state. During the specific implementation for each temperature zone (as will be detailed in Section 4), the mathematical order of this generalized formula is adaptively tailored. For electrochemically stable degradation zones, higher-order and interaction terms are intentionally omitted to form a robust first-order linear model, thereby preventing overfitting to measurement noise. Conversely, for extreme temperature zones exhibiting strong non-linearity, the full second-order polynomial with interaction terms is activated to accurately capture the accelerated aging trajectories.

#### 2.5. Definition of Relative Health Metrics

Furthermore, to eliminate the baseline inconsistencies caused by individual battery variability and different initial states across various continuous test stages, this study introduces two relative health metrics: Capacity Retention Rate (CRR) and Health Indicator Retention Rate (HIRR). These normalized metrics are designed to address the inherent challenges of cross-condition capacity estimation that will be discussed in the subsequent model validation.

Rather than relying solely on absolute capacity, CRR serves as a local SOH indicator. It effectively normalizes the initial available capacity differences caused by switching operating conditions across different test stages, as well as the influence of inherent indi-

vidual variability. CRR is defined as the ratio of the battery's real-time capacity within a continuous test stage to its initial capacity at the beginning of that specific stage:

$$CRR = \frac{C_{\text{current}}}{C_{\text{initial\_segmen}}} \times 100\%$$

where  $C_{\text{current}}$  is the current battery capacity (Ah), and  $C_{\text{initial\_segmen}}$  is the initial capacity (Ah) at the beginning of that continuous test stage.

Simultaneously, to maintain mathematical consistency on the model's input side with CRR, and to accurately reflect the relative evolution of the extracted health features, HIRR is established. It is defined as the ratio of the battery's current HI to the initial HI at the beginning of that stage:

$$HIRR = \frac{HI_{\text{current}}}{HI_{\text{initial\_segmen}}} \times 100\%$$

where  $HI_{\text{current}}$  is the current HI, and  $HI_{\text{initial\_segmen}}$  is the initial HI at the beginning of that continuous test stage. By employing these normalized relative metrics, the proposed modeling framework can effectively decouple the baseline variations from the true condition-induced degradation trends, laying the foundation for an optimized, highly accurate capacity estimation strategy.

## 2.6. Model Evaluation Metrics

To quantify the estimation accuracy and evaluate the model's performance, the Root Mean Square Error (RMSE) and MAPE are employed as the primary evaluation metrics. The RMSE evaluates the error in the absolute capacity domain and is expressed in Ampere-hours (Ah), while the MAPE represents the relative percentage error. They are mathematically defined as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - f(x_i))^2}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{Y_i - f(x_i)}{Y_i} \right| \times 100\%$$

where  $Y_i$  represents the true capacity value (Ah),  $f(x_i)$  represents the predicted capacity value (Ah) by the model, and  $n$  is the total number of data points within a specific operating condition segment.

Furthermore, to comprehensively evaluate the model's cross-condition robustness, the overall average performance is reported in the abstract and conclusions. The average RMSE and average MAPE are calculated by taking the arithmetic mean of the individual RMSE and MAPE values obtained across all distinct validation conditions and cells.

It is noteworthy that percentage errors like MAPE can become mathematically unstable and artificially inflated when evaluating extreme degradation conditions where the absolute capacity approaches zero (e.g., under the LT4A condition) due to excessively small denominators. To address this, the Normalized Root Mean Square Error (NRMSE) is introduced as an auxiliary robust metric for such specific regimes. The NRMSE normalizes the absolute error against the battery's nominal capacity ( $C_{\text{nom}} = 2 \text{ Ah}$ ), defined as follows:

$$NRMSE = \frac{RMSE}{C_{\text{nom}}} \times 100\%$$

## 3. Analysis of Battery Aging Characteristics

### 3.1. IC Curve Analysis Under Different Conditions

This study constructs health features for capacity estimation of lithium-ion batteries based on the analysis of IC curve features. To preliminarily investigate the characteristic

changes of IC curves under different operating conditions and their association with battery aging behavior, representative batteries (e.g., numbers #5, #29, #34, and #42) were selected as examples, and IC curves at different cycle degrees under some typical operating conditions were plotted. The results are shown in Figure 5. The cycle degree mentioned here is defined as the ratio of the current cycle number of a stage's operating condition to the total number of cycles for that stage's operating condition.

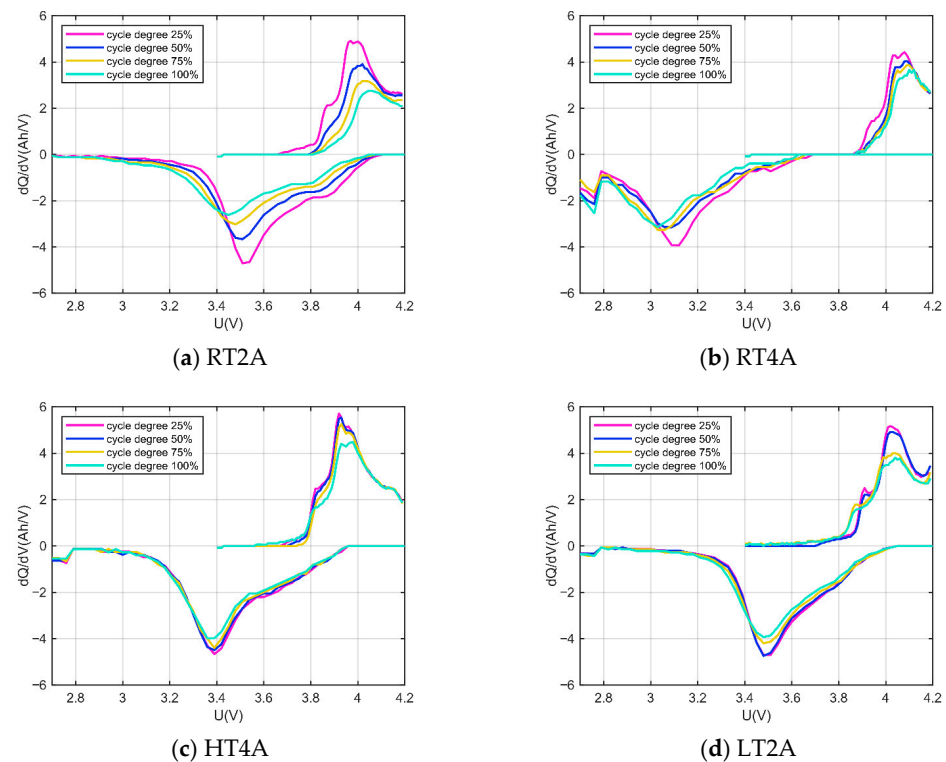


**Figure 5.** The IC curves for each operating condition.

From Figure 5, it can be seen that under different operating conditions, as the battery's cycle degree increases, the peak of the IC curve gradually decreases, and the area enclosed by the curve and the voltage axis also gradually reduces. This is consistent with the trend of battery available capacity decay, indicating that IC curve features can effectively reflect changes in battery capacity. Further observation reveals significant differences in the evolution patterns of IC curves under different temperature conditions. Under RT conditions, the decrease and shape changes of the IC curve are relatively smooth and show good regularity. However, under HT and LT conditions, especially in the later stages of cycling, the IC curve exhibits a different rate of decrease compared to the earlier stages, with the rate of capacity decay showing a tendency to accelerate. It should be explicitly noted that while Figure 5 only displays the IC curves at discrete 25% intervals for visual clarity and to prevent severe curve overlapping, the complete continuous cycle data were extracted and utilized for the subsequent health feature construction and model training.

This accelerated decay phenomenon observed in the IC curves is consistent with hypotheses in existing literature suggesting that non-RT conditions accelerate the aging process of internal battery materials [41]. Specifically, previous studies have hypothesized that high temperatures can exacerbate the structural degradation of electrode active materials, corrosion of current collectors, or side reactions of the electrolyte [42]. Conversely, LT conditions are widely theorized to induce active lithium deintercalation, abnormal Solid Electrolyte Interphase (SEI) film thickening, or lithium plating [43,44]. Although these specific micro-mechanisms are not directly diagnosed in this data-driven study, adopting

these literature-supported hypotheses provides a plausible explanation for the macroscopic nonlinear capacity fade in later stages. Indeed, our data show that this accelerated decay phenomenon is more evident and appears earlier under low-temperature conditions. These characteristic changes in the IC curves suggest that, compared to extreme temperatures, battery capacity decay under RT is closer to linear; while under HT and LT conditions, the deterioration of battery SOH is faster and highly nonlinear, with a rapid decline in performance occurring earlier.

### 3.2. Multi-Condition Capacity Fade Characteristics

To deeply investigate the rules of battery capacity fade under different operating conditions, particularly how changes in temperature and discharge current affect the battery's aging process, an in-depth analysis of capacity fade characteristics was further conducted based on battery samples with multi-condition continuous test data. Battery sets #38–#40 and #41–#44 from the dataset, which underwent continuous constant current discharge cycling tests under different temperature and discharge current combinations, were selected as research subjects for comparative analysis. These batteries' test sequences included condition switching, providing a valuable perspective for observing how condition changes affect battery capacity fade and being closer to the battery's operating mode in practical applications.

