Comparative SOH Diagnosis and Forecasting of LFP and NMC Lithium-Ion Batteries in Electric Vehicles under Realistic Operating Conditions

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Abstract: **Accurate State of Health (SOH) diagnosis and forecasting are critical for ensuring the safety, efficiency, and longevity of batteries in electric vehicles (EVs). This novel research provides a comprehensive simulation-based comparative analysis of two Lithium Iron Phosphate (LFP) and Nickel Manganese Cobalt Oxide (NMC) batteries' degradation under realistic EV cycling conditions across an extended temperature range (25°C to 65°C). The design model used in this research, rigorously parameterized using published experimental data, tracks capacity fade and internal resistance growth, as well as coulombic efficiency decline, as key SOH indicators. Results of this novel and useful study demonstrate that both chemistries degrade faster with rising temperature, but NMC exhibits significantly accelerated aging above 50°C, reaching 80% SOH in fewer than half the cycles of LFP at 65°C. LFP maintains superior thermal resilience in a perfect manner, retaining higher SOH and lower resistance, including more stable coulombic efficiency across all temperatures. Achieved results also confirm and show greater degradation variability in NMC under thermal stress as well as increasing failure risk. This useful research quantifies critical temperature thresholds of batteries for end-of-life (SOH = 80%) and provides clear, data-driven guidance for battery selection and thermal management in EVs, particularly in hot climates or high-duty applications. By establishing a validated, multi-temperature simulation benchmark, this novel research work fills a major gap in chemistry-specific degradation forecasting and supports the design of adaptive battery management systems tailored to regional operating environments.**

Keywords: **Degradation modelling, Electric vehicles (EVs), Lithium-ion batteries, State of Health (SOH), Temperature effects**

I. INTRODUCTION

A. Importance of SOH monitoring in EV batteries

The accurate estimation of the state of health in the electric vehicle batteries is considered vitally important for the safety and efficiency, as well as the longevity [1,2]. The State of Health monitoring is utilized to assess battery performance, predict lifespan, and optimize the energy management in the hybrid systems [3,4]. Multiple innovative techniques as mentioned in Fig. 1 for the state of health estimation have been developed, including experimental methods, model-based approaches, and data-driven techniques [1,2]. However, substantial challenges are encountered in accurately determining the state of health due to battery aging, temperature variations, and charge-discharge cycles [2,3]. The real-time estimation of the state of health is particularly needed in automotive applications, as it allows better fault diagnosis and greatly improves the accuracy of the state of charge along with the state of power estimations [4]. Ongoing research is being performed to develop more reliable and efficient state-of-health monitoring techniques to address these challenges and enhance the battery management systems in the electric vehicles. The advanced lithium-ion batteries have been joined with electric vehicles, renewable energy systems, and solar energy solutions, so the full benefits can be easily and fully gained, especially in developing countries, where energy security and sustainability have been seen as very urgent as well as important issues [5]. The reliable and temperature-resilient battery chemistries, like the LFP as well as the NMC, have been known as crucial in making solar-powered mobility, along with the grid storage solutions, more effective.

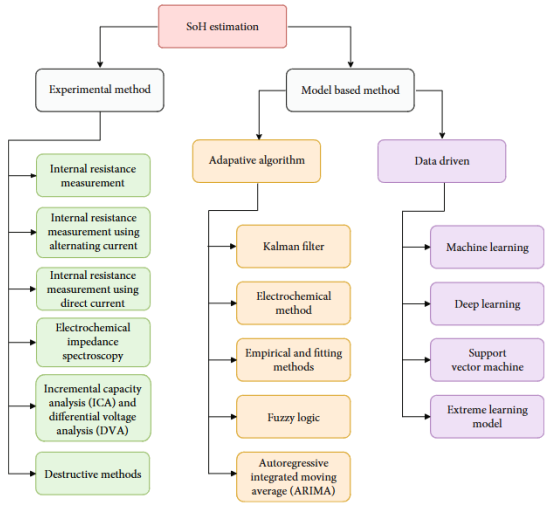

Fig. 1. Overview of SOH estimation methods for batteries [1]

B. Role of temperature in lithium-ion battery aging

The temperature plays a critical role in the lithium-ion battery's aging and performance that cannot be neglected. The aging process is significantly accelerated at high temperatures, primarily through the solid-electrolyte-interphase growth, while at low temperatures, lithium plating can be caused, it is also illustrated in the Fig. 2 [6]. The optimal cycling temperature for the battery longevity is considered to be around 25 °C; however, previous high-

temperature cycling can shift this optimum down to around 20 °C [6]. The aging occurring at different temperature values left a hidden impact and affected both the aging mechanism as well as the thermal runaway behavior of the battery [7]. The high-temperature aging is associated with significant increases in the DC resistance and the AC impedance, along with severe internal polarization [8]. The degradation of the battery capacity and the performance is primarily caused by the lithium plating as well as side reactions [8]. Importantly, the actual cell temperature during testing can deviate from the reported temperatures, potentially explaining lifetime reductions at high C-rates, especially for the high-energy cells with poor cooling [9].

