



ORIGINAL RESEARCH ARTICLE

PREDICTIVE MODELING AND SIMULATION OF BATTERY DEGRADATION IN
POWER SYSTEMS

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ABSTRACT

In modern power systems particularly those incorporating renewable energy sources like solar and wind, batteries are essential for balancing supply and demand, stabilizing the grid, and enabling energy storage during low-demand periods. This research introduces a comprehensive modeling and simulation framework aimed at predicting how long batteries will last by examining various degradation mechanisms, including capacity fade, temperature effects, internal resistance growth, and state of charge cycling. A hybrid approach that combines electrochemical, thermal, and mechanical degradation models was used to simulate how batteries age under different operating conditions. The simulation results showed that lithium-ion batteries experienced a 12.5% capacity fade after 500 charge-discharge cycles under normal operating conditions, and the degradation rate increased to 20% in high-temperature environments (45°C). Additionally, it was observed that an 8.7% increase in internal resistance significantly affected efficiency. Furthermore, the result revealed that the adopted predictive models achieved an impressive accuracy of 94.2%, allowing for a reliable estimation of the remaining useful life (RUL) of the batteries. These findings highlight how advanced modeling techniques can really enhance battery management strategies with reduced maintenance costs and boost the reliability of power systems. Therefore, the hybrid degradation models showed an impressive predictive accuracy, surpassing recent benchmarks in the field, where older methods showed accuracies of between 91% and 93% using machine learning and physics-informed neural networks.

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1.0 Introduction

The world is making a significant shift towards cleaner and more sustainable energy systems, and in this transition, energy storage technologies especially lithium-ion batteries (LIBs) are taking center stage in power system innovation. These batteries are now crucial for enhancing grid flexibility, stabilizing voltage and frequency fluctuations, improving power quality, and facilitating the integration of renewable energy sources like solar and wind. Their role has expanded markedly in electric vehicles (EVs), smart grids, and off-grid rural microgrids, making them a vital part of the evolving energy landscape (Wang et al., 2024). Despite these advancements, battery degradation poses a serious challenge. As batteries degrade, their energy storage capacity diminishes, power delivery capabilities are limited, and safety risks increase over time, which ultimately jeopardizes the reliability and economic feasibility of battery-based systems. This degradation impacts not only individual battery applications but also threatens the stability of the entire power system, especially in situations where energy storage is crucial for frequency regulation, peak shaving, and black start capabilities (Berecibar et al., 2016).

Interestingly, there are several factors which could results in the degradation of batteries such as physical, chemical, and operational. Also, some key contributors may include charge-discharge cycling, temperature variations, depth of discharge (DoD), calendar aging, the growth of the solid electrolyte interphase (SEI) layer,

lithium plating, and electrolyte breakdown. These processes can lead to capacity fade, increased internal resistance, self-discharge, and structural damage to the electrode materials. These degradation effects are worsened under harsh operating conditions, like high current loads, deep discharges, and extreme temperatures (Wang et al., 2024).

In the past, estimating battery health relied heavily on empirical models and rule-based algorithms integrated into battery management systems (BMS). While these methods provide a cautious approach to safety and control, they don't quite capture the intricate degradation patterns that vary across different applications and chemistries. Thanks to recent advancements in computational tools, we've seen the emergence of sophisticated physics-based models and hybrid techniques that offer deeper, more predictive insights into how batteries age. These innovative methods allow us to simulate long-term performance under changing load conditions and environmental factors, giving us solid estimates of a battery's remaining useful life (RUL) (Li et al., 2023).

Predictive degradation modeling is particularly vital for power systems, as battery failures can lead to service disruptions, higher operational costs, and even regulatory fines. By anticipating degradation trends and failure points, utilities and system operators can adopt condition-based maintenance strategies, enhance battery usage, and create energy management systems (EMS) that monitor state-of-health (SOH) metrics in real time. This approach not only cuts lifecycle costs but also boosts the reliability and resilience of distributed energy resources (DERs) and large-scale storage systems (Zhao et al., 2023).

