



Research paper

## Long-Term Capacity Degradation of Lithium-ion Batteries at 40°C: A Spline Regression Approach for Thermal Management Insights

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### Article information:

Received: 02/04/2025, Revision: 20/06/2025, Accepted: 21/06/2025

DOI: 10.29130/dubited.1669254

### ABSTRACT

Lithium-ion batteries are critical for modern energy storage systems, yet their capacity degradation under high temperatures remains a significant challenge. This study investigates the long-term capacity fade of lithium-ion batteries subjected to a consistent high-temperature environment using spline regression to model non-linear degradation trends. Utilizing the Oxford Battery Degradation Dataset, eight lithium-ion pouch cells were analyzed over extended cycles, and complex degradation behaviors and temperature-induced capacity losses were measured. Results demonstrated a strong correlation between elevated temperatures and accelerated degradation, with spline regression achieving near-perfect fits ( $R^2 = 1.0000$ ) to the observed data, highlighting its efficacy in modeling non-linear fade patterns. The analysis revealed uniform degradation trends across cells, with minor variations attributed to manufacturing inconsistencies. Temperature profiles during initial cycles underscored the role of thermal dynamics in accelerating side reactions like lithium plating and Solid Electrolyte Interface (SEI) growth. These findings emphasize the necessity of robust thermal management systems to mitigate degradation and extend battery lifespan. The study provides actionable insights for optimizing battery design and management strategies in high-temperature applications, such as electric vehicles and grid storage.

**Keywords:** *Lithium-ion Batteries, Capacity Fade, High-Temperature Degradation, Spline Regression, Thermal Management*

## I. INTRODUCTION

Lithium-ion batteries (LiBs) have emerged as the dominant energy storage technology for a wide range of applications, including electric vehicles (EVs), portable electronics, and renewable energy systems. Their high energy density, long cycle life, and relatively low self-discharge rate make them ideal for these applications. However, the performance and longevity of LiBs are significantly influenced by operating conditions, particularly temperature.

Temperature plays a critical role in the electrochemical processes within LiBs. Increased temperatures can accelerate degradation mechanisms such as solid-electrolyte interphase (SEI) growth, lithium plating, and electrode cracking, leading to capacity fade and reduced cycle life. Conversely, low temperatures can increase internal resistance and limit the battery's ability to deliver power. Understanding the relationship

between temperature and battery degradation is essential for optimizing battery design, improving thermal management systems, and extending battery lifespan.

The temperature-dependent behavior of batteries is largely attributed to chemical reactions and material characteristics. Specifically, the Arrhenius equation, given in the Equation (1), describes the relationship between temperature and chemical reaction rates, indicating that temperature fluctuations directly alter electrochemical reaction rates within the battery (Laidler, 1984). Furthermore, temperature influences the ionic conductivity of electrodes and electrolytes. Notably, the ionic conductivity of lithium-salt electrolytes diminishes at low temperatures (Zhang et al., 2003).

$$k = Ae^{\frac{-E_a}{RT}} \quad (1)$$

Where,  $k$  is rate constant,  $A$  is pre-exponential factor,  $E_a$  is activation energy,  $R$  is universal gas constant, and  $T$  is temperature. The impact of temperature on the degradation of various LiB Cell components has been the subject of numerous recent investigations. Leng et al. used an electrochemistry-based model (ECBE) to measure the effects on the aging behavior of cycled LiB operating within the temperature range of 25 °C to 55 °C. They found that the increasing degradation rate of the maximum charge storage of LiB during cycling at elevated temperature is related mainly to the degradations at the electrodes and that the degradation of LCO cathode is larger than graphite anode at elevated temperature (Leng et al., 2015). Apribowo et al., examined a problem about the optimization plan for the battery energy storage system (BESS) by considering battery degradation due to ambient temperature (Apribowo et al., 2022). They found that the ambient temperature has a significant influence on the capacity fading rate, especially when it surpasses 35 °C. Qu et al., investigated fast-charging degradation using a commercial 18650 Nickel-Manganese-Cobalt battery at different charging current rates (C-rates) and operating temperatures. They used techniques like electrochemical impedance spectroscopy and post-mortem analysis to identify degradation mechanisms such as lithium plating and SEI growth (Qu et al., 2022). They realized that with increasing operating temperatures, the most significant factor influencing the battery capacity fade changed gradually from lithium plating to the growth of the SEI. Ma et al., have discussed the effects of temperature to LiBs at both low and high-temperature ranges in their review article. They focused on monitoring the internal temperature of LiBs via both contact and contactless processes (Ma et al., 2018). They concluded that the contact measurement which implanting temperature probes will certainly lead to the destruction to the batteries, which will be challenging to implement such approach in practical use.

Overcharging, which accelerates battery degradation and is more likely at low temperatures due to the larger polarization effect making the charging cut-off voltage easier to exceed, can occur as a result of battery property inconsistencies or battery management system failures. Sun et al., experimentally investigated the characteristics of LiFePO<sub>4</sub> battery degradation caused by overcharging to 4.0–4.8 V with 0.2–1 C currents at –10 °C. The results that obtained showed that capacity fading increases with increasing charging current (Sun et al., 2022).

Given that previous studies have shown non-uniform temperature distribution in Li-ion battery modules (Fan et al., 2013; Wang et al., 2014) and single cells (Robinson et al., 2014; Wu et al., 2015; Zhang et al., 2014; Fleckenstein et al., 2011; Li et al., 2013), it logically follows that this non-uniformity would result in accelerated and uneven degradation. Cavalheiro et al. conducted a test on a Li-ion battery stack consisting of five 3 Ah pouch cells connected in parallel. The results that obtained, supported the hypothesis that non-uniform temperature distribution causes non-uniform and accelerated degradation (Cavalheiro et al., 2020).