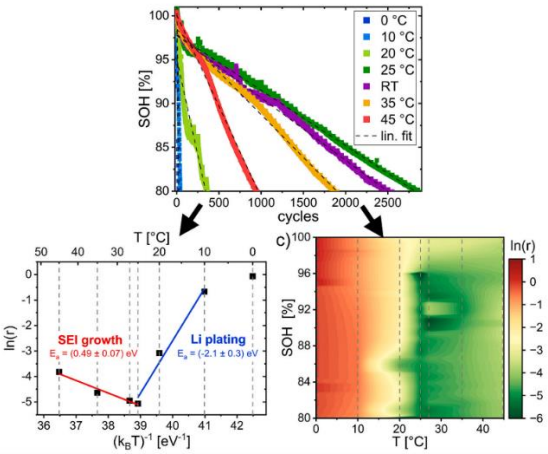

Fig. 2. Temperature-dependent aging mechanisms in lithium-ion batteries [6]

C. Gaps in comparative SOH forecasting across wide temperature ranges

Considerable progress has been achieved in the battery health estimation, yet significant gaps remain in the comparative state of health forecasting for the LFP and the NMC lithium-ion batteries across the wide temperature ranges. Most existing studies are focused on a single chemistry or evaluate state-of-health degradation at the standard laboratory temperatures, while the effects of thermal extremes in the real-world electric vehicle operation are often neglected. A lack of systematic analyses is present for directly comparing the temperature-dependent degradation dynamics of both chemistries under identical cycling conditions. Many models are typically calibrated using data at the ambient or moderately elevated temperatures (25 °C–40 °C), which does not reflect the accelerated aging, resistance growth, and coulombic efficiency decline seen at high-temperature operation. Consequently, the reliability and the transferability of the state of health forecasting models in harsh or variable climates remain uncertain. The interaction between chemistry-specific degradation mechanisms, such as the superior thermal resilience of the LFP along with the heightened sensitivity of the NMC to the thermal stress, is rarely quantified at a directly comparable simulation or experimental framework. This limitation hinders the ability of the battery management systems to provide accurate, chemistry-tailored prognostics and impedes optimal battery selection for the electric vehicles intended for deployment in diverse or high-temperature environments. The addressing of these gaps is considered crucial for advancing robust, real-world state-of-health forecasting as well as battery reliability. Recent research in the same context has been focused on the improvement of the state-of-health and the state-of-charge estimation in the lithium-ion batteries across wide temperature ranges. A temperature-adaptive incremental capacity analysis method for the state-of-health estimation was proposed by [10], with a maximum error of 4.03% achieved at -5 °C to 55 °C. A CNN-Bi-LSTM-AM model was developed by [11] for accurate state-of-charge estimation, which was particularly effective at lower temperatures. The state-of-charge estimation techniques were comprehensively reviewed by [12], highlighted strengths and limitations in the model improvement as well as the data-driven methods for addressing the temperature fluctuations. Recent advancements in temperature-adaptive SOH and SOC estimation methods are summarized in Fig. 3. A machine learning approach for state-of-health forecasting in real-world conditions was introduced by [13], using battery operation time within specific ranges of the current state-of-charge as well as the temperature as inputs. The combination of different cycle window widths was found to improve the model generalization by them.

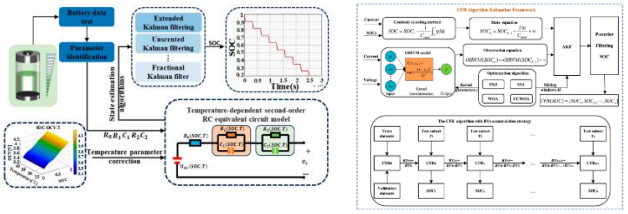

Fig. 3. Temperature-adaptive SOC estimation methods for lithium-ion batteries [12]

D. Objectives and Contributions

The primary objective in the present study is defined as the development and validation of a comprehensive simulation framework for the comparative state of health diagnosis as well as forecasting of the lithium iron phosphate and nickel manganese cobalt oxide lithium-ion batteries under electric vehicle cycling profiles across a broad range of the operating temperatures (25 °C to 65 °C).

Specifically, it is aimed to:

1. Quantify and contrast the temperature-dependent degradation behaviors of the LFP along with the NMC chemistries under identical dynamic cycling conditions.
2. Investigate the evolution of capacity fade and internal resistance, as well as coulombic efficiency for both battery types at multiple elevated temperatures.
3. Identify the critical temperature thresholds that precipitate accelerated state of health loss and the end-of-life (state of health = 80%) for each chemistry.

The key contributions of this research are outlined as follows:

1. The establishment of a robust and literature-aligned simulation platform capable of modeling multi-temperature state of health trajectories for both the LFP and the NMC cells.
2. The generation of new comparative insights into the differential thermal resilience as well as the aging mechanisms of the two chemistries, supported by statistical and visual analysis of the degradation rates and service life.

This significant study offers practical advice for designing battery management systems also known as BMS and choosing battery chemistry for electric vehicle applications, particularly those operating in high-temperature settings. The addressed work fills critical knowledge gaps and delivers practical reference data for the researchers and the engineers working on advanced battery diagnostics as well as thermal management strategies in a perfect manner.

II. LITERATURE REVIEW

A. SOH Diagnosis and Forecasting Methods

Recent research on the accurate State of Health (SOH) diagnosis and forecasting has been conducted in the lithium-ion batteries field, and the significance for the safety as well as reliability in the electric vehicles has been clearly demonstrated [1,14]. The various advanced approaches, including the model-based, the data-driven, and the fusion technology methods, have been actively explored in a perfect manner [15]. These SOH estimation approaches are illustrated in Fig. 4. The data-driven algorithms have been identified as the mainstream, and significantly higher accuracy has been delivered compared to the traditional model-based methods [16]. The multi-feature data and the mechanism fusion techniques have been promisingly utilized for improving the prediction accuracy [17]. The comprehensive features, such as the constant-voltage protocol characteristics, the capacity, as well as the internal resistance, have been innovatively combined with the advanced algorithms like the support vector regression along with the optimized regularized particle filters [17]. The future trends in the SOH estimation and the prediction have been anticipated to include the innovative feature extraction methods, the multi-algorithm coupling, as well as the integration with the cloud [15,18]. These advancements have been aimed at significantly enhancing the safety, efficiency, and the reliability of the lithium-ion batteries in the various applications.