Figure 6 shows the capacity fade curves of batteries #41–#44 as a function of cycle number. According to the description in Table 1, battery #41 underwent a two-stage test from LT4A discharge to LT1A discharge, while batteries #42–#44 completed a three-stage test of LT2A → LT4A → LT1A discharge. From the figure, it can be seen that under LT conditions, high current discharge (4 A) leads to a significant decrease in available capacity and a noticeably accelerated capacity fade rate. When the condition switched from LT4A to low current discharge (LT1A), a significant partial capacity recovery characteristic was observed. Comparing the test results of #41 (starting from LT4A) and #42–#44 (starting from LT2A), it appears that undergoing medium current discharge (2 A) beforehand can effectively mitigate the subsequent capacity fade caused by high current discharge (4 A) and exhibit higher capacity recovery efficiency when switching back to low current (1 A), which suggests that the battery's aging history and test sequence influence subsequent capacity performance.

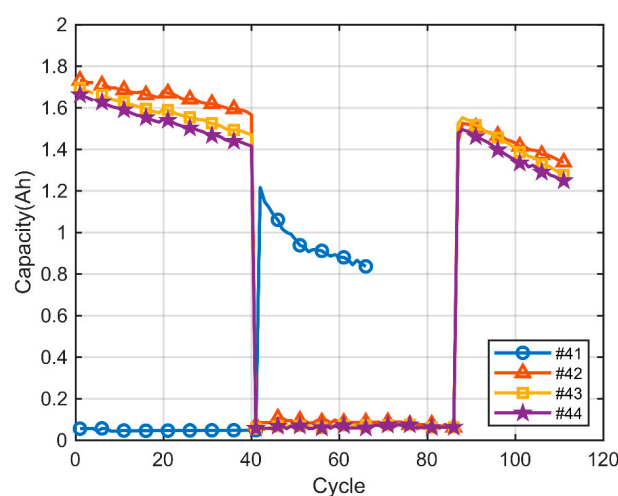


**Figure 6.** The relationship between the capacity and the number of cycles of battery #41 to #44.

Figure 7 shows the capacity fade curves of batteries #38–#40 under multi-condition operation. This set of batteries sequentially underwent three main stages: RT4A discharge, HT1A discharge, and HT2A discharge (Note: a brief HT4A discharge test was conducted

in cycles 45–46, but was not included in the main analysis due to insufficient data points). Experimental results indicate: (1) Under HT conditions, as the discharge current gradually increased from 1 A to 2 A, battery capacity exhibited a clear step-wise decay and a faster fade rate, which further verifies the influence of current magnitude on aging speed. (2) Comparing Figures 6 and 7, it can be observed that under similar high current conditions (e.g., 4 A), the magnitude of capacity fade under HT conditions is relatively smaller than under LT conditions, which indicates that temperature significantly influences the manner and extent of capacity fade. (3) Despite the complex test sequence, by comparing the capacity and fade trends in each stage, it is found that batteries under HT conditions generally exhibit higher usable capacity than in the initial RT4A stage (e.g., the initial capacity of the HT1A stage is higher than the capacity at the end of the RT4A stage), which may be attributed to the elevated temperature promoting electrode reaction kinetics and electrolyte ion transport, allowing more capacity to be released.

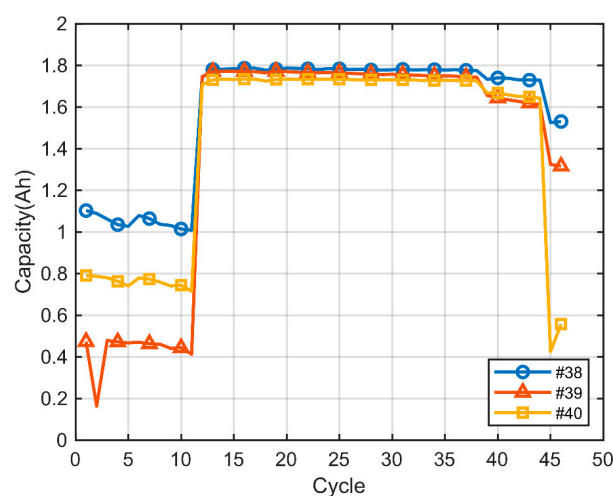


**Figure 7.** The relationship between the capacity and the number of cycles of battery #38 to #40.

It is particularly worth noting that the capacity fade rate during the RT4A discharge phase (0.00855 Ah per cycle) is significantly higher (more than 50 times greater) than during the HT1A discharge phase (0.00017 Ah per cycle), despite the RT4A discharge occurring during the relatively initial stage of battery life decay, where theoretically the decay should be slower. This contrary pattern strongly indicates the complex and significant influence of temperature and discharge current on battery capacity fade, and that simple cycle number alone cannot fully measure the degree of aging. The underlying physical reasons for this drastic difference can be attributed to the coupled effects of reaction kinetics and internal mechanical stress. Under the RT4A condition, the rapid extraction of lithium ions induces severe polarization and significant mechanical stress within the electrode particles, thereby accelerating the structural degradation of active materials. Conversely, under the HT1A condition, the elevated temperature significantly enhances electrolyte ionic conductivity and interfacial reaction kinetics. Coupled with the low discharge current, the battery experiences minimal polarization and mechanical stress, rendering it an extremely benign operating condition with an exceptionally slow degradation rate. Furthermore, the observed difference in fade rate between the HT1A and HT2A discharge phases might be influenced by the test sequence and accumulated aging effects, making it difficult to attribute simply to current change alone. This further suggests that aging history needs to be considered in modeling.

Collectively, the detailed analysis of capacity fade characteristics under continuously changing operating conditions (Figures 6 and 7) vividly demonstrates the complex, nonlin-

ear influence and interaction of temperature and discharge current on the battery aging process. The observed phenomena, such as capacity step changes upon condition switching, significant differences in fade rates under various conditions, low-temperature capacity recovery, and the apparent influence of aging history, strongly indicate the necessity of developing multi-variable capacity estimation models in Section 4 that can effectively capture these complex relationships and history dependence.

### 3.3. Quantitative Analysis of Capacity Fade Dominant Factors

To deeply investigate the quantitative influence mechanisms of temperature and discharge current on battery capacity fade and to clarify their dominant roles, this study further processes the experimental data by calculating and analyzing the capacity fade rate per cycle. This aims to quantitatively analyze the contribution of these two variables to battery lifespan decay, thereby revealing their intrinsic rules of action.

This study introduces Capacity Fade Rate per Cycle (CFRPC) as a quantitative analysis indicator. According to the data processing method used in this study, CFRPC is defined as the relative capacity fade rate of each stage divided by the corresponding difference in cycle numbers ( $\Delta_{\text{Cycle}}$ ). The specific calculation formula is as follows:

$$\text{CFRPC} = \frac{(C_{\text{initial}} - C_{\text{end}})/C_{\text{initial}}}{\Delta_{\text{Cycle}}}$$

where  $C_{\text{initial}}$  and  $C_{\text{end}}$  are the initial and final capacity, respectively, for a continuous test stage, and  $\Delta_{\text{Cycle}}$  is the number of cycles in that stage. This indicator reflects how quickly the battery's capacity fades per cycle relative to the initial capacity of that stage. In the preliminary analysis, CFRPC values were calculated based on data from some batteries under different operating conditions. The results are shown in Figure 8, where different colors distinguish different batteries, from left to right being #5, #38, #29, and #42, and different operating conditions are indicated with superscripts 1–3, representing the stage in the battery's complete cycling process.

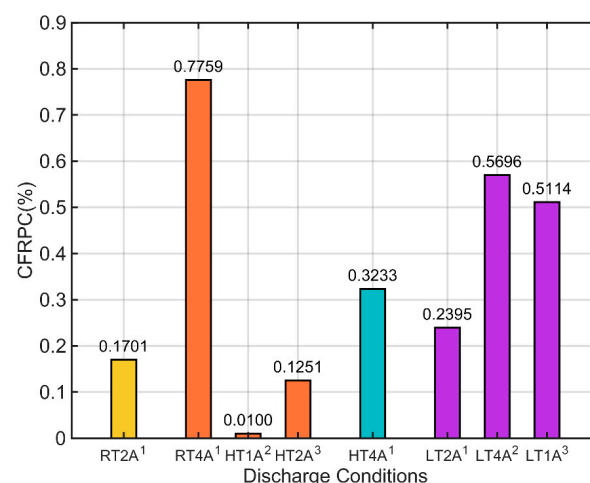


**Figure 8.** The CFRPC under different operating conditions.

However, when calculating and comparing CFRPC for multi-condition continuous test data, there are potential confounding factors that may affect the reliability of the analysis results. Firstly, a single battery undergoing multiple stages of continuous testing experiences accumulated aging effects, where degradation from the previous stage can influence the decay behavior in the subsequent stage. Secondly, there is inherent variability between individual batteries, and using data from different batteries for cross-condition comparison

introduces uncertainty. Furthermore, differences in the number of cycles ( $\Delta_{\text{Cycle}}$ ) across different test stages may affect the stability of the CFRPC calculation, especially when ( $\Delta_{\text{Cycle}}$ ) is small.