Elevated temperature aging significantly compromises both the safety and performance of LiBs. Shen et al., investigated the evolution of heat generation characteristics upon discharging and electrochemical performance and the degradation mechanism during high-temperature aging. Post-mortem characterization analysis in their work revealed that lithium plating is the main degradation mechanism. The occurrence of side reactions leads to cell capacity fading and electrochemical performance degradation (Shen et al., 2022).

The charging and discharging capabilities of LiBs are significantly diminished at temperatures below 0 °C, a consequence of the marked rise in internal resistance (Lindgren & Lund, 2016; Lei et al., 2013; Liao et al., 2012). The results of the experiment conducted by Lu et al. showed that the battery charging

characteristics are nearly independent on the charging temperature ranged from 20 °C to 40 °C, while the battery charging/discharging performance degrade dramatically for the battery temperature lower than 20 °C (Lu et al., 2019).

Despite extensive research on LiB degradation, the specific impact of temperature variability on capacity fade remains a topic of significant interest. While it is well-established that high temperatures accelerate degradation, the quantitative relationship between temperature and capacity fade, as well as the identification of an optimal temperature range for minimizing degradation, are still areas requiring further investigation. This study aims to address these gaps by analyzing real-world battery degradation data and quantifying the impact of temperature on capacity fade.

Battery degradation under high temperatures poses significant challenges for the reliability and efficiency of LiBs. Elevated temperatures accelerate chemical reactions within the battery, leading to increased rates of capacity fade and reduced lifespan. This degradation can compromise the performance of batteries in applications ranging from consumer electronics to EVs, where consistent and reliable energy storage is essential.

Understanding the specific impact of high temperatures on battery degradation is crucial for developing effective thermal management strategies. Despite extensive research, the complex interactions between temperature, cycle number, and capacity fade remain challenging to model accurately. This study addresses these critical gaps by precisely quantifying long-term degradation patterns at 40°C, a common and challenging operational condition for many battery applications.

This research's primary objective is to establish a robust and highly accurate modeling framework for predicting lithium-ion battery degradation under sustained high-temperature stress. By utilizing the "Oxford\_Battery\_Degradation\_Dataset\_1.mat" and "ExampleDC\_C1.mat" data files, we employ advanced spline regression to meticulously capture and analyze the complex, non-linear trends in capacity fade. The profound insights derived from this unprecedented modeling precision will directly inform the development of more resilient battery systems, optimize battery design, and significantly enhance thermal management strategies, ultimately extending battery lifespan in demanding high-temperature environments

## II. MATERIAL AND METHOD

This study utilizes a comprehensive dataset to analyze the long-term capacity degradation of LiBs under high-temperature conditions (Howey & Birkel, 2017; Birkel, 2017).

### A. Data Processing

This study utilizes the Oxford Battery Degradation Dataset 1, which contains detailed measurements of battery aging data from eight small lithium-ion pouch cells (Kokam CO LTD, SLPB533459H4, 740mAh). The features of the batteries are shown in Table 1 (Kokam Battery Manufacturing Co., Ltd., 2025).

Table 1. The features of the batteries

Model	Thickness (mm)	Width (mm)	Height (mm)	Weight (g)	Capacity (mAh)	Max. Discharge Rate (C)
SLPB533459H4	5 $\pm$ 0.2	33.5 $\pm$ 0.5	58.5 $\pm$ 0.5	19.5 $\pm$ 0.5	740	20 (Continuous) / 40 (Pulse)

The dataset is divided into two files:

Oxford\_Battery\_Degradation\_Dataset\_1.mat: This dataset contains hierarchical data for eight cells, with measurements taken every 100 cycles. It includes 1C charge/discharge cycles and pseudo-open circuit voltage cycles, capturing time, voltage, charge, and temperature. Cycle numbers, capacity values, and temperature readings were extracted for each cell, with a focus on the 1C discharge data to assess capacity fade.

ExampleDC\_C1.mat: This dataset provides detailed information on the first charge-discharge cycle, including a 2C constant current charge and a variable current discharge. We extracted time, voltage, charge, and temperature data to analyze initial cycle behavior.

All tests were conducted in a Binder thermal chamber at a constant environmental temperature of 40°C, using a Bio-Logic MPG-205 battery tester. The dataset provides a comprehensive record of battery performance under controlled conditions, making it ideal for studying the impact of high-temperature on degradation.

Preprocessing involved cleaning and organizing the extracted data to ensure consistency and accuracy. Missing or anomalous values were identified and addressed to maintain data integrity. The cycle numbers and corresponding capacity values were converted into NumPy arrays for efficient computation and modeling.

To facilitate analysis, the data was structured to align with the modeling requirements, ensuring that each cycle's capacity and temperature were accurately paired. This structured approach enabled the application of spline regression to capture complex degradation trends effectively. By meticulously extracting and preprocessing the data, we ensured a robust foundation for subsequent analysis, allowing for accurate modeling and insightful interpretation of battery degradation under high-temperature conditions.