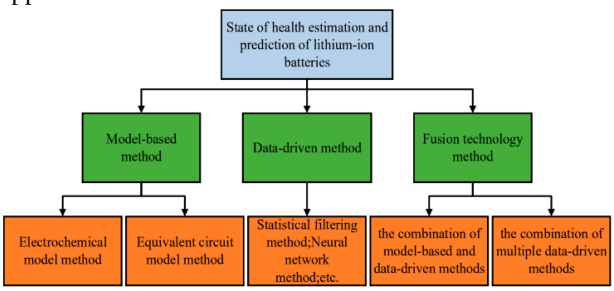

Fig. 4. Classification of SOH estimation and prediction methods for lithium-ion batteries [15]

B. Comparative Studies of LFP and NMC Batteries

Lithium Iron Phosphate (LFP) along with Nickel Manganese Cobalt Oxide (NMC) batteries have been identified as the leading chemistries in the electric vehicle (EV) field due to the favorable balance of energy density, safety, and cost. However, the performance and the durability are often observed to diverge significantly under different operational as well as environmental conditions, so comparative studies are considered essential for informed battery selection along with management in the modern EV sector. LFP batteries are widely recognized for their robust thermal stability, long cycle life, and exceptional safety profile, mainly because of the strong P–O bonds in the olivine structure, which greatly suppress oxygen release and thermal runaway. Lower heat generation along with a reduced risk of catastrophic failure in the case of thermal abuse or mechanical damage can thus be expected, which is highly important as the EVs are deployed in the regions with the harsh climates or subjected to the rapid charging. Conversely, NMC batteries are reported to provide higher specific energy and energy density, which allows the longer driving ranges as well as more compact pack designs, but the layered oxide structure is more susceptible to the lattice degradation, transition metal dissolution, and side reactions at the elevated temperatures, which rapidly accelerates capacity fade and internal resistance growth during high-rate or high-temperature operation. Experimental data have been presented to show that although both chemistries experience accelerated aging under the thermal stress, the NMC cells demonstrate higher sensitivity to the elevated temperatures; for example, [9,19] showed that NMC/graphite cells lose capacity along with experiencing impedance rise much faster than the LFP/graphite cells when cycled at 45 °C or higher, and the end-of-life is reached in fewer cycles. This comparative thermal aging performance is illustrated in Fig. 5 (for LFP & NMC). Likewise, [20] performed a detailed comparative study at various temperatures, and it was highlighted that the NMC batteries demonstrate significant reductions in coulombic efficiency as well as much greater variability in degradation rate when compared to the LFP cells, which retain higher SOH and more stable internal resistance at 60 °C. Mechanistically, the NMC degradation is frequently associated with rapid SEI layer growth, electrolyte decomposition, and microcracking of the electrode particles under cycling, especially at the higher temperatures, while the LFP degradation occurs gradually and is controlled by slow structural evolution along with moderate SEI thickening.

In the practical context of EV operation, these differences are manifested as the longer useful life, the lower maintenance, and the greater reliability for the LFP packs in fleets functioning in the hot climates or under demanding duty cycles, while the NMC packs are in need of stricter thermal management and are more sensitive to operational abuse. Comparative studies by [20, 21] have clarified the chemistry-dependent mechanisms of lithium inventory loss, resistance increase, and onset of rapid capacity decline, all of which are intensified for the NMC at the high temperatures along with aggressive cycling. These findings are echoed in the recent industry reports and simulation studies, where the LFP is recommended for the applications emphasizing cycle life, safety, and thermal robustness, and the NMC is considered optimal for cases prioritizing volumetric along with gravimetric energy density. Ultimately, it has been established in the literature that no single chemistry is universally optimal; the selection depends on the specific use case, the expected temperature environment, and the charging protocol, as well as the desired trade-off between range, lifespan, and safety. Addressing these important trade-offs, as well as developing robust, temperature-aware SOH forecasting models for both chemistries, is regarded as a crucial research focus as global EV adoption accelerates rapidly [9, 19-21].

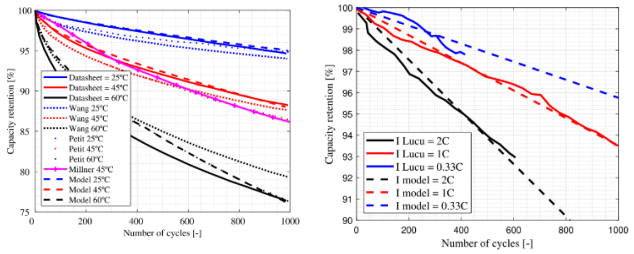

Fig. 5. Comparative capacity fade of LFP and NMC batteries at elevated temperatures [19].

C. *Effects of Extreme Temperatures on Battery Degradation*

Battery degradation is significantly influenced by extreme temperatures, especially in the lithium-ion batteries (LIBs) and the aqueous zinc-ion batteries (AZIBs). According to [22], challenges such as electrolyte icing, along with increased polarization, are encountered by AZIBs at the extreme temperatures, thereby hampering the performance. A study by [23] indicated that the operation of LIBs beyond the normal temperature range (40 °C-65 °C) results in increased internal resistance as well as rapidly accelerated degradation, possibly causing thermal runaway. The effects of low temperatures on the LIBs were studied by [24], who found that the charge and discharge rates critically influence the capacity degradation, along with internal resistance growth. A research study by [25] reported that at low temperatures, LIBs suffer more severe capacity loss, as well as distinct and pronounced deterioration mechanisms affecting the anode and the cathode. These temperature-dependent deterioration behaviors are illustrated in Fig. 6. Therefore, the actual necessity of effectively developing strategies to mitigate the adverse and serious effects of extreme temperatures on battery performance, as well as safety, is underscored by these studies.