To exclude or mitigate the impact of the aforementioned confounding factors on the analysis results, this study supplemented and screened the data. Battery set data not listed in Table 1 but meeting the criteria were supplemented, increasing the sample size for each operating condition (detailed data sources are listed in Table 3). Subsequently, data were screened and CFRPC was calculated based on the following principles: prioritizing independent operating conditions or the initial stage (Stage 1) of multi-condition tests to minimize the influence of accumulated aging effects; analyzing data from the same group of batteries as much as possible to reduce individual variability; and excluding test stage data with too few cycles ( $\Delta_{\text{Cycle}}$ ) to improve the reliability of CFRPC calculation. For homogeneous data meeting the screening criteria, the average CFRPC was calculated as the representative fade rate for that operating condition. The supplemented, screened, and averaged CFRPC data are summarized in Table 4, and visualized in Figure 9. Based on the screened and averaged CFRPC data shown in Table 4 and Figure 9, a more reliable analysis of the dominant roles and mutual influence of temperature and discharge current can be conducted.

**Table 3.** The CFRPC under different operating conditions after supplementing data.

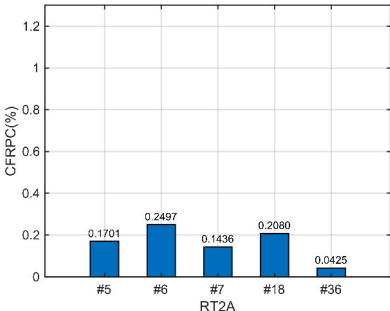
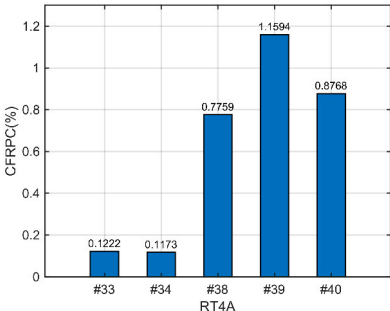
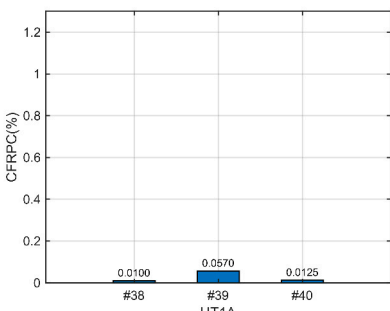
| Operating Condition | Data Description                                                        | CFRPC                                                                                                                                                                                                                                                                                                                                                                |            |          |     |        |     |        |     |        |     |        |     |        |
|---------------------|-------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------|----------|-----|--------|-----|--------|-----|--------|-----|--------|-----|--------|
| RT2A                | Independent condition                                                   |  <table><thead><tr><th>Battery ID</th><th>CFRPC(%)</th></tr></thead><tbody><tr><td>#5</td><td>0.1701</td></tr><tr><td>#6</td><td>0.2497</td></tr><tr><td>#7</td><td>0.1436</td></tr><tr><td>#18</td><td>0.2080</td></tr><tr><td>#36</td><td>0.0425</td></tr></tbody></table>    | Battery ID | CFRPC(%) | #5  | 0.1701 | #6  | 0.2497 | #7  | 0.1436 | #18 | 0.2080 | #36 | 0.0425 |
|                     | Battery ID                                                              | CFRPC(%)                                                                                                                                                                                                                                                                                                                                                             |            |          |     |        |     |        |     |        |     |        |     |        |
| #5                  | 0.1701                                                                  |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |
| #6                  | 0.2497                                                                  |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |
| #7                  | 0.1436                                                                  |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |
| #18                 | 0.2080                                                                  |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |
| #36                 | 0.0425                                                                  |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |
| RT4A                | #33, #34 Independent condition; #38, #39, #40 Multi-condition (Stage 1) |  <table><thead><tr><th>Battery ID</th><th>CFRPC(%)</th></tr></thead><tbody><tr><td>#33</td><td>0.1222</td></tr><tr><td>#34</td><td>0.1173</td></tr><tr><td>#38</td><td>0.7759</td></tr><tr><td>#39</td><td>1.1594</td></tr><tr><td>#40</td><td>0.8768</td></tr></tbody></table> | Battery ID | CFRPC(%) | #33 | 0.1222 | #34 | 0.1173 | #38 | 0.7759 | #39 | 1.1594 | #40 | 0.8768 |
|                     | Battery ID                                                              | CFRPC(%)                                                                                                                                                                                                                                                                                                                                                             |            |          |     |        |     |        |     |        |     |        |     |        |
| #33                 | 0.1222                                                                  |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |
| #34                 | 0.1173                                                                  |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |
| #38                 | 0.7759                                                                  |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |
| #39                 | 1.1594                                                                  |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |
| #40                 | 0.8768                                                                  |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |
| HT1A                | Multi-condition (Stage 2)                                               |  <table><thead><tr><th>Battery ID</th><th>CFRPC(%)</th></tr></thead><tbody><tr><td>#38</td><td>0.0100</td></tr><tr><td>#39</td><td>0.0570</td></tr><tr><td>#40</td><td>0.0125</td></tr></tbody></table>                                                                         | Battery ID | CFRPC(%) | #38 | 0.0100 | #39 | 0.0570 | #40 | 0.0125 |     |        |     |        |
| Battery ID          | CFRPC(%)                                                                |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |
| #38                 | 0.0100                                                                  |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |
| #39                 | 0.0570                                                                  |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |
| #40                 | 0.0125                                                                  |                                                                                                                                                                                                                                                                                                                                                                      |            |          |     |        |     |        |     |        |     |        |     |        |

Table 3. Cont.

| Operating Condition | Data Description                                                                                                            | CFRPC                                                                                                                                                                                                                                                                                                                                                                                                                                                                |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
|---------------------|-----------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------|----------|-----|--------|-----|--------|-----|--------|-----|--------|-----|--------|-----|--------|-----|--------|-----|--------|-----|--------|-----|--------|-----|--------|
| HT2A                | Multi-condition (Stage 3)                                                                                                   | <table><tr><th>Sample</th><th>CFRPC(%)</th></tr><tr><td>#38</td><td>0.1251</td></tr><tr><td>#39</td><td>0.3832</td></tr><tr><td>#40</td><td>0.2980</td></tr></table>                                                                                                                                                                                                                                                                                                 | Sample | CFRPC(%) | #38 | 0.1251 | #39 | 0.3832 | #40 | 0.2980 |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| Sample              | CFRPC(%)                                                                                                                    |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #38                 | 0.1251                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #39                 | 0.3832                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #40                 | 0.2980                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| HT4A                | Independent condition                                                                                                       | <table><tr><th>Sample</th><th>CFRPC(%)</th></tr><tr><td>#29</td><td>0.3233</td></tr><tr><td>#30</td><td>0.3149</td></tr><tr><td>#31</td><td>0.2316</td></tr><tr><td>#32</td><td>0.3496</td></tr></table>                                                                                                                                                                                                                                                             | Sample | CFRPC(%) | #29 | 0.3233 | #30 | 0.3149 | #31 | 0.2316 | #32 | 0.3496 |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| Sample              | CFRPC(%)                                                                                                                    |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #29                 | 0.3233                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #30                 | 0.3149                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #31                 | 0.2316                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #32                 | 0.3496                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| LT1A                | #41 Multi-condition (Stage 2); #42, #43, #44 Multi-condition (Stage 3); #45, #46, #47, #48 Independent condition            | <table><tr><th>Sample</th><th>CFRPC(%)</th></tr><tr><td>#41</td><td>1.1297</td></tr><tr><td>#42</td><td>0.5114</td></tr><tr><td>#43</td><td>0.7401</td></tr><tr><td>#44</td><td>0.6846</td></tr><tr><td>#45</td><td>0.4872</td></tr><tr><td>#46</td><td>0.3366</td></tr><tr><td>#47</td><td>0.3397</td></tr><tr><td>#48</td><td>0.2658</td></tr></table>                                                                                                             | Sample | CFRPC(%) | #41 | 1.1297 | #42 | 0.5114 | #43 | 0.7401 | #44 | 0.6846 | #45 | 0.4872 | #46 | 0.3366 | #47 | 0.3397 | #48 | 0.2658 |     |        |     |        |     |        |
| Sample              | CFRPC(%)                                                                                                                    |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #41                 | 1.1297                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #42                 | 0.5114                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #43                 | 0.7401                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #44                 | 0.6846                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #45                 | 0.4872                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #46                 | 0.3366                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #47                 | 0.3397                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #48                 | 0.2658                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| LT2A                | #42, #43, #44 Multi-condition (Stage 1); #49, #50, #51, #52 Independent condition; #53, #54, #55, #56 Independent condition | <table><tr><th>Sample</th><th>CFRPC(%)</th></tr><tr><td>#42</td><td>0.2395</td></tr><tr><td>#43</td><td>0.3334</td></tr><tr><td>#44</td><td>0.3721</td></tr><tr><td>#49</td><td>2.1392</td></tr><tr><td>#50</td><td>4.1567</td></tr><tr><td>#51</td><td>1.9826</td></tr><tr><td>#52</td><td>1.5686</td></tr><tr><td>#53</td><td>0.2307</td></tr><tr><td>#54</td><td>0.2794</td></tr><tr><td>#55</td><td>0.2469</td></tr><tr><td>#56</td><td>0.1586</td></tr></table> | Sample | CFRPC(%) | #42 | 0.2395 | #43 | 0.3334 | #44 | 0.3721 | #49 | 2.1392 | #50 | 4.1567 | #51 | 1.9826 | #52 | 1.5686 | #53 | 0.2307 | #54 | 0.2794 | #55 | 0.2469 | #56 | 0.1586 |
| Sample              | CFRPC(%)                                                                                                                    |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #42                 | 0.2395                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #43                 | 0.3334                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #44                 | 0.3721                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #49                 | 2.1392                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #50                 | 4.1567                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #51                 | 1.9826                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #52                 | 1.5686                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #53                 | 0.2307                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #54                 | 0.2794                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #55                 | 0.2469                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #56                 | 0.1586                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| LT4A                | #41 Multi-condition (Stage 2); #42, #43, #44 Multi-condition (Stage 3)                                                      | <table><tr><th>Sample</th><th>CFRPC(%)</th></tr><tr><td>#41</td><td>0.3244</td></tr><tr><td>#42</td><td>0.5696</td></tr><tr><td>#43</td><td>0.1958</td></tr><tr><td>#44</td><td>0.1963</td></tr></table>                                                                                                                                                                                                                                                             | Sample | CFRPC(%) | #41 | 0.3244 | #42 | 0.5696 | #43 | 0.1958 | #44 | 0.1963 |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| Sample              | CFRPC(%)                                                                                                                    |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #41                 | 0.3244                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #42                 | 0.5696                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #43                 | 0.1958                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |
| #44                 | 0.1963                                                                                                                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |        |          |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |     |        |