The Oxford Battery Degradation Dataset 1, comprising 740mAh lithium-ion pouch cells, was selected for this study due to its controlled testing conditions (e.g., consistent 40°C environment) and detailed characterization cycles, which enable accelerated yet systematic observation of long-term degradation mechanisms. While small-format cells are advantageous for isolating degradation trends under repeatable laboratory conditions, their applicability to larger commercial batteries (e.g., automotive-scale cells) warrants discussion. High-capacity batteries often exhibit more pronounced thermal gradients, heterogeneous current distribution, and mechanical stresses due to their size and electrode architecture, factors that may alter degradation kinetics. To address generalizability, this study assumes that core mechanisms like SEI growth and lithium plating, observed here, are fundamental across Cell formats. However, future validation using high-capacity cells is recommended to confirm scalability, particularly for applications requiring thermal management strategies tailored to real-world operational complexities. This limitation is explicitly acknowledged, ensuring transparency while highlighting the dataset's value in foundational degradation analysis.

### B. Modeling Approach

To analyze the long-term capacity degradation of LiBs under high-temperature conditions, we employed spline regression (Studden, 1971) which is given in Equation (2) conceptually. This technique was chosen for its ability to capture complex, non-linear degradation trends observed in the dataset.

$$y = \beta_0 + \beta_1 B_1(x) + \beta_2 B_2(x) + \dots + \beta_k B_k(x) + \varepsilon \quad (2)$$

Where  $B_i(x)$  are basis functions from the B-spline basis.

Spline regression provides a flexible approach to modeling capacity fade by fitting piecewise polynomials through the data. This method allows for smooth transitions between different segments, effectively capturing local variations in degradation patterns. The spline model is particularly useful for identifying non-linear trends without overfitting, as it balances fit and smoothness.

The spline regression was applied to the extracted capacity data using Python's `scipy.interpolate` library. The goodness of fit was evaluated using metrics such as R-squared ( $R^2$ ) and Mean Squared Error (MSE), ensuring that the model accurately represents the observed data. By employing spline regression, we aimed to capture the nuanced degradation behavior of batteries under high-temperature conditions.

To rigorously assess the reliability of our degradation model, we performed uncertainty quantification on the spline parameters. Standard errors were calculated to quantify the precision of the fit, and 95% confidence intervals were established using the t-distribution. This approach allowed us to evaluate the statistical significance of the model and provide realistic bounds on lifetime predictions.

The uncertainty in derived quantities, such as predicted cycle life to reach 80% of initial capacity, was determined using error propagation techniques. This comprehensive uncertainty analysis enables us to assess the statistical significance of observed differences between cells and provide realistic bounds on lifetime predictions that reflect inherent uncertainties in the degradation process.

All uncertainty analyses were performed using Python libraries, ensuring robust and reliable modeling of battery degradation under high-temperature conditions. To ensure the accuracy and reliability of our analysis, a robust data processing methodology was employed. This involved the careful extraction, cleaning, and structuring of raw experimental data obtained from the dataset of Oxford\_Battery\_Degradation\_Dataset\_1.mat and the ExampleDC\_C1.mat. The systematic workflow presented in Figure 1, for preparing the data for subsequent modeling is critical for minimizing noise and ensuring that the capacity fade trends are accurately represented.

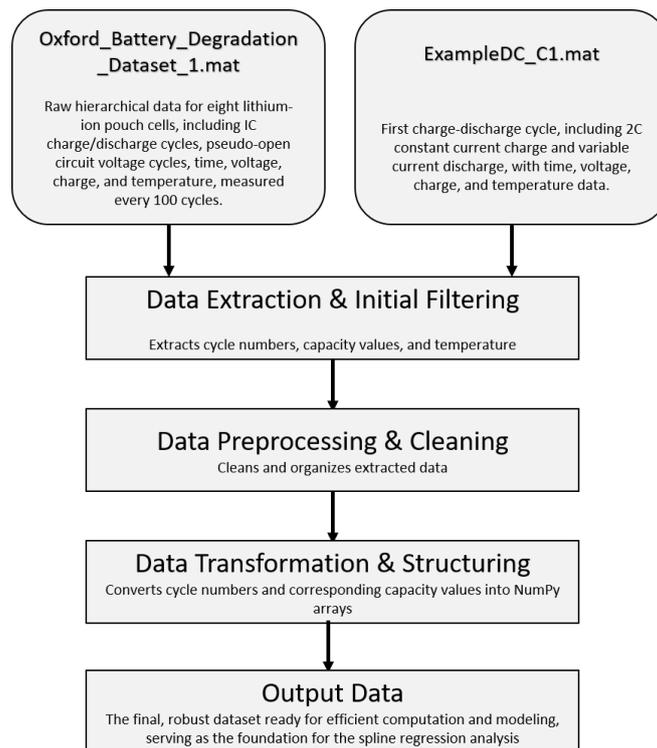


Figure 1. Data Processing Workflow for Lithium-ion Battery Degradation Analysis

### III. RESULTS AND DISCUSSIONS

Using spline regression, we modeled the capacity fade over cycles for each of the eight lithium-ion cells tested at 40°C. The spline model effectively captured the complex, non-linear degradation patterns, providing a smooth fit that highlighted both consistent trends and unique behaviors among the cells. This detailed analysis revealed how prolonged exposure to high temperatures impacts battery performance, with the model capturing local variations and overall trends.

Figure 2 illustrates the spline regression fit for Cell#1, serving as a representative example of how spline models capture capacity degradation trends in LiBs. This graphic demonstrates the model's ability to fit complex, non-linear patterns over extended cycles.