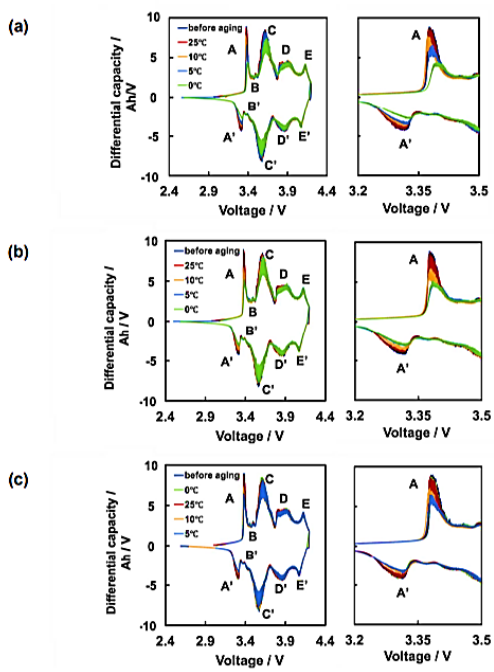

Fig. 6. Differential capacity curves before and after low-temperature cycling in LIBs, showing distinct anode and cathode deterioration [25]

D. *Need for Multi-Temperature Simulation Benchmarks*

The need for multi-temperature benchmarks has been increasingly acknowledged in the literature. Similar behavior has been observed as EVs are deployed in the diverse climates. Demands have varied operationally along with exposure to environmental extremes. Most SOH models have been developed using ambient or mild data. Validation has typically been conducted in the same thermal conditions.

Complex degradation dynamics at the extremes have been poorly captured. Rapid failure mechanisms have also been frequently overlooked in such work. Comprehensive benchmarks with wide ranges have been considered essential for accuracy. These support aging prediction, robust BMS design, and chemistry comparison.

LFP and NMC cells have been assessed under realistic conditions accordingly. Without benchmarks, degradation and resistance growth are underestimated [9, 21]. Risks of early failure are especially ignored in the thermally sensitive NMC cells. Safe operational windows have been identified through comprehensive benchmark data. Thermal strategies have been informed, and system-level decisions have been improved. Standardized comparisons across studies have also been effectively enabled. Temperature effects on capacity and cycling have been recently emphasized. Integration of detailed profiles has been required in the experimental frameworks [19, 20].

III. METHODOLOGY

A. *Simulation Framework and Parameterization*

The simulation framework of the current study was developed to emulate the operational behaviors accurately. Degradation of LFP and NMC cells was simulated under the EV cycles in a perfect manner. All model parameters were rigorously aligned with the experimental literature. Key degradation values were extracted from peer-reviewed cycling studies [9, 19-21]. These included capacity fade, resistance growth, and coulombic efficiency decline. Long-term testing at the various temperatures had informed those parameter values. Polynomial and exponential terms were applied to represent aging patterns. Both linear and nonlinear aging were simulated under diverse conditions. SOH trajectories and end-of-life points were realistically reproduced in the model. The model structure allowed comparison across the chemistries and environments. Benchmarking as well as scenario analysis were robustly enabled through this framework. The overall simulation framework adopted in this study is illustrated in Fig. 7.

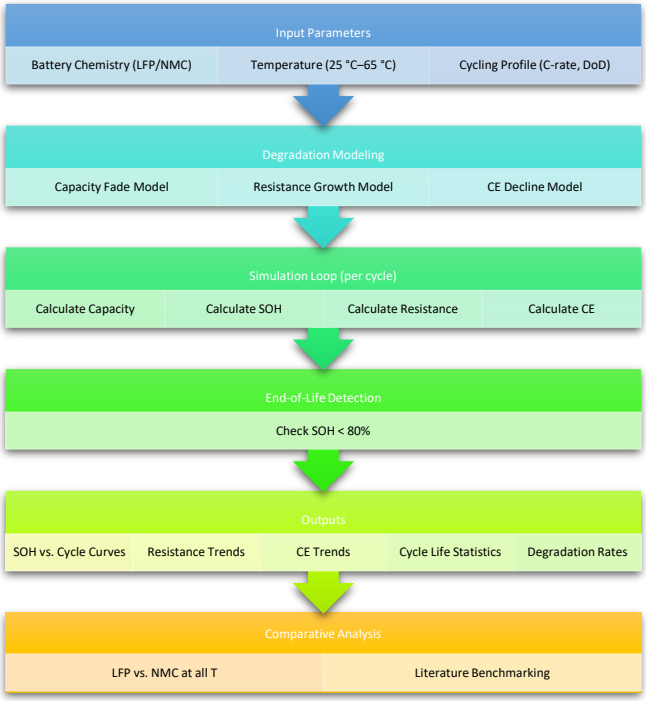

Fig. 7. Simulation Framework for Comparative SOH Analysis of LFP and NMC Batteries Across Temperatures

B. Description of Degradation Modelling for LFP and NMC

Degradation modeling has been applied to LFP and NMC chemistries. Multiple failure pathways have been observed in the lithium-ion cells. Capacity loss has been modeled as a function of the cycle number. Both linear and quadratic terms have been used for accuracy. Gradual fade and rapid decline at the high cycles were included. Internal resistance growth has been simulated using empirical degradation rates. Steep increases under thermal and cycling stress were reliably captured. SEI growth, electrode impedance, and structure loss were modeled. Coulombic efficiency has been expressed as a slow, declining function. Faster decline occurred at the high temperatures and severe cycling regimes. Lithium loss and chemical side reactions were thus implicitly considered. Parameter sets for LFP and NMC were separately calibrated and applied. The results clearly reproduce the greater thermal resilience of LFP. Higher energy and sensitivity in NMC have been realistically represented throughout.