Analysis reveals that the CFRPC values under LT conditions are generally (average around 0.31%) significantly higher than under RT and HT conditions. This indicates that

within the operating conditions studied, low temperature is the dominant factor leading to rapid battery capacity fade. Under HT conditions, the influence of discharge current is very significant: the CFRPC for HT4A (0.30%) is much higher than for HT1A (0.03%), with a difference of approximately 10 times, calculated from Table 4 data. This indicates that increasing current in an HT environment drastically accelerates decay. Under RT conditions, the current influence is relatively smaller: the CFRPC for RT4A (0.12%) is about 3 times that for RT2A (0.04%), calculated from Table 4 data. This shows that the degree of influence of discharge current on capacity fade strongly depends on temperature, indicating a significant temperature-current interaction. Furthermore, at the same discharge current (e.g., 2 A), the decay differences caused by temperature variations are also significant (comparing RT2A and LT2A CFRPC), further supporting temperature’s role as a dominant factor.

Table 4. Detailed data sources and calculated CFRPC values.

| Operating Condition | Data Source (Average)                                             | CFRPC (%) |
|---------------------|-------------------------------------------------------------------|-----------|
| RT2A                | #36 (Independent condition)                                       | 0.04      |
| RT4A                | #33–34 (Independent condition)                                    | 0.12      |
| HT4A                | #29–32 (Independent condition)                                    | 0.30      |
| LT1A                | #45–48 (Independent condition)                                    | 0.35      |
| LT2A                | #42–44 Multi-condition Stage 1;<br>#53–56 (Independent condition) | 0.26      |
| HT1A                | #38–40 (Multi-condition Stage 2)                                  | 0.03      |
| HT2A                | #38–40 (Multi-condition Stage 3)                                  | 0.27      |
| LT4A                | #41 (Stage 2); #42–44 (Stage 3)                                   | 0.32      |

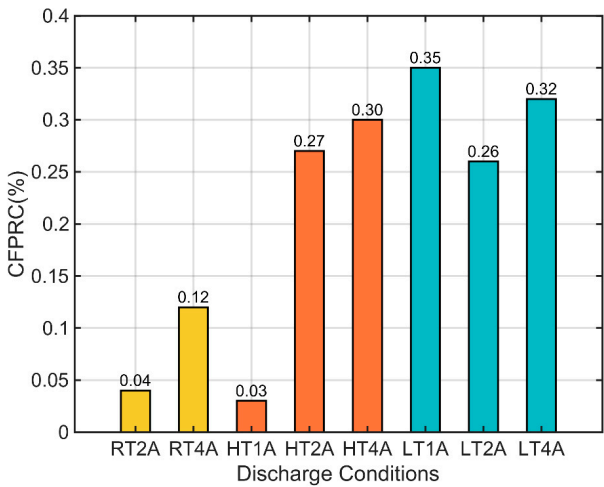


Figure 9. Comparison of CFRPC values across different temperature and discharge conditions.

It is crucial to highlight the underlying reasons why the RT2A and HT1A conditions exhibit significantly lower CFRPC values compared to their peers in Figures 8 and 9. The primary driver for this distinct behavior is their electrochemically mildest nature. Specifically, under the HT1A condition, the elevated temperature significantly enhances electrolyte ionic conductivity and interfacial reaction kinetics. When paired with a low discharge current, the battery operates with minimal polarization and negligible internal mechanical stress, establishing an optimal environment for slow degradation. Similarly, RT2A represents a mild baseline state where standard room temperature avoids extreme thermal stress, and a moderate current prevents the severe concentration polarization observed in its RT4A peer. Although the dataset’s multi-stage testing sequence inherently introduces varying initial aging states for different conditions, the exceptionally low CFRPC values of RT2A and HT1A are predominantly attributed to these physically benign characteristics.

Under LT conditions, CFRPC is observed to show non-monotonic behavior with current: LT1A (0.35%) > LT4A (0.32%) > LT2A (0.26%). Considering that some LT condition data (e.g., LT4A) comes from multi-stage tests and may be influenced by some accumulated aging effects, the actual single-condition CFRPC values might differ slightly. However, this non-monotonic trend, especially the phenomenon of LT1A being higher than LT2A/LT4A, suggests that the mechanism of current's influence on capacity fade under low temperature may be more complex and nonlinear. This provides important insights for selecting appropriate function forms when constructing subsequent models.

It should be noted that despite the data screening and averaging process, the data used to calculate CFRPC for some operating conditions may still be influenced by some aging history, as indicated by the multi-condition stage data listed in Table 4. This analysis provides the most reliable quantitative assessment based on the available dataset.

This section, through the quantitative analysis of CFRPC, clearly establishes the dominant roles of temperature on capacity fade, the dependence of current's influence on temperature, and the nonlinear characteristics of current's influence under low temperature. These findings provide crucial quantitative basis and data insights for constructing multi-variable capacity estimation models in Section 4 that are based on temperature zones and capable of capturing the nonlinear influence of current.

## 4. Multi-Variable Model Implementation and Validation

Based on the preliminary analysis in the preceding Section 3, the study found that temperature and discharge current have significant and complex nonlinear influences on battery capacity fade, with temperature being the dominant factor. These findings strongly indicate that constructing multi-variable models capable of simultaneously capturing the coupled influence of temperature and discharge current is crucial for achieving high-accuracy and robust capacity estimation under complex operating conditions. Building upon the Generalized Temperature-Zoned Modeling Framework established in Section 2.4, this section implements specific multi-variable estimation sub-models targeting three main temperature ranges: RT, HT, and LT. Subsequently, a rigorous cross-condition model validation is conducted, followed by the application and evaluation of the enhanced estimation strategy utilizing the relative health metrics defined in Section 2.5.

### 4.1. Implementation of Temperature-Zoned Sub-Models

#### 4.1.1. Room Temperature Model Parameterization

For the battery data under RT conditions, considering that only two discrete discharge current data points (2 A and 4 A) are available for this condition, the fitting order for discharge current is limited to one to avoid model overfitting. Simultaneously, as visualized in Figure 10, an approximately linear relationship among HI, discharge current, and capacity is observed under RT conditions. From an electrochemical perspective, this linear degradation trajectory is physically justified: under standard room temperature, the battery operates in a mild environment where the dominant aging mechanism is the steady, continuous thickening of the SEI, lacking the severe non-linear stress accelerators induced by extreme high or low temperatures.

Therefore, based on the generalized modeling framework established in Section 2.4, the higher-order and interaction terms were omitted, and a first-order linear polynomial was selected. This linear constraint helps maintain model simplicity, significantly reduces computational burden for real-time BMS applications, and effectively ensures estimation robustness. Data from battery #5 and #38 were used as inputs for model fitting. The fitted parameters are shown in Table 5, and the goodness of fit is detailed in Table 6.

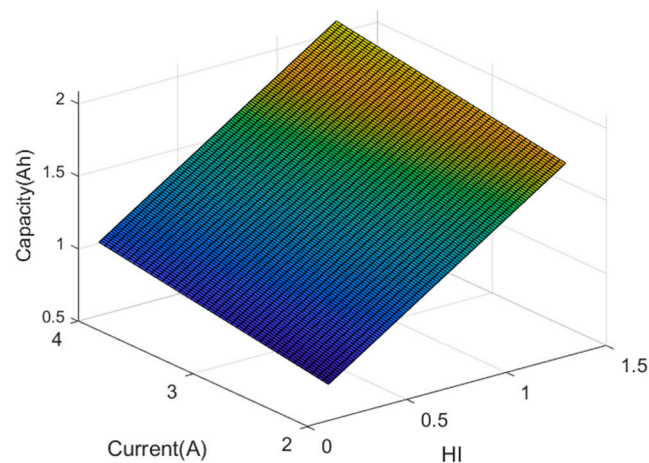


**Figure 10.** The relationship of HI and discharge current to capacity under RT condition.

**Table 5.** The model parameters under RT condition.

| $P_{00}$ | $P_{10}$ | $P_{01}$ |
|----------|----------|----------|
| 0.4049   | 0.9088   | 0.1263   |

**Table 6.** The goodness of fit of the model under RT condition.

| SSE     | R-Square | Adjusted R-Square | RMSE    |
|---------|----------|-------------------|---------|
| 0.02615 | 0.997    | 0.997             | 0.01226 |

#### 4.1.2. High Temperature Model Parameterization

Under HT conditions, the fitting order for HI remains one to maintain consistency. However, for the discharge current, considering data from three current levels (1 A, 2 A, and 4 A) were utilized, and the analysis in Section 3.3 indicated a nonlinear influence, a higher-order fitting is required. As explicitly demonstrated by the representative aging cycles in Figure 11, the relationship between the SOH and the discharge current at specific aging levels exhibits a distinct non-linear trajectory, which cannot be accurately described by a single linear plane.