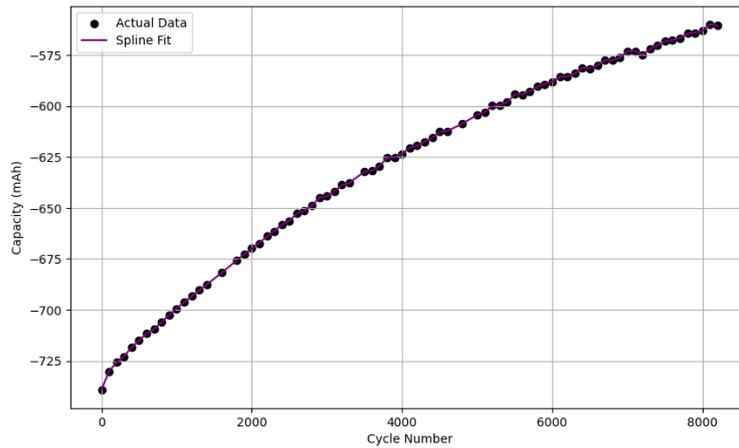


Figure 2. Spline regression for Cell#1.

The spline regression for Cell#1 provides an excellent fit to the actual (discharge) capacity data, effectively capturing both the overall trend and local variations. The smooth curve aligns closely with the observed data points, indicating the model's precision in representing capacity fade under high-temperature conditions.

To ensure the reliability of the spline regression model, we evaluated its performance using  $R^2$  and MSE metrics. The high  $R^2$  value (1.0000) and low MSE (0.0132) for the Cell#1, further validate the model's accuracy, confirming its robustness in predicting long-term degradation. This example highlights the spline model's adaptability to complex degradation behaviors, offering valuable insights into the battery's performance over thousands of cycles. The results from Cell#1 are consistent with those observed across other cells, reinforcing the reliability of spline regression in modeling battery degradation at increased temperatures.

To comprehensively model the capacity degradation of cells, we explored various regression techniques, including linear, polynomial, and Huber regression, alongside spline regression. Each model was evaluated for its ability to capture the non-linear degradation patterns observed in the data. Among these, spline regression emerged as the most effective, providing a superior fit to the actual data. Figure 3 gives the comparison of the models for Cell#1.

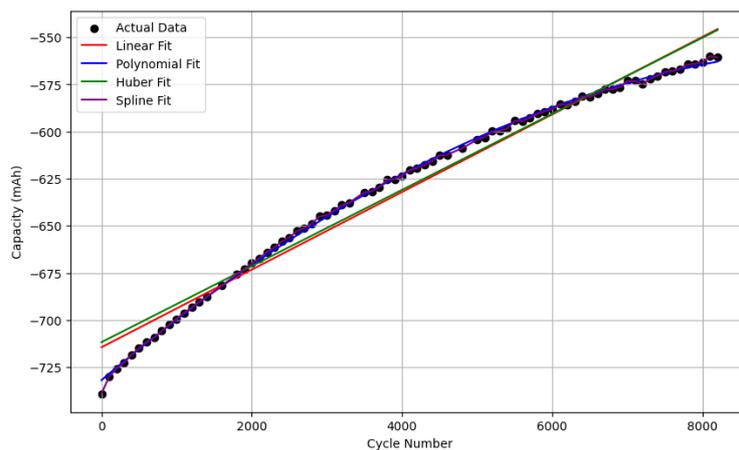


Figure 3. Comparative model fittings for Cell#1.

The figure 3 illustrates the performance of each regression model in fitting the capacity data for Cell#1. The spline regression, represented by the purple curve, closely aligns with the observed data points, capturing both the overall trend and local variations. In contrast, the linear, polynomial, and Huber models, while providing reasonable fits, do not capture the nuances of the degradation pattern as effectively as the spline model.

The high  $R^2$  value and low MSE for the spline regression further validate its accuracy and robustness. This analysis demonstrates the spline model's superior ability to adapt to complex degradation trends, making it the preferred choice for modeling battery performance in this study.

Figure 4 illustrates the application of spline regression to model the capacity degradation of Cell#1 over its cycle life. The data was split into training and test sets to evaluate the model's predictive accuracy. This approach allows us to assess how well the spline model captures the non-linear degradation patterns and predicts future capacity fade.

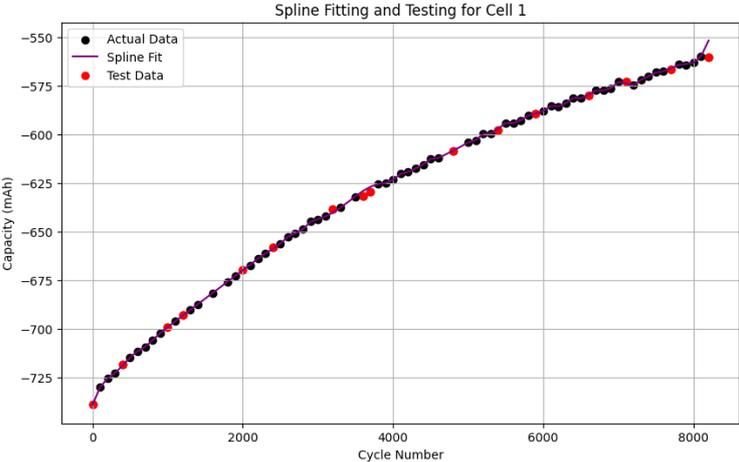


Figure 4. Application of spline regression to model the capacity degradation of Cell#1.

The spline regression model provides an excellent fit to the actual capacity data, as evidenced by the close alignment of the spline curve with the observed data points. The high  $R^2$  value and low MSE for the test data further validate the model's accuracy and robustness. The test data points, highlighted in red, closely follow the spline fit, indicating the model's strong predictive capability.