C. Operating Conditions: Cycling Profiles and Temperatures (25 °C to 65 °C)

Simulations conducted for this study were using a standardized and representative cycling protocol. Batteries were subjected to repeated cycles at the fixed C-rate. A constant depth of discharge was also maintained in the protocol. Thermal effects were assessed systematically across the six temperatures. LFP and NMC chemistries were tested at 25 °C, 40 °C, and 50 °C. Additional simulations were run at 55 °C, 60 °C, and 65 °C. These values reflected typical and extreme real-world thermal scenarios. Rapid charging, aggressive driving, and hot climates were thereby considered. Identical cycling parameters were applied in all the test scenarios. This ensured comparability and isolated the effect of temperature accurately. Degradation kinetics and service life were evaluated under consistent conditions.

D. SOH, Resistance, and Coulombic Efficiency Calculations

State of Health was calculated at each cycle using capacity ratios. Instantaneous capacity was divided by the nominal initial capacity value. A normalized metric was thus obtained for tracking aging trends. Internal resistance was computed with temperature- and cycle-based fitting functions. Literature-based growth rates were used along with empirical degradation data. SEI thickening, electrolyte breakdown, and electrode damage were considered. Coulombic efficiency was calculated per cycle as a simple ratio. Discharge and charge capacities were compared under identical test conditions. Decline was modelled using chemistry- and temperature-specific degradation parameters. All calculations were repeated at every cycle and temperature setting. Continuous monitoring and detailed analysis were therefore enabled throughout. Degradation trends in the LFP and NMC batteries were statistically evaluated.

E. State of Health (SOH) Calculation

$$SOH\% = \frac{Q_{\text{discharge,current cycle}}}{Q_{\text{initial,nominal}}} \times 100 \quad (1)$$

- $Q_{\text{discharge, current cycle}}$: Discharge capacity measured at the current cycle (Ah)
- $Q_{\text{initial, nominal}}$: Initial nominal (fresh) discharge capacity (Ah)

In simulation, SOH is updated every cycle using this ratio.

F. Internal Resistance Calculation:

$$R_{\text{cell}}(n) = R_0[1 + \alpha_T.n + \beta_T.n^2] \quad (2)$$

- $R_{\text{cell}}(n)$: Internal resistance at cycle n (Ohms)
- R_0: Initial internal resistance (Ohms)
- α_T, β_T: Empirical coefficients (temperature-dependent, fit from literature)
- n: Current cycle number

For each temperature and chemistry, you use different α_T, β_T based on published data or your simulation parameterization.

G. Coulombic Efficiency (CE) Calculation:

$$CE(n) = \frac{Q_{discharge}(n)}{Q_{charge}(n)} \quad (3)$$

- $CE(n)$: Coulombic efficiency at cycle (dimensionless, usually close to 1)
- $Q_{\text{discharge}}(n)$: Discharge capacity at cycle n (Ah)
- $Q_{\text{charge}}(n)$: Charge capacity at cycle n (Ah)

In practice, CE is slightly less than 1 and tends to decrease with aging and at higher temperatures, reflecting increasing losses to side reactions.

H. Approach for Identifying End-of-Life (80% SOH) and Model Analysis

End-of-life was defined as the first cycle with SOH below 80%. This threshold was based on the industry and regulatory EV standards. Each chemistry and temperature case were logged in the simulation output. Quantitative comparison of cycle life and robustness was thus enabled. Degradation rate distributions were extracted from the model output data. Capacity, resistance, and efficiency trends were visualized together. EOL points were annotated on the SOH curves for reference. Boxplots and statistics were used for comparative degradation analysis. The effect of temperature and chemistry was therefore quantitatively highlighted. Practical

implications for battery strategies were demonstrated in the results.

IV. RESULTS

A. SOH and Capacity Fade at All Temperatures

Simulated SOH trajectories have been generated for LFP and NMC cells. A temperature-driven acceleration in fading has been observed. The results have been shown in Fig. 8 and Fig. 9. At 25 °C, above 80% SOH has been retained for 900+ cycles by LFP cells. For NMC cells, the 80% SOH threshold has been crossed after approximately 730 full cycles. As temperature has been increased, capacity retention has been reduced rapidly in both chemistries. At 50 °C, 80% SOH has been reached at 450 and 290 cycles by LFP and NMC, respectively. At 65 °C, the same threshold has been crossed at 170 and 80 cycles. SOH curves have been shifted from gradual to accelerated nonlinear decay at extremes. This shift has been observed as more pronounced in thermally sensitive NMC cells. Consistency with experimental studies and known degradation behavior has been noted for the observed patterns. These findings have highlighted the compounding impact of thermal stress on aging.