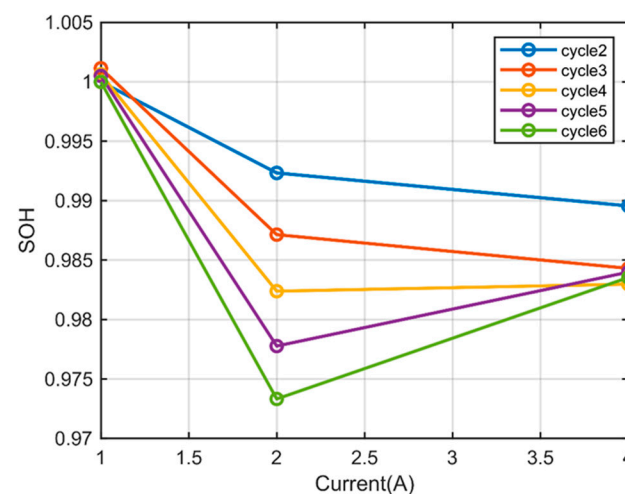


**Figure 11.** The relationship of discharge current to SOH under HT condition.

Therefore, referencing the generalized framework (Section 2.4), the order of the discharge current is increased to two, and an interaction term between HI and current is

activated to capture this complex dynamic. Data from battery #39 and #29 were used for model fitting. The fitted model parameters and the goodness of fit are shown in Table 7 and Table 8, respectively.

**Table 7.** The model parameters under HT condition.

| $P_{00}$ | $P_{10}$ | $P_{01}$ | $P_{11}$ | $P_{02}$ |
|----------|----------|----------|----------|----------|
| 2.265    | −0.329   | −0.5738  | 0.3757   | 0.01862  |

**Table 8.** The goodness of fit of the model under HT condition.

| SSE    | R-Square | Adjusted R-Squared | RMSE    |
|--------|----------|--------------------|---------|
| 0.0082 | 0.9665   | 0.9646             | 0.01106 |

The model's goodness of fit is shown in Table 8.

To strictly justify the selection of the second-order polynomial with interaction terms over a simpler linear alternative, a comparative model-selection evaluation was conducted. Using the strictly separated unseen validation dataset (detailed in Table 1), the predictive performance of a baseline first-order linear model was directly compared against the proposed quadratic model.

Figure 12 illustrates the RMSE comparison under distinct high-temperature validation conditions. The statistical evidence demonstrates a profound improvement when the higher-order and interaction terms are activated. For instance, under the HT2A condition, the baseline linear model yields an RMSE of 0.0464 Ah, whereas the selected quadratic model drastically reduces the error to 0.0172 Ah—a substantial error reduction of approximately 63%. This significant enhancement on unseen data quantitatively proves that a simple linear plane is fundamentally insufficient to capture the complex, non-linear degradation kinetics induced by varying discharge currents under elevated temperatures. Therefore, the selection of the generalized second-order structure is statistically and physically warranted for non-room-temperature zones. The resulting 3D relationship is visualized in Figure 13.

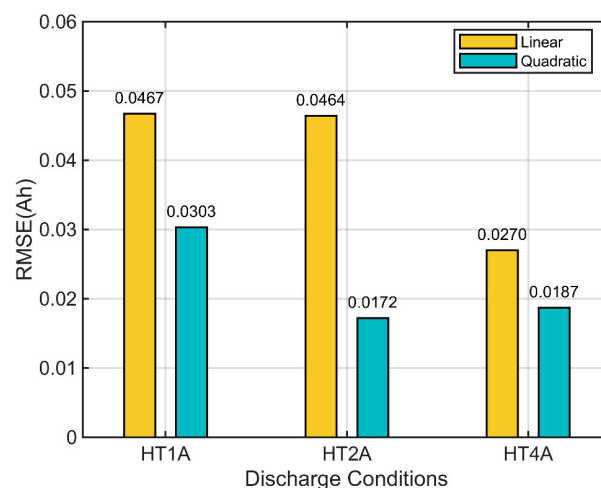


**Figure 12.** Validation RMSE comparison between linear and quadratic models under HT conditions.

#### 4.1.3. Low Temperature Model Parameterization

Given that the input current values under LT conditions align with the HT conditions (1 A, 2 A, and 4 A), and the influence of current on capacity fade under LT is highly complex and nonlinear (as analyzed in Section 3.3), the LT model adopts the same full second-order polynomial structure with an interaction term defined in Section 2.4.

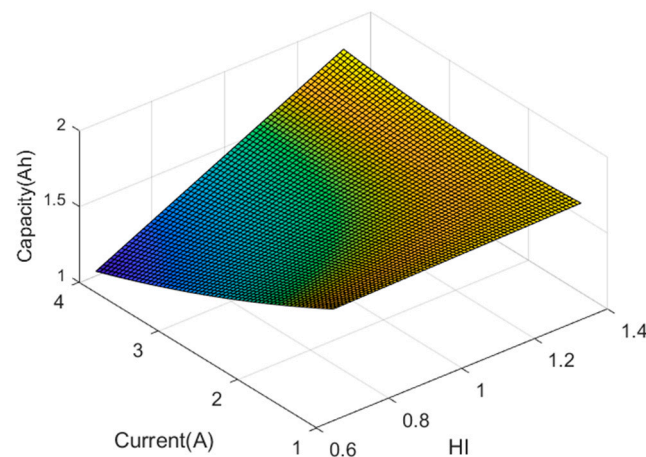


**Figure 13.** The relationship of HI and discharge current to capacity under HT condition.

However, compared to RT and HT, the LT data exhibit more complex characteristics, especially under high current (e.g., 4 A), where remaining capacity stays extremely low.

Based on findings in the existing literature, the rapid macroscopic capacity fade observed under such extreme low-temperature and high-current conditions is often hypothesized to be associated with complex internal degradation mechanisms, such as lithium plating [44]. While direct diagnostic evidence is not within the scope of this data-driven study, this hypothesis provides a plausible explanation for the highly nonlinear behavior observed in our dataset.

Given these characteristics, the study evaluated different robust least squares methods to handle potential outliers (results shown in Table 9). Considering the marginal performance improvement and the desire to maintain structural and methodological consistency across all temperature zones for direct comparison, the standard least squares method was ultimately selected.

**Table 9.** The goodness of fit of the model of different least squares methods under LT condition.

| Robust Method | SSE      | R-Square | Adjusted R-Squared | RMSE     |
|---------------|----------|----------|--------------------|----------|
| Off           | 0.02805  | 0.9995   | 0.9995             | 0.01634  |
| LAR           | 0.005195 | 0.9999   | 0.9999             | 0.007034 |
| Bisquare      | 0.01149  | 0.9998   | 0.9998             | 0.01046  |

From Table 9, it can be seen that robust least squares methods to some extent reduce the influence of points with larger residuals, thereby slightly improving the goodness of fit metrics. Considering the magnitude of performance improvement and in order to maintain consistency with the model structure and standard least squares fitting method under HT conditions, facilitating subsequent model interpretation and direct comparison across temperature zones, this study ultimately selected the standard least squares method for modeling. The fitted model parameters are shown in Table 10. The relationship between HI and discharge current to battery capacity captured by the model is visualized in Figure 14.

**Table 10.** The model parameters under LT condition.

| $P_{00}$ | $P_{10}$ | $P_{01}$ | $P_{11}$ | $P_{02}$ |
|----------|----------|----------|----------|----------|
| 0.5302   | 1.598    | 0.3319   | −0.3881  | −0.1112  |

#### 4.2. Model Applicability Analysis

Due to the discrete and limited nature of the discharge current data used for constructing the capacity estimation sub-models for each temperature zone, the applicability range

of the models is primarily limited to the current intervals covered by the training data. Specifically, the model construction under RT conditions is based on discharge current data of 2 A and 4 A, thus this model is mainly applicable for capacity estimation within the current range of 2 A to 4 A. Similarly, models under HT and LT conditions are trained using discharge current data of 1 A, 2 A, and 4 A, and their applicability range is mainly the current interval of 1 A to 4 A. For operating conditions outside these training current ranges, the accuracy of the model's estimation results cannot be guaranteed and may require cautious use or evaluation of extrapolation performance.