This analysis demonstrates the effectiveness of spline regression in capturing complex degradation trends, offering valuable insights into the long-term performance of LiBs. The model's ability to generalize well to unseen data underscores its potential for predicting battery life and informing management strategies.

Table 2 provides a summary of the  $R^2$  and MSE metrics for each of the eight lithium-ion cells analyzed using spline regression. These metrics offer a quantitative assessment of the model's performance in capturing the capacity degradation trends over cycles.

Table 2.  $R^2$  and MSE metrics of the cells.

Cell Number	$R^2$	MSE
1	1.0000	0.0128
2	1.0000	0.0137
3	1.0000	0.0132
4	1.0000	0.0213
5	1.0000	0.0217
6	1.0000	0.0217
7	1.0000	0.0130
8	1.0000	0.0132

The  $R^2$  values of 1.0000 across all cells indicate an excellent fit, demonstrating the spline model's ability to accurately capture the complex, non-linear degradation patterns observed in the dataset. The low MSE values further confirm the model's precision, highlighting its effectiveness in predicting capacity fade under

high-temperature conditions. These results underscore the robustness and reliability of spline regression in modeling battery degradation, providing valuable insights into the long-term performance of lithium-ion cells.

By comparing individual and group results, we identified consistent degradation trends across the cells, while also noting variations that may arise from manufacturing differences or testing conditions. The combined spline model for all cells offers a broader perspective, serving as a valuable tool for predicting capacity fade in similar battery types under high-temperature conditions.

The initial charge and discharge cycles provide critical insights into the battery's early performance characteristics, serving as a baseline for understanding long-term degradation trends as they are presented in Figure 5.

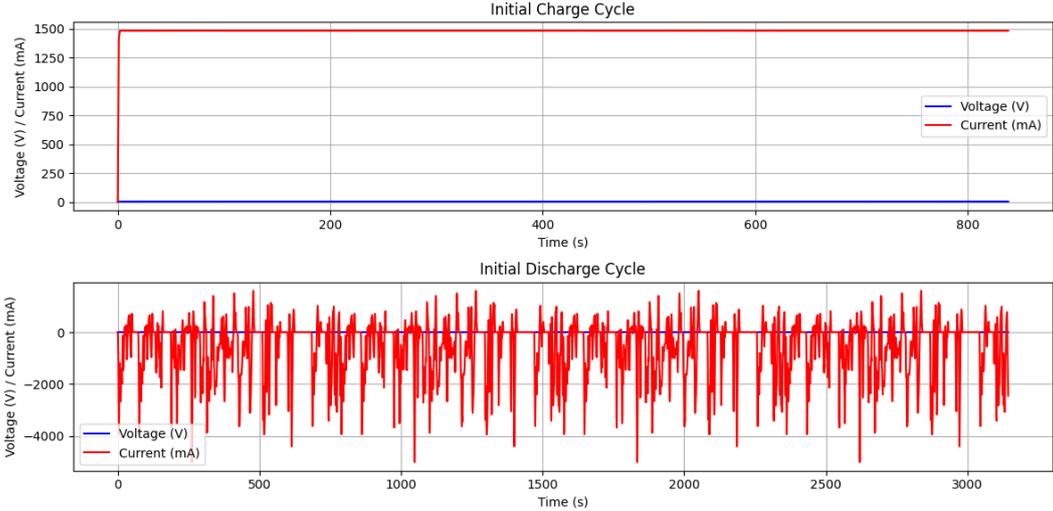


Figure 5. The initial charge and discharge cycles.

The charge cycle demonstrates a rapid increase in current, reaching a high-level indicative of a constant current charge phase. Throughout this phase, the voltage remains stable, reflecting the battery's ability to handle high-current conditions effectively. This stability is crucial for assessing the battery's initial performance and its capacity to manage charging stress.

In contrast, the discharge cycle exhibits significant current variability, likely due to the variable current discharge profile based on the Urban Artemis driving cycle. Despite these fluctuations, the voltage remains relatively stable, showcasing the battery's resilience in maintaining voltage under varying load conditions. This behavior provides valuable insights into the battery's response to real-world driving scenarios.

The analysis of the initial cycles highlights the battery's capability to manage high-current charging and variable discharge conditions. Understanding these early behaviors is essential for predicting long-term performance and degradation patterns. The initial cycle analysis serves as a foundational reference, offering a snapshot of the load profile that influences subsequent cycles and overall battery life.

Figure 6 illustrates the temperature profiles during the initial charge and discharge cycles of the battery. Understanding these temperature variations is crucial, as they can significantly impact battery performance and efficiency. By analyzing the temperature changes, we can gain insights into the thermal behavior of the battery under high-current conditions.