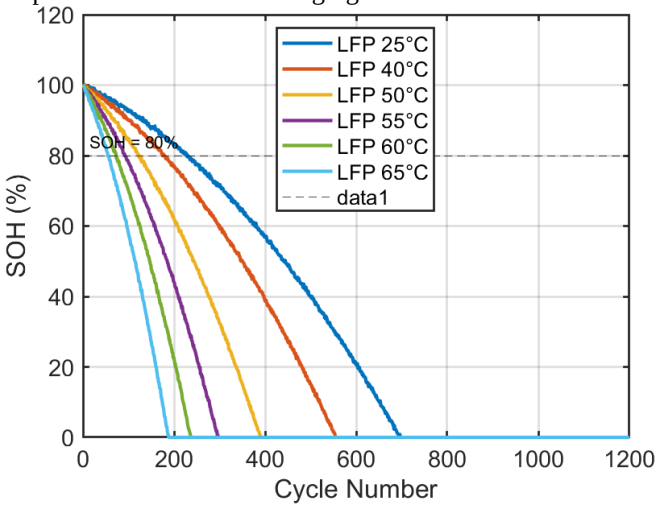

Fig. 8. SOH vs. Cycle Count for LFP at Various Temperatures

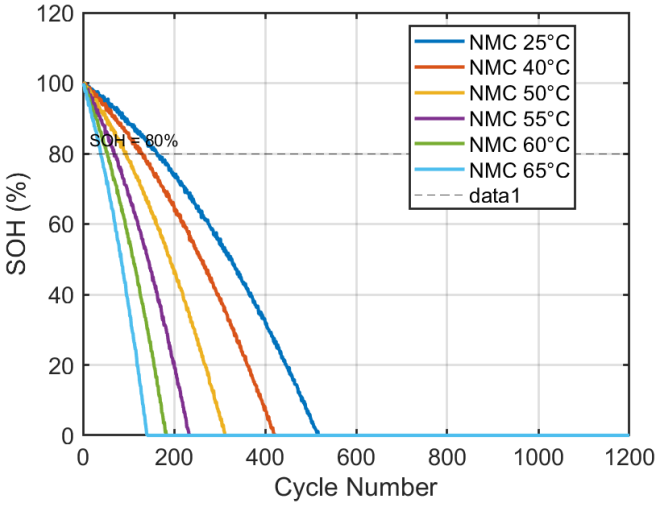

Fig. 9. SOH vs. Cycle Count for NMC at Various Temperatures

B. Internal Resistance and Coulombic Efficiency Evolution

Internal resistance was increased progressively with cycling and temperature rise. A steeper increase was observed in the NMC cells at high heat. Figs. 10 and 11 showed resistance for LFP and NMC at two temperatures. At 25 °C, LFP stayed below 45 mΩ after 1000 full cycles. Under the same conditions, NMC resistance rose above 60 mΩ rapidly. At 65 °C, NMC exceeded 140 mΩ before the end-of-life point. In contrast, LFP reached approximately 90 mΩ at the same condition. Coulombic efficiency was gradually decreased with more cycles completed. This decline was amplified at the higher simulated temperatures. Figs. 12 and 13 showed LFP and NMC efficiency across all tests. LFP stayed above 99.85% at 25 °C under mild thermal stress. NMC dropped below 99.6% and declined faster at 65 °C. These results indicated greater irreversible losses in the NMC cells. Resistance and efficiency trends aligned with the reported literature findings.