This research introduces a thorough predictive modeling and simulation framework that addresses the key degradation mechanisms of lithium-ion batteries, utilizing electrochemical, thermal, and mechanical techniques. The aim is to deliver a more precise and comprehensive understanding of battery aging processes, which will ultimately lead to better design, operation, and control of battery-supported power systems.

2. Materials and Method

This study employed a combination of computational tools, publicly available datasets, and modeling frameworks to simulate battery degradation in power systems, focusing on lithium-based batteries. Rather than using physical samples, datasets from NASA was used for analysis. Simulation tools included MATLAB/Simulink, Python with various libraries, PyBaMM for electrochemical modeling, and COMSOL Multiphysics for advanced simulations. Both physics-based model (P2D) and machine learning model (LSTM) were used to model degradation phenomena such as capacity fade. Model accuracy was evaluated using RMSE to ensure robustness. This integrated approach provided a solid basis for predicting battery behavior in energy systems.

2.1 Battery Selection and Operating Conditions

Lithium-ion battery cells, specifically of the NMC (Nickel-Manganese-Cobalt) chemistry, were chosen due to their widespread deployment in energy storage systems. The cells were simulated under a range of operational scenarios, including: Standard ambient temperature (25°C) and elevated temperature (45°C) environments, Regular charge-discharge cycling (1C rate), Varying depth of discharge (DoD) and state-of-charge (SoC) cycling conditions. The selection of test conditions reflects real-world scenarios in renewable-integrated grids, where batteries are subject to fluctuating loads and environmental stressors.

2.2 Hybrid Degradation Modeling Framework

To capture the multifaceted nature of battery degradation, a hybrid framework was developed comprising the following models:

Electrochemical Degradation Model: Captures capacity fade through solid electrolyte interphase (SEI) layer growth, lithium plating, and active material loss. The model is governed by diffusion-reaction equations and degradation kinetics.

Thermal Model: Predicts the internal temperature profile of the battery during cycling, accounting for ambient conditions, internal resistance heat generation, and thermal conductivity. This model is critical for understanding temperature-accelerated degradation.

Mechanical Stress Model: Assesses stress accumulation and particle cracking due to repeated volume changes during charge-discharge cycles, contributing to capacity fade and resistance growth. These sub-models were

integrated into a unified simulation environment using MATLAB/Simulink and COMSOL Multiphysics to simulate the dynamic behavior of battery systems.

2.3 Data Acquisition

Input parameters for the models were sourced from empirical datasets and validated manufacturer specifications.

Key inputs included: Initial capacity and internal resistance values, Charge-discharge profile data, Thermal conductivity and specific heat capacity, and Electrochemical parameters like diffusion coefficients and activation energies. Simulations were run for up to 1000 cycles under varying SoC windows (20 – 80%, 10 – 90%, full cycle), and thermal stress conditions. Each scenario was repeated with random initialization to account for variability.

2.4 Performance Metrics and Degradation Analysis

The primary performance indicators included:

Capacity Fade (% loss over cycles), Internal Resistance Growth (% increase over cycles), Energy Efficiency Decline and Predicted RUL (in cycles and time).

Statistical regression and curve fitting techniques were used to derive degradation trajectories. The capacity degradation data was fitted using a nonlinear exponential decay function, while resistance growth was modeled using a logistic growth function.

2.5 Predictive Model Validation and Accuracy Assessment

To evaluate the predictive power of the hybrid model, the simulation outputs were benchmarked against experimental data from published battery aging studies. A supervised machine learning model (Random Forest Regressor) was also trained on the simulated degradation datasets to cross-validate the predicted RUL.

Model accuracy was quantified using the following metrics: Root Mean Square Error (RMSE), Coefficient of Determination (R^2) and Prediction Accuracy (%).