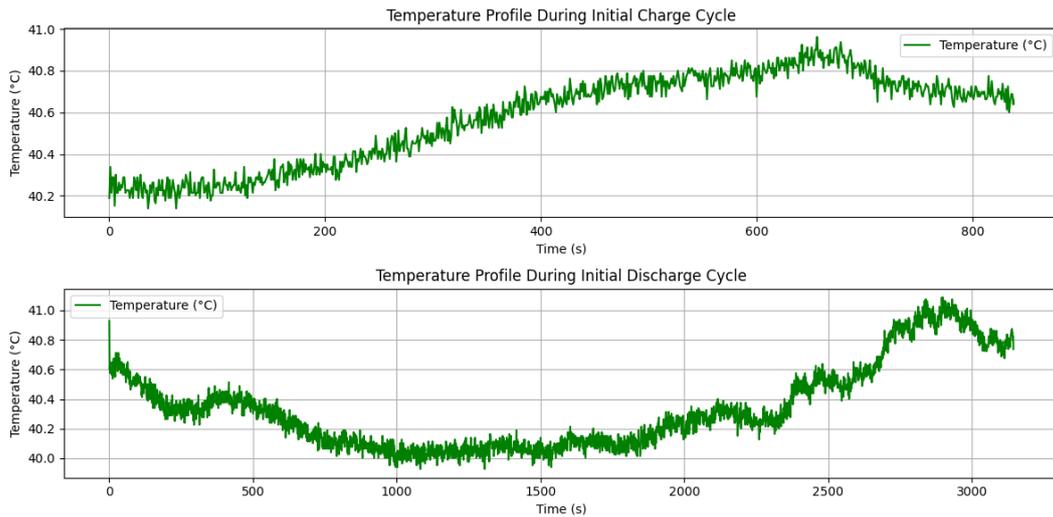


Figure 6. Temperature profiles during the initial charge and discharge cycles.

The temperature gradually rises during the charge cycle due to internal resistance and high-current flow. Nonetheless, the temperature stays within a manageable range, indicating the necessity of a successful thermal management during charging. The discharge cycle shows more variability in temperature, likely due to the variable current profile of the Urban Artemis driving cycle. The initial drop followed by a gradual increase reflects the dynamic thermal response of the battery to changing load conditions.

The ability to maintain temperature within a specific range is crucial for battery longevity and performance. Understanding these temperature profiles helps in assessing how thermal conditions affect efficiency and capacity during the initial cycle.

Figure 7 illustrates the relationship between voltage and current during the initial charge and discharge cycles. Understanding this relationship is crucial for assessing the battery's electrical characteristics and identifying any unique behaviors or anomalies.

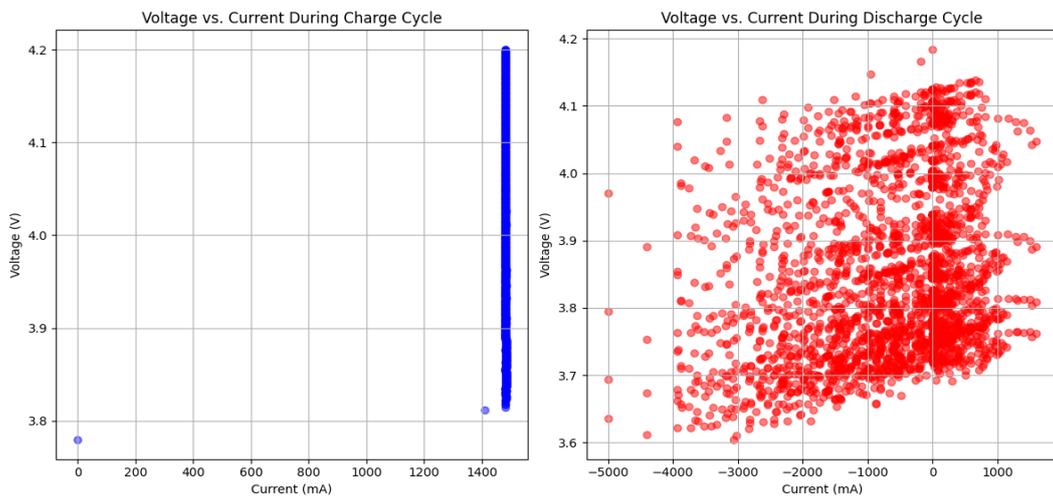


Figure 7. Voltage-current relationship during the initial charge and discharge cycles.

The voltage remains relatively stable while the current varies, indicating a constant voltage charge phase. This pattern is typical during charging, where the voltage is held constant as the current decreases. The discharge cycle shows a more dispersed pattern, reflecting the variable current profile of the Urban Artemis driving cycle. The voltage fluctuates with changes in current, highlighting the battery's response to dynamic load conditions. The charge cycle's stability and the discharge cycle's variability provide insights

into the battery's performance under different conditions. In this analysis, no significant anomalies are observed, suggesting typical behavior for this type of battery.

The analysis of charge and discharge durations provides valuable insights into the cycle dynamics of the battery during the initial cycle.

The charge phase lasted approximately 838 seconds, reflecting the high-current used during the 2-C constant current charge. This relatively short duration is typical for rapid charging scenarios, where the battery is quickly brought to its full capacity. In contrast, the discharge phase extended over 3144 seconds, aligning with the variable current profile of the Urban Artemis driving cycle. This longer duration simulates real-world conditions, where energy is released more gradually to match typical usage patterns.

The distinct difference in charge and discharge durations highlights the unique characteristics of each process. The rapid charge phase ensures quick energy replenishment, while the extended discharge phase provides a more controlled energy release, beneficial for applications requiring consistent power delivery. No immediate anomalies were observed in the cycle timings, indicating that the battery's performance aligns with expected behavior for the given profiles. This analysis enhances the understanding of the battery's efficiency and dynamics under different operational conditions.

The analysis revealed that high temperatures significantly influence battery degradation. The temperature profiles during the initial charge and discharge cycles showed fluctuations that can affect battery efficiency and longevity. Consistent exposure to elevated temperatures accelerates chemical reactions within the battery, leading to increased capacity fade over time. Effective thermal management is crucial to mitigate these effects and enhance battery performance.

By applying spline regression across all cells, we observed consistent degradation trends, with some variations likely due to manufacturing differences or testing conditions. The high  $R^2$  values across cells indicate a robust fit, capturing both individual and collective behaviors. This consistency underscores the reliability of the dataset and the models used, providing a comprehensive understanding of degradation patterns.