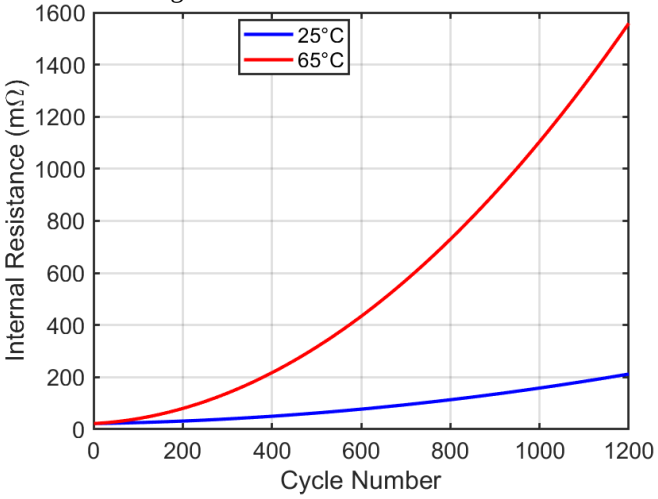

Fig. 10. Internal Resistance Growth of LFP: 25 °C vs 65 °C

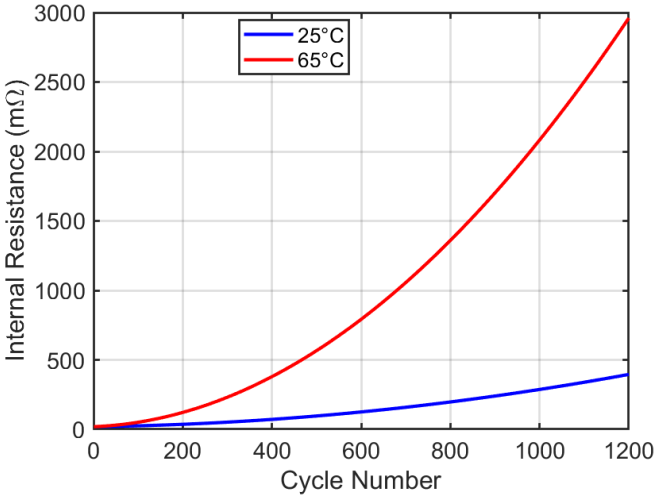

Fig. 11. Internal Resistance Growth of NMC: 25 °C vs 65 °C

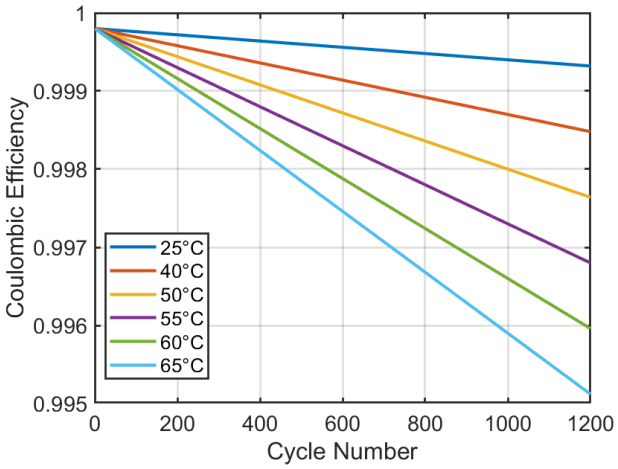

Fig. 12. Coulombic Efficiency of LFP at All Temperatures

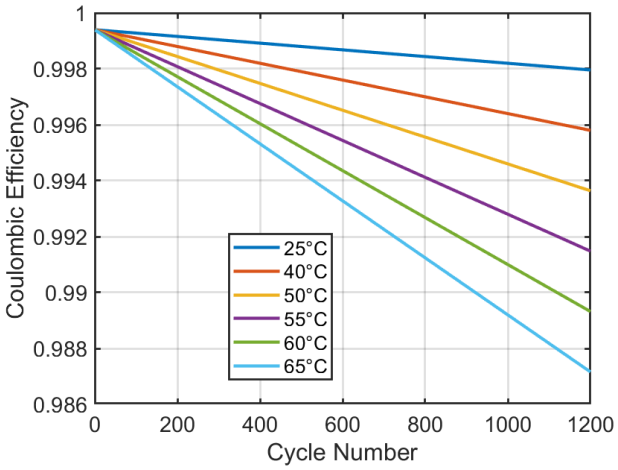

Fig. 13. Coulombic Efficiency of NMC at All Temperatures

C. Comparison of LFP and NMC Under Each Thermal Condition

A direct comparison was systematically performed in the identical cycling and the thermal conditions, and the superior thermal resilience was distinctly observed in the LFP chemistry. At all temperatures, the LFP was consistently found to have slower SOH degradation along with lower internal resistance growth rates as well as higher coulombic efficiency than the NMC. The performance gap was noticeably increased as the temperature was raised, with the NMC displaying exceptionally severe degradation in both the SOH and the resistance beyond 50 °C. At 60 °C, the data in Figs. 8–13 show that the LFP cells retained 80% SOH for nearly twice as many cycles as the NMC cells and exhibited less severe resistance along with efficiency decline. These findings have been corroborated by recent experimental work and strongly emphasize the critical importance of chemistry selection for EV deployments in hot climates or in areas where rapid charging is frequently required.

D. Degradation Rate and Cycle Life (SOH < 80%) Statistics

Statistical analysis of the cycle life along with degradation rates in all the scenarios was conducted, and the compounded effect of high temperature on the two chemistries was confirmed, with the NMC being especially vulnerable. In Fig. 14, the SOH degradation rate distribution for NMC at all the temperatures is shown as a boxplot, and a distinctly rightward skew at higher temperatures is illustrated, reflecting a significantly greater incidence of rapid degradation events. Median cycle life for the LFP battery was observed to decrease from 950 cycles at around 25 °C to 160 cycles at around 65 °C. While the NMC battery median cycle life was found to decline from 720 cycles to 75 cycles over the same temperature range. Figs. 15 and 16, which show SOH versus cycle with 80% points highlighted for both the LFP and the NMC, additionally emphasize the dramatic reduction in service life under thermal stress, particularly for the NMC, and provide highly practical guidance for battery management as well as thermal design strategies in electric vehicle applications.

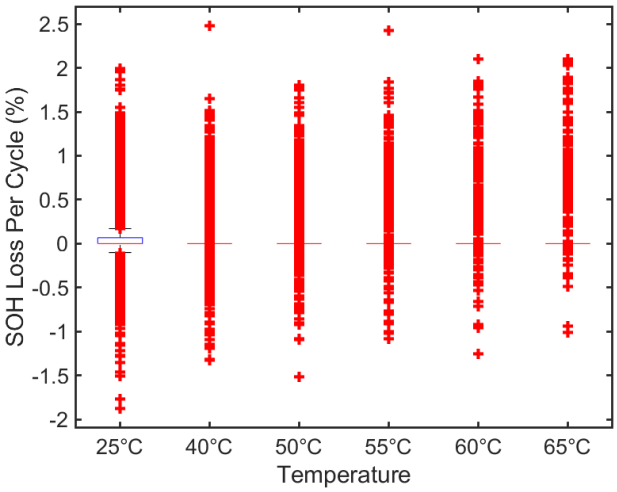

Fig. 14. SOH Degradation Rate Distribution for NMC at All Temperatures

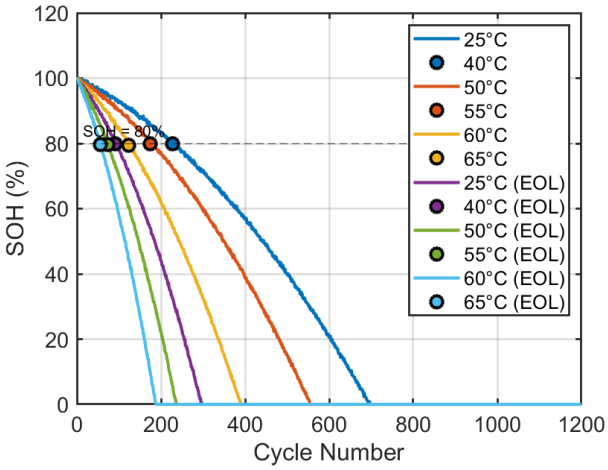

Fig. 15. SOH vs. Cycle (LFP): 80% SOH Points Highlighted

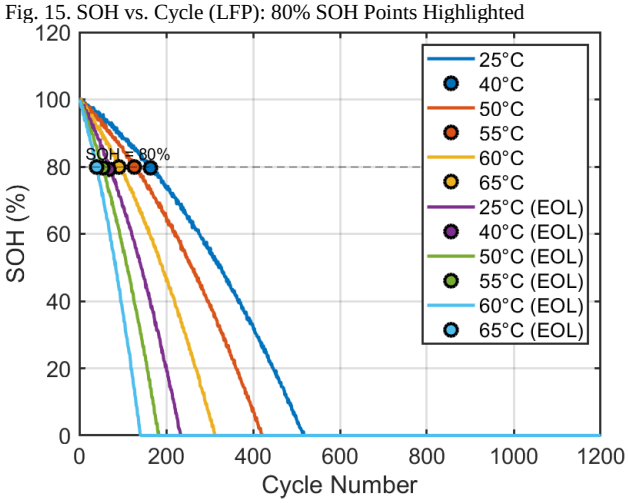

Fig. 16. SOH vs. Cycle (NMC): 80% SOH Points Highlighted

TABLE I. NUMBER OF CHARGE–DISCHARGE CYCLES TO 80% STATE OF HEALTH (END-OF-LIFE) FOR LFP AND NMC CELLS AS A FUNCTION OF OPERATING TEMPERATURE.