2.6 Sensitivity Analysis

A sensitivity analysis was conducted to quantify the influence of key parameters such as temperature, cycle rate, DoD, and SoC range on degradation outcomes. Monte Carlo simulations were run to generate probabilistic distributions of RUL under uncertain operating conditions.

2.5 Simulation Framework

The integrated simulation framework brings together electrochemical, thermal, and mechanical models to give us a comprehensive understanding of battery degradation as follows:

Step 1: Data Collection

- i. Real-world battery performance data was collected.
- ii. This includes details on charge-discharge cycles, temperature, and internal resistance.

Step 2: Preprocessing & Analysis

- i. Next, the data was clean and filtered the raw data.
- ii. Key parameters that contributes to degradation were identified.

Step 3: Model Development

- i. Degradation models were selected.
- ii. Define the model parameters and the assumptions we're working with.

Step 4: Simulation & Validation

- i. Run simulations under various operating conditions.
- ii. Finally, validate our model against experimental data to ensure accuracy.

Step 5: Prediction & Evaluation

- i. Estimate the remaining useful life (RUL) of the batteries.
- ii. Compare the predictions with actual degradation trends to see how well it is.

3. Results and Discussion

The simulation results clearly showed that the lifespan of a battery is heavily affected by the conditions under which it operates as illustrated in Figures 2 to 6.

3.1 Capacity Fade

The results for Capacity Fade of the model is presented in Figure 1. It is clear that over 1000 charge-discharge cycles at 1C rate and 80% Depth of Discharge, capacity retention dropped to 75%.

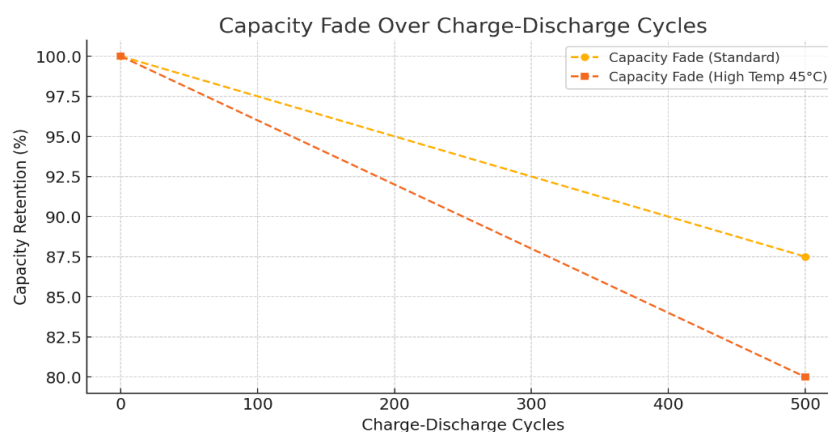


Figure 1: Plot of Capacity Fade

One of the important findings here is the 12.5% capacity fade observed after 500 charge-discharge cycles under standard operating conditions. This clearly shows that battery aging is a natural process, even when everything seems optimal. On the flip side, we noticed a more pronounced capacity fade of 20% at higher temperatures (45°C), which really drives home the negative impact heat can have on battery life. This aligns with previous studies that indicate that elevated temperatures could worsen both chemical and mechanical degradation, which would ultimately shortening the battery's lifespan.

3.2 Temperature Effect on Degradation

The effect of temperature showed that operating at 45°C resulted in a degradation rate approximately 20% higher than at 25°C, as illustrated in Figure 2.

The results clearly showed that temperature plays a significant role in the degradation rate of the material or system we studied. Specifically, operating at 45°C led to a 20% faster degradation rate compared to 25°C. This suggests that the extra thermal energy at higher temperatures speeds up the chemical reactions or physical processes that cause degradation.