The insights gained from this study have practical applications in battery management and design. Understanding the impact of high temperatures on degradation can inform strategies to optimize thermal management, extending battery life and improving performance. Future research could explore broader temperature ranges, different battery chemistries, or real-world testing conditions to validate and expand upon these findings. Additionally, addressing the challenges encountered in efficiency calculations could provide a more complete picture of battery performance.

#### IV. CONCLUSION

This study provides a comprehensive analysis of long-term capacity degradation in LiBs under high-temperature conditions (40°C) using spline regression. The results demonstrate that elevated temperatures significantly accelerate capacity fade, primarily driven by mechanisms such as SEI growth and lithium plating. Spline regression effectively captured the non-linear degradation trends, achieving excellent fits ( $R^2 = 1.0000$ ) across all cells, highlighting its utility for modeling complex aging behaviors. Uniform degradation patterns were observed across cells, with minor variations likely attributable to manufacturing inconsistencies, underscoring the reproducibility of the findings under controlled conditions. The numerical results obtained from the spline regression analysis confirm the model's exceptional accuracy and robustness in predicting long-term degradation. Across all eight cells analyzed, the  $R^2$  values were consistently 1.0000, indicating a near-perfect fit between the spline model and the observed capacity degradation data. Furthermore, the MSE values were remarkably low, ranging from 0.0128 to 0.0217 for the individual cells, further validating the model's precision in capturing the complex, non-linear degradation patterns. This high level of accuracy underscores the spline model's adaptability and reliability in providing valuable insights into battery performance over thousands of cycles under high-temperature conditions.

The analysis of initial charge and discharge cycles revealed critical insights into the battery's thermal and electrical dynamics. Figure 6 illustrates the temperature profiles during these cycles, showing gradual increases during charging and more pronounced variability during discharge, reflecting the battery's response to dynamic load conditions. These temperature fluctuations correlate with localized degradation,

emphasizing the importance of effective thermal management. Figure 7 depicts the voltage-current relationship, with stable voltage during high-current charging and more dispersed patterns during discharge, consistent with the variable current profile of the Urban Artemis driving cycle. These observations provide valuable insights into the battery's performance under real-world operational stresses.

To extend the applicability of this work, future research should explore degradation in other battery chemistries, such as Nickel-Manganese-Cobalt (NMC) and Lithium Iron Phosphate (LFP), which are widely used in commercial applications. Additionally, validating these findings on high-capacity cells would address scalability concerns, as larger batteries often experience more pronounced thermal gradients and mechanical stresses. Integrating advanced thermal management strategies, such as phase-change materials or active cooling systems, could further mitigate degradation and enhance battery lifespan.

While this study focuses on controlled laboratory conditions, the methodologies and insights offer a robust foundation for optimizing battery systems in real-world applications, including electric vehicles and grid storage. Addressing scalability and operational complexities will be critical for bridging the gap between experimental findings and industrial implementation.

## DECLARATIONS

**Acknowledgements:** The author/authors do not wish to acknowledge any individual or institution.

**Author Contributions:** All parts of the study were conducted by the Author.

**Conflict of Interest Disclosure:** Any potential conflicts of interest must be explicitly declared. If there are none, it should be stated as: "The author/authors declare no conflict of interest."

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**Funding/Supporting Organizations:** This research received no external funding.

**Ethical Approval and Participant Consent:** This study does not involve human or animal participants. All procedures followed scientific and ethical principles, and all referenced studies are appropriately cited.

**Plagiarism Statement:** This article has been evaluated for plagiarism and no instances of plagiarism were detected.

**Availability of Data and Materials:** The dataset(s) analyzed during the current study were obtained from the Center for Advanced Life Cycle Engineering (CALCE) at the A. James Clark School of Engineering, University of Maryland. These data are publicly available in the CALCE Data repository, which can be accessed at <https://calce.umd.edu/battery-data>.

**Use of AI Tools:** The author/authors declare that no Artificial Intelligence (AI) tools were used in the creation of this article.

## REFERENCES

- Apriboowo, C. H. B., Sarjiya, S., Hadi, S. P., & Wijaya, F. D. (2022). Optimal planning of battery energy storage systems by considering battery degradation due to ambient temperature: A review, challenges, and new perspective. *Batteries*, 8(12), Article 290. <https://doi.org/10.3390/batteries8120290>
- Birkl, C. R., (2017). *Diagnosis and prognosis of degradation in lithium-ion batteries* (Doctoral dissertation, Department of Engineering Science, University of Oxford).