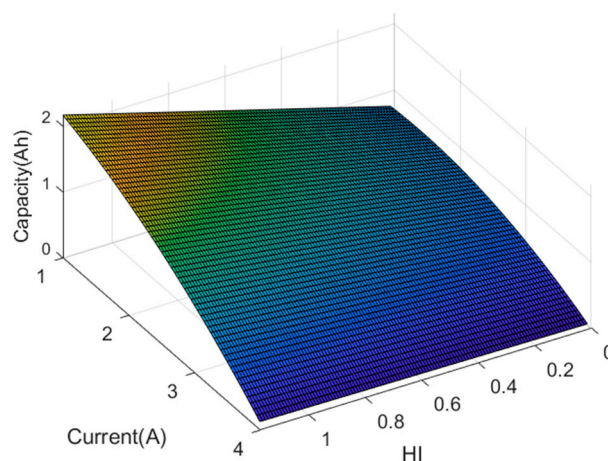


**Figure 14.** The relationship of HI and discharge current to capacity under LT condition.

However, in practical application scenarios such as EVs, the typical range of discharge current variation is usually limited. For the 2 Ah battery used in this study, discharge currents of 1 A, 2 A, and 4 A correspond to discharge rates of 0.5 C, 1 C, and 2 C, respectively. This current range of 0.5 C to 2 C covers the main discharge current requirements during normal EV driving and some acceleration/deceleration conditions, possessing a certain representativeness and broadness. Nevertheless, for extreme high or very low currents outside this range, the model's estimation performance may decrease. For these edge cases, extending the model's applicability might require supplementing corresponding data for model retraining or exploring more complex model structures.

Furthermore, the proposed temperature-zoned modeling approach presents certain practical limitations when implemented in a real-world BMS. Since the current sub-models are constructed based on discrete temperature nodes (4 °C, 24 °C, and 44 °C), handling intermediate temperatures requires additional engineering strategies. In practice, estimating capacity at intermediate temperatures could be handled using a weighted interpolation method or fuzzy logic blending, where the final capacity is calculated as a weighted average of the outputs from the two adjacent temperature sub-models based on the real-time temperature's distance to the respective zone centers. Additionally, managing temperature-zone switching is critical. If the battery temperature fluctuates around a boundary, switching models abruptly could cause discontinuous jumps in the SOH estimation. To mitigate this in practice, a transition buffer zone with hysteresis logic or a moving average filter must be implemented to ensure a smooth and continuous SOH trajectory. The lack of continuous temperature-varying training data to intrinsically model these transitions remains a limitation of this study.

#### 4.3. Validation of Absolute Capacity Models

To rigorously evaluate the accuracy and generalization capability of the constructed multi-variable sub-models, a strict cross-cell and cross-condition validation protocol was

implemented. Specifically, the models were validated using entirely independent battery cells that were strictly excluded from the training phase (i.e., strict separation by cell identity). For example, as detailed in the Tables 1 and 11, the LT model was trained solely on cell #42 and validated exclusively on cell #43. Furthermore, the selected validation cells inherently experienced continuous multi-stage operating condition changes throughout their life cycles (e.g., cell #43 underwent LT2A  $\rightarrow$  LT4A  $\rightarrow$  LT1A). By utilizing models trained on one set of cells to predict the capacity of completely different cells undergoing dynamic condition switches, the cross-condition robustness and the ability to handle individual cell inconsistency are explicitly substantiated. Estimation accuracy was quantified using error metrics such as RMSE and MAPE. It should be noted that while the optimized models (Section 4.4) are constructed using normalized relative metrics (CRR and HIRR) to ensure stability, their final estimation errors (RMSE) are evaluated in absolute Ampere-hours (Ah) to allow a direct and fair comparison with the absolute capacity models (Sections 4.1–4.3). Furthermore, to stably evaluate relative errors under extreme conditions where actual capacities approach zero (e.g., LT4A), robust metrics such as the NRMSE are specifically employed.

**Table 11.** The model parameters under different operating conditions and the batteries used for verification.

| Condition | Model $f(x,y) = P_{00} + P_{10}x + P_{01}y + P_{11}xy + P_{02}y^2$ |          |          |          |          |
|-----------|--------------------------------------------------------------------|----------|----------|----------|----------|
|           | $P_{00}$                                                           | $P_{10}$ | $P_{01}$ | $P_{11}$ | $P_{02}$ |
| RT        | 0.4049                                                             | 0.9088   | 0.1263   | 0        | 0        |
| HT        | 2.265                                                              | −0.329   | −0.5738  | 0.3757   | 0.01862  |
| LT        | 0.5302                                                             | 1.598    | 0.3319   | −0.3881  | −0.1112  |

The fitting results under different operating conditions are visually presented in Figure 15, and the corresponding estimation errors under different operating conditions are summarized in Figure 16. Different colors are used to visually distinguish the respective temperature zones.

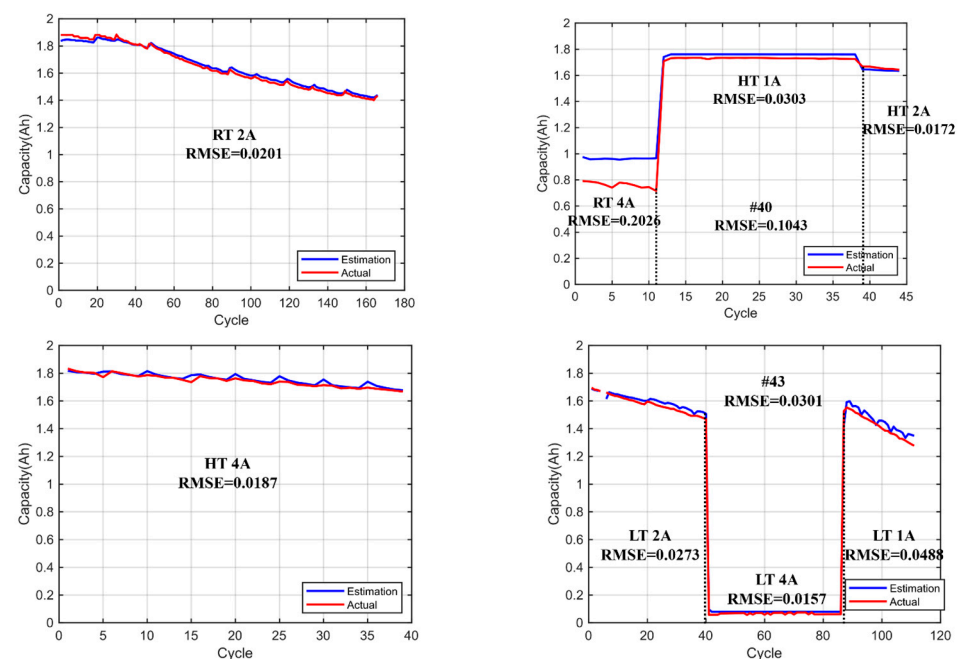


**Figure 15.** The fitting results of the absolute capacity models under different operating conditions.

Analysis of the validation results shown in Figures 15 and 16 reveals that the constructed multi-variable models based on temperature zones can estimate battery capacity

relatively accurately under most tested operating conditions, indicating that this method is effective in capturing the influence of temperature and discharge current on capacity. However, the model's estimation error is relatively large under specific conditions, particularly under RT4A conditions. This increase in error is partly related to the accelerated aging and complexity under this condition, but to a large extent stems from the inherent inconsistency between individual batteries. Despite using batteries from the same group, individual differences exist. A model estimating absolute capacity directly is highly susceptible to these varying initial states and individual inconsistencies across different operating segments. Furthermore, as highlighted in Section 2.1, evaluating models based strictly on absolute capacity across different degradation trajectories is inherently biased. To overcome these inherent limitations of absolute capacity modeling and the varying EOL standards, the subsequent Section 4.4 employs the relative health metrics defined earlier to comprehensively optimize the estimation framework.

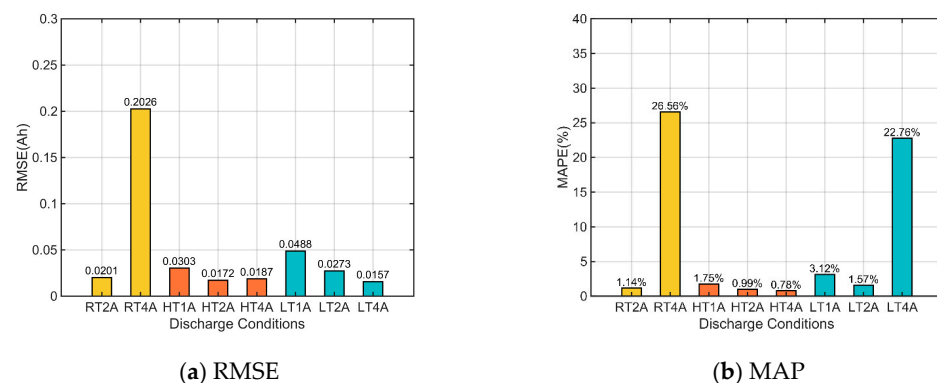


**Figure 16.** The capacity estimation errors of the absolute capacity models under different operating conditions.

#### 4.4. Enhanced Estimation via Relative Health Metrics

To eliminate the baseline inconsistencies caused by individual battery variability and different initial states across continuous test stages, this section implements the model optimization strategy based on the relative health metrics (CRR and HIRR) explicitly defined in Section 2.5.

The dependent variable of the previously constructed multi-variable models for each temperature zone is replaced from original absolute capacity to CRR, and the independent variable HI is replaced with HIRR, while the discharge current is retained. The mathematical polynomial structures for each temperature zone remain consistent with those established in Section 4.1.