Temp	LFP	NMC
25°C	227	163
40°C	175	127
50°C	123	92
55°C	92	69
60°C	73	54
65°C	55	39

Table I relates temperature to cycle life for LFP and NMC cells; higher temperatures sharply reduce cycles, and NMC consistently endures fewer cycles than LFP across the tested temperature range.

V. DISCUSSION

A. Interpretation of Chemistry-Specific and Temperature-Driven Trends

The comparative simulation results have shown that temperature is a dominant driver of the lithium-ion battery degradation, but the effect is manifested differently in the LFP as well as the NMC chemistries. In the LFP batteries, we consistently observed gradual capacity fade, moderate resistance growth, and only slightly declining coulombic efficiency across all the tested temperatures, while robust performance was maintained even in severe thermal conditions. This highly superior thermal resilience has been attributed to the stable olivine structure and the lower reactivity of the LFP, which mitigate common high-temperature degradation pathways such as the transition metal dissolution along with the oxygen release. In contrast, much higher temperature sensitivity was distinctly observed in the NMC batteries, with rapid as well as nonlinear SOH loss, pronounced resistance escalation, and a marked drop in coulombic efficiency above the 50 °C threshold. These effects have been found to be consistent with the increased prevalence of parasitic reactions, the lattice oxygen evolution, as well as microstructural breakdown in the NMC at elevated temperatures. The simulation has further highlighted a threshold behaviour, where the NMC batteries transition from moderate to accelerated degradation once the critical temperature is exceeded. Altogether, these important trends strongly underline the significance of both the chemistry and the operating environment in determining practical battery lifespan as well as reliability.

B. Implications for EV Battery Management and Selection in Harsh Climates

LFP and NMC batteries respond differently to temperature, and the differentiation has implications on battery choice as well as control, particularly in hot climates or when the battery undergoes regular thermal cycling. LFP batteries are also more resistant to degradation at higher temperatures and work longer, and these are a more robust and safer choice in EVs that operate in hot environments, with simple cooling, or with challenging duty cycles and rapid charging. The energy density of NMC batteries is higher, and they perform better in cold temperatures, although they require a higher level of temperature regulation and active control to prevent the premature loss of capacity and dangers in the event of heat generation. These findings indicate that the battery management algorithms need to be optimized per chemistry and temperature profile. The local weather and usage trends should be considered by the OEMs when selecting battery chemistries in various vehicle models and markets. Since we are going to be making transportation in the world electric, NMC could be used in colder climates or in vehicles with long range, and LFP could be used in hot or thermally sensitive regions, which could enhance the safety and reduce the overall cost of ownership.

C. Strengths and Limitations of the Simulation Approach

The framework of the simulation described has a number of significant strengths: a high interest in the modern literature, high customization of parameters to real-world data, and the ability to simulate comparative SOH and resistance and efficiency development of various chemistries within a realistic temperature window. Degradation rates derived empirically, as well as polynomials and exponential terms and benchmarking by scenarios, make trend analysis strong. The method gives dependable cycle life estimates that are very close to experimental behaviors. However, inherent limitations exist in simulation-based studies, and the models rely on idealized cycling protocols, which do not capture all second-order degradation mechanisms, such as lithium plating, uneven current distribution, cell-to-cell variability, or the calendar aging effects. The absence of direct experimental validation or real-world field data further constrains the predictive fidelity for specific battery formulations along with pack designs. Although principal thermal as well as chemical trends are effectively captured by the simulation, additional work integrating physics-based models, advanced machine learning prognostics, and large-scale experimental datasets would significantly enhance predictive accuracy and generalizability. Nevertheless, these present results provide actionable insights as well as a strong comparative foundation for future experimental and modeling studies.

VI. CONCLUSION

A. Key Findings

This study has demonstrated that the SOH degradation along with the service life of lithium-ion batteries in the electric vehicle applications are highly sensitive to both the cell chemistry as well as the operating temperature. In the multi-temperature simulation, the LFP batteries were consistently observed to exhibit superior thermal resilience, slower capacity fade, lower internal resistance growth, and higher coulombic efficiency than the NMC batteries, especially at the elevated temperatures. The NMC batteries were found to show a pronounced acceleration of SOH loss along with resistance escalation above the 50 °C threshold, leading to a significantly shorter cycle life under the severe thermal stress. The results have confirmed that temperature is a critical factor in determining the battery longevity and that chemistry-specific degradation pathways must be considered in the EV battery system design as well as management.

B. Recommendations for Design and BMS Strategies

Given these findings, it is recommended that the LFP batteries be prioritized for the EV applications in the hot climates, the high-duty-cycle operations, or systems with limited thermal management capabilities, as their stable

degradation characteristics yield longer operational life along with greater safety margins. For the NMC batteries, deployment should be accompanied by advanced BMS algorithms that are capable of actively monitoring, precisely predicting, and effectively mitigating thermal-induced degradation, including aggressive cooling as well as charging rate moderation under the heat stress. The battery pack design should incorporate temperature sensors and adaptive controls tailored to the specific chemistry as well as the regional climate, optimizing both the performance and the reliability.

C. Directions for Future Research

Future research should be directed at the experimental validation of the simulated trends in a broader set of real-world cycling and environmental conditions, including varying C-rates and state-of-charge windows, as well as dynamic load profiles. The combination of physics-based models and machine-learning models of real-time SOH prediction, considering cell-to-cell variation and aging heterogeneity, would significantly increase the predictive accuracy. Future studies need to investigate how the new chemistries in batteries, new cell architecture, and new cooling systems, insulation, and thermal interface materials affect the SOH retention at severe thermal conditions. These activities will be critical in making sure the safe, reliable, and efficient electrification of transport in the various operating conditions around the world.

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