- Cavalheiro, G. M., Iriyama, T., Nelson, G. J., Huang, S., & Zhang, G. (2020). Effects of nonuniform temperature distribution on degradation of lithium-ion batteries. *Journal of Electrochemical Energy Conversion and Storage*, 17(2), Article 021101. <https://doi.org/10.1115/1.4045205>
- Fan, L., Khodadadi, J. M., & Pesaran, A. A. (2013). A parametric study on thermal management of an air-cooled lithium-ion battery module for plug-in hybrid electric vehicles. *Journal of Power Sources*, 238, 301–312. <https://doi.org/10.1016/j.jpowsour.2013.03.050>
- Fleckenstein, M., Bohlen, O., Roscher, M. A., & Bäker, B. (2011). Current density and state of charge inhomogeneities in Li-ion battery cells with LiFePO<sub>4</sub> as cathode material due to temperature gradients. *Journal of Power Sources*, 196(10), 4769–4778. <https://doi.org/10.1016/j.jpowsour.2011.01.043>
- Howey, D., & Birkel, C. (2017). Oxford Battery Degradation Dataset 1 [Data set; Data collected: 2015-01-08 – 2016-12-31]. University of Oxford. <https://doi.org/10.5287/BODLEIAN:K02KDMYGG>
- Kokam Battery Manufacturing Co., Ltd. (2025). *Kokam Battery Manufacturing Co., Ltd.* Retrieved March 17, 2025, from <http://www.kokamcom.com/>
- Laidler, K. J. (1984). The development of the Arrhenius equation. *Journal of Chemical Education*, 61(6), Article 494. <https://doi.org/10.1021/ed061p494>
- Lei, Z., Zhang, C., Li, J., Fan, G., & Lin, Z. (2013). A study on the low-temperature performance of lithium-ion battery for electric vehicles. *Qiche Gongcheng (Automotive Engineering)*, 35(10), 927–933. <https://pure.bit.edu.cn/en/publications/a-study-on-the-low-temperature-performance-of-lithium-ion-battery>
- Li, Z., Zhang, J., Wu, B., Huang, J., Nie, Z., Sun, Y., An, F., & Wu, N. (2013). Examining temporal and spatial variations of internal temperature in large-format laminated battery with embedded thermocouples. *Journal of Power Sources*, 241, 536–553. <https://doi.org/10.1016/j.jpowsour.2013.04.117>
- Liao, L., Zuo, P., Ma, Y., Chen, X. Q., An, Y., Gao, Y., & Yin, G. (2012). Effects of temperature on charge/discharge behaviors of LiFePO<sub>4</sub> cathode for Li-ion batteries. *Electrochimica Acta*, 60, 269–273. <https://doi.org/10.1016/j.electacta.2011.11.041>
- Lindgren, J., & Lund, P. D. (2016). Effect of extreme temperatures on battery charging and performance of electric vehicles. *Journal of Power Sources*, 328, 37–45. <https://doi.org/10.1016/j.jpowsour.2016.07.038>
- Lu, Z., Yu, X. L., Wei, L. C., Cao, F., Zhang, L. Y., Meng, X. Z., & Jin, L. W. (2019). A comprehensive experimental study on temperature-dependent performance of lithium-ion battery. *Applied Thermal Engineering*, 158, Article 113800. <https://doi.org/10.1016/j.applthermaleng.2019.113800>
- Ma, S., Jiang, M., Tao, P., Song, C., Wu, J., Wang, J., Deng, T., & Shang, W. (2018). Temperature effect and thermal impact in lithium-ion batteries: A review. *Progress in Natural Science: Materials International*, 28(6), 653–666. <https://doi.org/10.1016/j.pnsc.2018.11.002>
- Qu, J. G., Jiang, Z. Y., & Zhang, J. F. (2022). Investigation on lithium-ion battery degradation induced by combined effect of current rate and operating temperature during fast charging. *Journal of Energy Storage*, 52(Part A), Article 104811. <https://doi.org/10.1016/j.est.2022.104811>
- Robinson, J. B., Darr, J. A., Eastwood, D. S., Hinds, G., Lee, P. D., Shearing, P. R., Taiwo, O. O., & Brett, D. J. L. (2014). Non-uniform temperature distribution in Li-ion batteries during discharge—a combined thermal imaging, X-ray micro-tomography and electrochemical impedance approach. *Journal of Power Sources*, 252, 51–57. <https://doi.org/10.1016/j.jpowsour.2013.11.059>
- Shen, W., Wang, N., Zhang, J., Wang, F., & Zhang, G. (2022). Heat generation and degradation mechanism of lithium-ion batteries during high-temperature aging. *ACS Omega*, 7(49), 44733–44742. <https://doi.org/10.1021/acsomega.2c04093>
- Studden, W. J. (1971). Optimal designs and spline regression. In J. S. Rustagi (Ed.), *Optimizing methods in statistics* (pp. 63–76). Academic Press. <https://doi.org/10.1016/B978-0-12-604550-5.50008-0>
- Sun, P., Zhang, X., Wang, S., & Zhu, Y. (2022). Lithium-ion battery degradation caused by overcharging at low temperatures. *Thermal Science and Engineering Progress*, 30, Article 101266. <https://doi.org/10.1016/j.tsep.2022.101266>
- Wang, T., Tseng, K. J., Zhao, J., & Wei, Z. (2014). Thermal investigation of lithium-ion battery module with different cell arrangement structures and forced air-cooling strategies. *Applied Energy*, 134, 229–238. <https://doi.org/10.1016/j.apenergy.2014.08.013>
- Wu, B., Li, Z., & Zhang, J. (2015). Thermal design for the pouch-type large-format lithium-ion batteries: I. thermo-electrical modeling and origins of temperature non-uniformity. *Journal of The Electrochemical Society*, 162(1), A181–A191. <https://doi.org/10.1149/2.0831501jes>

- Zhang, G., Cao, L., Ge, S., Wang, C.-Y., Shaffer, C. E., & Rahn, C. D. (2014). In situ measurement of radial temperature distributions in cylindrical Li-ion cells. *Journal of The Electrochemical Society*, 161(10), 1499–1507. <https://doi.org/10.1149/2.0051410jes>
- Zhang, S., Xu, K., & Jow, T. (2003). Low-temperature performance of Li-ion cells with a LiBF<sub>4</sub>-based electrolyte. *Journal of Solid State Electrochemistry*, 7, 147–151. <https://doi.org/10.1007/s10008-002-0300-9>