The new model parameters, refitted using these normalized metrics, are presented in Table 12. Subsequently, this CRR-based optimized model was validated using the identical cross-cell validation dataset applied in Section 4.3 (Table 11). The fitting and validation results are visualized in Figure 17, and the corresponding estimation errors are summarized in Figure 18.

**Table 12.** The new model parameters under different operating conditions and the batteries used for verification.

| Condition | Model $CRR = P_{00}' + P_{10}'x + P_{01}'y + P_{11}'xy + P_{02}'y^2$ |           |           |           |           | Batteries Used for Validation |
|-----------|----------------------------------------------------------------------|-----------|-----------|-----------|-----------|-------------------------------|
|           | $P_{00}'$                                                            | $P_{10}'$ | $P_{01}'$ | $P_{11}'$ | $P_{02}'$ |                               |
| RT        | 0.281                                                                | 0.6095    | 0.04473   | 0         | 0         | #7, #40                       |
| HT        | 1.259                                                                | −0.2583   | −0.2798   | 0.2751    | 0.0002777 | #40, #31                      |
| LT        | 0.497                                                                | 0.5025    | −0.03248  | −0.07583  | 0.04799   | #43                           |

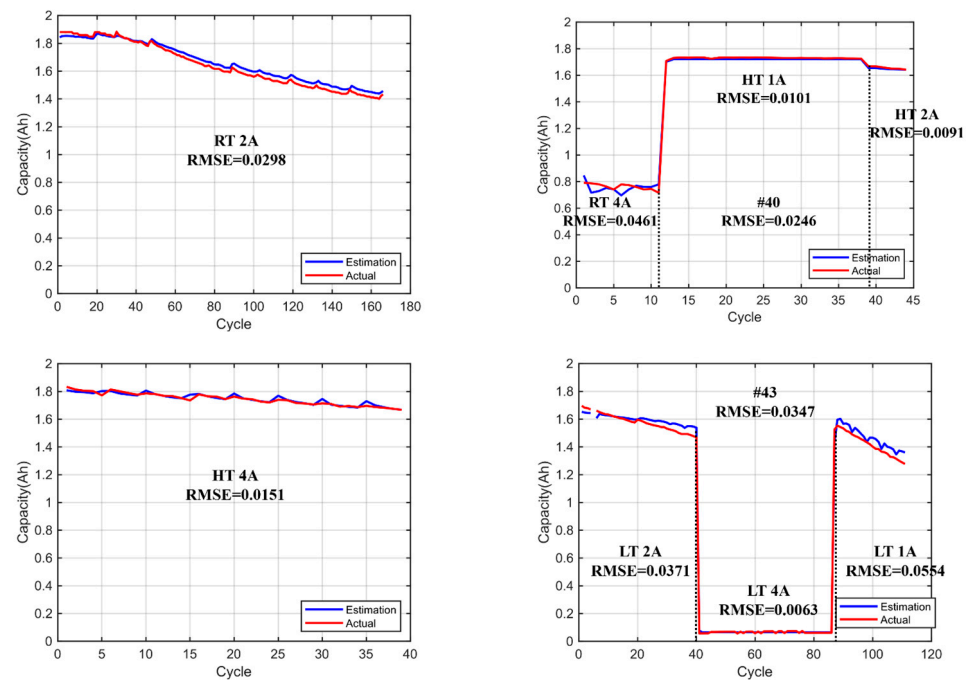


**Figure 17.** The fitting results of the CRR-based optimized model under different operating conditions.

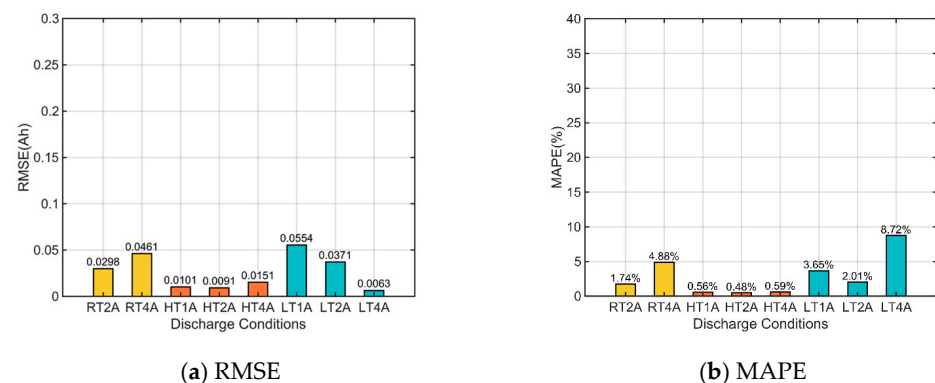


**Figure 18.** The capacity estimation errors of the CRR-based optimized model under different operating conditions.

Analysis of the validation results shown in Figure 18 indicates that using the CRR-based optimized model significantly improves estimation accuracy. Particularly, under the RT4A condition, where the error was previously large, the RMSE significantly reduces from approximately 0.2026 to approximately 0.0461 Ah, demonstrating the effectiveness of the CRR-HIRR strategy for this condition. The optimized model also maintains low errors in the remaining operating conditions. The average RMSE across all conditions is 0.026 Ah, and the average MAPE is 2.8%. The overall estimation error is significantly reduced and controlled at a low level, indicating that the optimized model can adapt better to these operating conditions.

Particularly for the extreme LT4A condition, where the absolute remaining capacity is near zero, the traditional MAPE metric becomes unstable due to the exceedingly small denominator. By evaluating the performance using the robust NRMSE metric normalized to the nominal capacity (2 Ah), the proposed CRR-HIRR model yields an outstanding NRMSE of merely 0.31% (corresponding to an absolute RMSE of 0.0063 Ah). This unequivocally proves the model's exceptional accuracy and stability even in the most severely degraded states.

To explicitly respond to the mechanisms underlying the capacity estimation improvement and to conduct a rigorous diagnostic check for systematic trends, residual distributions (calculated as the actual measured capacity minus the predicted value) were analyzed

before and after the CRR optimization. Figure 19 presents a comprehensive “Before and after” comparison of the residuals plotted against both the HI and the discharge current across all three temperature zones.

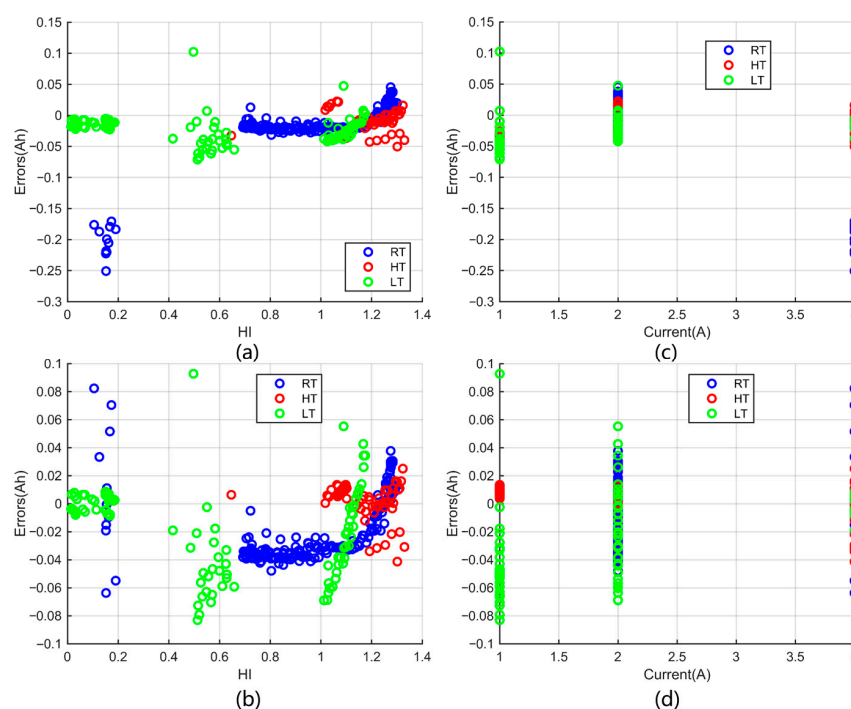


**Figure 19.** Comparison of residual diagnostics across all temperature zones before optimization (a,c) and after CRR optimization (b,d).

Analyzing the absolute capacity models (Figure 19a,c), severe systematic biases are readily apparent rather than a random white-noise distribution. The Error vs. HI plot (Figure 19a) exhibits extreme vertical stratification, with the error span reaching from  $-0.3$  to  $+0.15$  Ah. Notably, the RT condition develops a massive underestimation cluster. The root cause of this systematic failure is precisely localized in the Error vs. Current plot (Figure 19b): this extreme RT negative cluster occurs exclusively under the 4 A high-rate discharge condition. This diagnostic visually proves that the systematic bias is not primarily due to missing higher-order polynomial terms, but rather inherently caused by the discrete, severe absolute capacity baseline drops induced by high discharge currents, which a static polynomial surface cannot seamlessly bridge. The color-coded differentiation further reveals that the severity of this current-induced baseline shift is highly temperature-dependent.