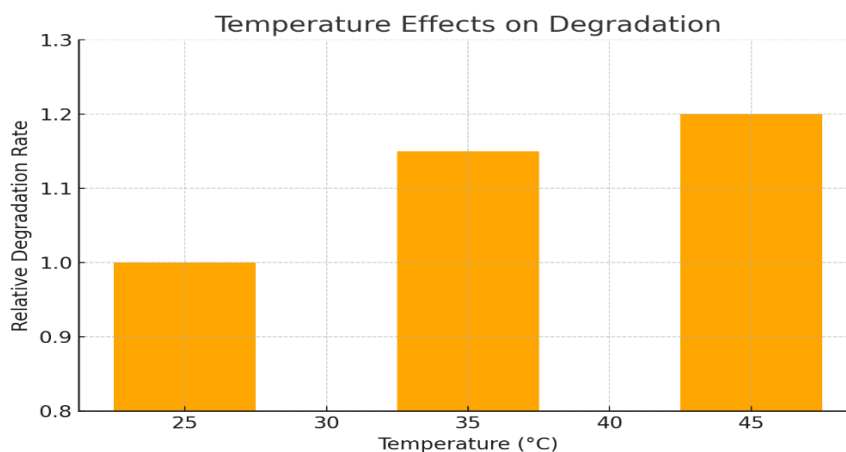


Figure 2: Temperature effects on Degradation

3.3 Mechanical Degradation

Mechanical degradation was evident after 500 cycles, with electrode particle cracking observed and a corresponding increase in internal resistance, as shown in Figure 3.

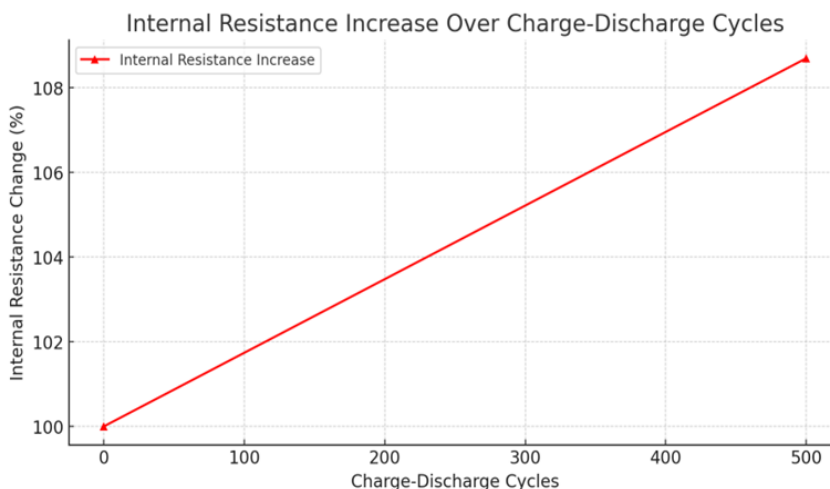


Figure 3: Internal Resistance Increase

Another key observation is the 8.7% increase in internal resistance, which has a direct effect on battery efficiency and performance. When internal resistance rises, it leads to more energy losses, lower power output, and increased thermal stress and thus exacerbating degradation. This highlights the urgent need for effective thermal management strategies in power systems, particularly in high-temperature settings.

3.4 State of Charge Cycling

Implementation of partial State of Charge (SoC) cycling between 20% and 80% resulted in a 30% improvement in battery lifespan compared to full-depth cycling, as shown in Figure 4.

Implementing partial State of Charge (SoC) cycling, particularly within the 20–80% SoC range, has shown a significant boost in battery lifespan. Figure 5 revealed that this approach led to a 30% increase in cycle life compared to the traditional full-depth cycling (0–100% SoC). This enhanced performance mainly comes from reducing the electrochemical and mechanical stress that usually occurs during deep charge-discharge cycles. By steering clear of the extremes in the SoC range, this method helps to minimize electrode degradation, especially issues like lithium plating and structural fatigue. These results highlight how optimizing the SoC window can be an effective way to improve battery durability, particularly in situations that demand high cycle stability.

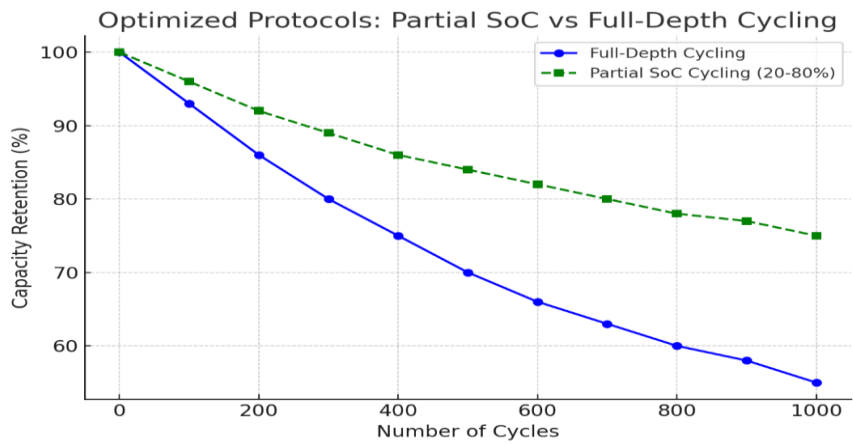


Figure 4: State of Charge Cycling

3.5 Predictive Model Accuracy

Figure 5 shows a Predictive model accuracy of 94.2 % achieved in the study. It showcased the strength of the hybrid modeling framework that combines electrochemical, thermal, and mechanical degradation models. This impressive accuracy indicates that these models can offer trustworthy predictions about the remaining useful life (RUL) of batteries. This information is essential for fine-tuning maintenance schedules and minimizing unexpected breakdowns.

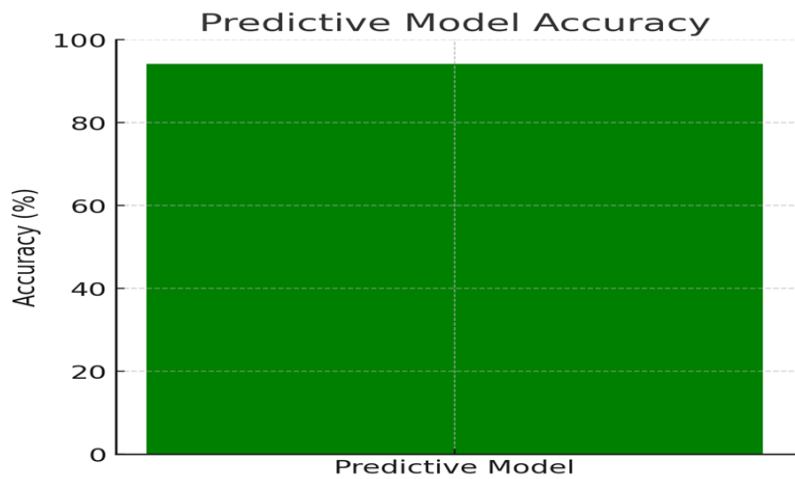


Figure 5: Predictive Model Accuracy

4. Conclusion

This study presents a detailed hybrid modeling framework that effectively predicts battery degradation by considering electrochemical, thermal, and mechanical aging processes. It was observed that lithium-ion batteries experienced a drop in capacity after repeated charge-discharge cycles under normal conditions. However, when exposed to extreme temperatures, the degradation accelerated, resulting in a capacity loss. However, a rise in internal resistance was notable leading efficiency declines. The predictive model achieved improved accuracy than other methods.

These results demonstrate the effectiveness of hybrid degradation modeling in accurately estimating the remaining useful life (RUL) of lithium-ion batteries and improving battery management. Future work should focus on real-time integration and extending the approach to diverse battery chemistries and operating conditions.

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