Conversely, the residual plots for the CRR-optimized models (Figure 19b,d) vividly demonstrate the profound decoupling effect of the proposed strategy. By normalizing the degradation segment-by-segment using relative metrics, the massive vertical error scale is drastically compressed to within  $\pm 0.1$  Ah. Most remarkably, in Figure 19d, the severe  $-0.25$  Ah error cluster previously observed at the 4 A condition is successfully pulled back towards the zero-error baseline. Although minor local stratifications inevitably remain—reflecting the extremely complex non-linear kinetic differences at varying currents—the predominant systematic baseline shifts have been completely dismantled across all temperature zones.

This comparative residual diagnostic provides statistical evidence that the CRR-HIRR framework robustly mitigates the current-induced initial state inconsistencies, rendering a significantly more reliable multi-variable cross-condition estimation.

To more comprehensively demonstrate the advantages of the method proposed in this study, the estimation errors of different capacity estimation methods under various operating conditions are compared. Figure 20 plots the comparison of RMSE and MAPE validation

results across different operating conditions for the C-HI model, the C-HI+Current absolute capacity model, and the final multi-variable optimized model based on CRR-HIRR+Current.

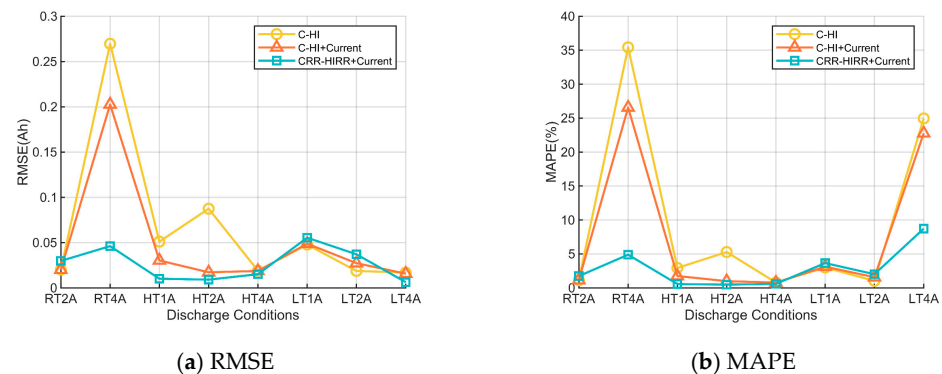


**Figure 20.** The comparison of capacity estimation errors of different methods under different operating conditions.

As corroborated by the preceding residual diagnostics, the absolute capacity models exhibit significant error spikes under specific extreme conditions (e.g., RT4A and LT1A). This vulnerability stems directly from their inability to adapt to the current-induced initial baseline shifts. In stark contrast, the final CRR-HIRR+Current optimized model dynamically normalizes these discrete initial states segment-by-segment. Consequently, as clearly seen in Figure 20, the proposed method successfully flattens these error peaks, exhibiting the best and most stable overall performance across all tested operating conditions. This confirms that the relative metric framework not only corrects underlying statistical biases but also translates directly into exceptionally high accuracy and strong cross-condition robustness for practical applications.

## 5. Conclusions

Accurate estimation of lithium-ion battery SOH and capacity is crucial for ensuring its safe and reliable operation and optimizing its entire life cycle management. However, complex and variable actual operating conditions and their complex nonlinear influence on the battery aging process pose severe challenges to achieving high-accuracy and robust SOH and capacity estimation across different conditions. To address this issue, this study conducted in-depth research.

This study, based on experimental data featuring continuous variations in operating conditions, conducted data-driven analysis. Firstly, IC curve features were extracted and analyzed. Combined with multi-condition capacity fade characteristics and quantitative CFRPC analysis, the study deeply revealed the complex nonlinear influence rules of temperature and discharge current on battery capacity fade, the dominant role of temperature, and the coupling relationship between them, providing critical data insights for constructing high-accuracy capacity estimation models. Based on these findings, this research proposed and constructed a capacity estimation method to address complex operating conditions, employing a temperature-zoned multi-variable modeling strategy to capture the influence and interaction of temperature and discharge current. Through the innovative introduction of a CRR-HIRR optimization method, the method effectively overcame the challenges to capacity estimation accuracy caused by battery individual variability and inconsistent initial states across different operating conditions. Ultimately, the constructed optimized model demonstrated excellent estimation performance across all tested operating conditions, with an average RMSE of 0.0261 Ah and an average MAPE of 2.83%. This validated the effectiveness of the layered modeling and CRR-HIRR optimization strategy proposed in this study for achieving high-accuracy and robust SOH estimation under complex multi-variable operating conditions.

The multi-variable cross-condition capacity estimation method based on IC features proposed in this paper provides significant technical support and methodological references for precise health management of batteries in practical application scenarios such as on board BMS. It notably expands the application range and robustness of capacity estimation methods based on IC features. However, despite the significant progress made in this study, there is still room for further exploration and improvement. For example, although a temperature-zoned modeling approach was adopted, the coupling mechanisms of temperature and current are complex, and the segmented approach poses practical challenges regarding intermediate temperature handling and smooth zone-switching. Future research could explore more in-depth variable coupling modeling approaches or develop a more complex, continuous nonlinear model structure capable of uniformly handling all operating conditions without the need for discrete zone boundaries. Furthermore, the non-monotonic phenomenon of discharge current's influence on capacity fade at low temperatures is worth investigating in more detail, and more complex function forms could be explored for precise characterization. How to incorporate the complex variations in charging conditions and their interaction with discharging conditions into the model is also a direction worthy of future research.

**Author Contributions:** N.Z. made contributions to the conception and design of the work. N.Z., D.H. and Y.X. performed the algorithm, experiments and result analysis. N.Z., D.H. and Y.X. contributed to the revision and editing of the manuscript. All authors have read and agreed to the published version of the manuscript.

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**Conflicts of Interest:** The authors declare no conflicts of interest.

## Abbreviations

|          |                                                     |
|----------|-----------------------------------------------------|
| AC       | Alternating Current                                 |
| ANN      | Artificial Neural Network                           |
| BESS     | Battery Energy Storage System                       |
| BMS      | Battery Management System                           |
| BP       | Back Propagation                                    |
| CC       | Constant Current                                    |
| CFRPC    | Capacity Fade Rate per Cycle                        |
| CNN-LSTM | Convolutional Neural Network-Long Short-Term Memory |
| CRR      | Capacity Retention Rate                             |
| CV       | Constant Voltage                                    |
| DV       | Differential Voltage                                |
| DVA      | Differential Voltage Analysis                       |
| ECM      | Electrochemical Model                               |
| EIS      | Electrochemical Impedance Spectroscopy              |
| EOL      | End of Life                                         |
| EV       | Electric Vehicle                                    |
| FOIs     | Features of Interest                                |
| GBR      | Gradient Boosting Regression                        |
| GPF      | Genetic Particle Filter                             |
| GPR      | Gaussian Process Regression                         |

|            |                                                |
|------------|------------------------------------------------|
| HI         | Health Indicator                               |
| HIRR       | Health Indicator Retention Rate                |
| HPPC       | Hybrid Pulse Power Characterization            |
| HT         | High Temperature                               |
| IC         | Incremental Capacity                           |
| ICA        | Incremental Capacity Analysis                  |
| KF         | Kalman Filtering                               |
| LAR        | Least Absolute Residual                        |
| LFP        | Lithium Iron Phosphate                         |
| LT         | Low Temperature                                |
| LTO        | Lithium Titanium Oxide                         |
| MAPE       | Mean Absolute Percentage Error                 |
| MIGA       | Multi-Island Genetic Algorithm                 |
| NASA       | National Aeronautics and Space Administration  |
| NCA        | Nickel Cobalt Aluminum                         |
| NMC        | Nickel Manganese Cobalt                        |
| NRMSE      | Normalized Root Mean Square Error              |
| PCoE       | Prognostics Center of Excellence               |
| PF         | Particle Filter                                |
| PSO-BiLSTM | Particle Swarm Optimization-Bidirectional LSTM |
| RMSE       | Root Mean Square Error                         |
| RT         | Room Temperature                               |
| RUL        | Remaining Useful Life                          |
| RVM        | Relevance Vector Machine                       |
| SEI        | Solid Electrolyte Interphase                   |
| SOH        | State of Health                                |
| SSE        | Sum of Squared Errors                          |
| SVM        | Support Vector Machine                         |
| VC         | Voltage-Capacity                               |

## Appendix A

**Table A1.** General information and specifications of the NASA PCoE battery dataset.

| Parameter                  | Specification/Description                                                                                                                          |
|----------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------|
| Data Source                | NASA PCoE Battery Dataset [37]                                                                                                                     |
| Battery Form Factor        | 18650-type cylindrical cell                                                                                                                        |
| Cathode Chemistry          | Nickel Cobalt Aluminum Oxide (LiNiCoAlO <sub>2</sub> /NCA)                                                                                         |
| Nominal Capacity           | 2.0 Ah                                                                                                                                             |
| Standard Charging Protocol | CC at 1.5 A until 4.2 V; followed by CV at 4.2 V until current drops to 20 mA.                                                                     |
| Discharge Protocol         | CC at varying temperatures (4 °C, 24 °C, 44 °C) and currents (1 A, 2 A, 4 A) until cut-off voltage.                                                |
| EOL Definition             | Generally 30% capacity fade (to 1.4 Ah).<br>Note: Set to 20% fade (to 1.6 Ah) for specific cells (#38, #39, #40) based on original dataset design. |

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