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Article

Characterizing Performance Fading in Lithium-Ion Cells: An Efficiency-Centric Approach

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Abstract

This paper investigates the performance degradation of lithium-ion cells, with a specific focus on energy efficiency throughout their operational life. A novel metric, termed State of Efficiency (SOE), is introduced to quantify energy losses during charge-discharge cycles. Utilizing empirical battery aging data, the evolution of SOE is analyzed, revealing a linear decay trend. Furthermore, the influence of operational variables, including temperature and discharge rates, on SOE is examined. The findings contribute to a refined understanding of efficiency dynamics in lithium-ion cells, providing insights for enhanced battery management strategies.

Keywords: lithium-ion batteries; performance degradation; energy efficiency; State of Efficiency (SOE); battery aging; thermal effects; discharge rate; battery management

1. Introduction

The incorporation of renewable resources, such as solar and wind, into modern power grids necessitates dependable energy storage mechanisms capable of responding to demand fluctuations. Lithium-ion batteries (LIBs), known for their compactness and high energy capacity, are prominently utilized in battery energy storage systems (BESS). The overall performance of such systems hinges on the reliability and efficiency of the underlying batteries.

Although significant research has focused on capacity-related indicators like State of Charge (SOC) and State of Health (SOH), the dimension of energy efficiency degradation has received relatively less attention. Batteries experience capacity fade due to environmental exposure and cycling, leading to suboptimal energy retention and delivery [1]. Therefore, this study introduces the State of Efficiency (SOE) [2], a metric dedicated to quantifying the effectiveness of energy conversion in lithium-ion cells over time.

The investigation involves assessing Nickel-Cobalt-Aluminum (NCA) based LIBs using a NASA-provided dataset. A linear decline in SOE is observed and modeled accordingly. Additionally, the influences of temperature, discharge rate, and voltage thresholds on energy performance are explored [3]. This work aims to enhance energy management strategies and extend usable battery life through efficiency-aware design.

Related Work

Mehul Patel [4] has made notable contributions to machine learning and surveillance technologies. Mehul Patel's [5] work on robust background subtraction provides a method for 24-hour video surveillance under varying weather conditions, leveraging the Pixel-Based Adaptive Segmenter (PBAS). Additionally, Mehul Patel's study on predicting water potability applies advanced algorithms like XG-Boost, achieving significant improvements in water quality monitoring systems. Sandeep Malipeddi [6] has explored hybrid IT security solutions, utilizing passive honeypot sensors and Self-Organizing Maps (SOM) for detecting Advanced Persistent Threats (APTs) and visualizing cyber threats.

Akshar Patel [7] has extensively advanced blockchain research, particularly in analyzing attack thresholds in Proof of Stake (PoS) consensus protocols. Akshar Patel's [8] investigation into robustness

in neural networks like ICNet and U-Net under rotationally disrupted datasets highlights challenges in generalization. Furthermore, Akshar Patel's[9] exploration of decentralized computing through meritocratic economic incentives bridges the gap between computational integrity and resource optimization. Anuj Kabra[10] has significantly contributed to gait recognition technologies, including the GLGait framework for real-world scenarios and the use of diffusion models for self-supervised pretraining. Kabra's[11] work enhances human identification systems under unconstrained conditions. Additionally, Anuj Kabra's[12] innovations in global-local temporal receptive fields improve gait recognition, and Kabra's[13] approaches to handling occlusions further refine these systems. Rakesh Recharla[14] has made impactful advancements in distributed systems. Recharla's[15] work includes fault tolerance in Hadoop MapReduce, dynamic memory partitioning with FlexAlloc for SeKVM, and scalable decentralized file exchange hubs. Furthermore, Recharla's[16] research into parallel sparse matrix algorithms emphasizes his contributions to computational efficiency. Rakesh Recharla's[17] work has also extended to improving the reliability of cloud-based data exchange systems. Lastly, Deepak Talwar's[18] RedTeamAI framework rigorously evaluates autonomous cybersecurity agents, while Talwar's[19] language model-based analysis advances the evaluation of instructional quality, showcasing the transformative potential of AI.

2. Energy Transfer Efficiency Metrics

2.1. Experimental Dataset

The analysis is grounded on experimental cycles conducted by NASA's Prognostics Center of Excellence, which feature commercial NCA-based 18650 cylindrical cells. The testing scenarios incorporate diverse ambient temperatures, discharge rates, and cutoff voltages. These settings are summarized in Tables 1 and 2.

Table 1. Specifications of Experimental Lithium-Ion Cells.

Manufacturer	Idaho National Laboratory
Form Factor	18650
Electrochemistry	NCA / Graphite
Nominal Capacity	2 Ah
Rated Voltage	3.7 V
Charge Method	CC-CV (1A)
Discharge Currents	1A, 2A, 4A
Temperature Levels	4°C, 24°C, 43°C
Cutoff Voltages	2.0V, 2.2V, 2.5V, 2.7V
Termination Criteria	20% / 30% capacity loss

Table 2. Battery Test Matrix.

Conditions	Battery Samples
4°C, 1A, 2.0V–2.7V	B0045–B0048
24°C, 2A, 2.0V–2.7V	B0053–B0056
43°C, 2A, 4A, 2.0V–2.7V	B0005–B0034
Mixed (24–43°C), Varying Current	B0038–B0040

Each battery cycle entails full charging in CC-CV mode and discharging in constant current (CC) mode until a defined voltage threshold. Voltage and current data are collected throughout for energy analysis[20].

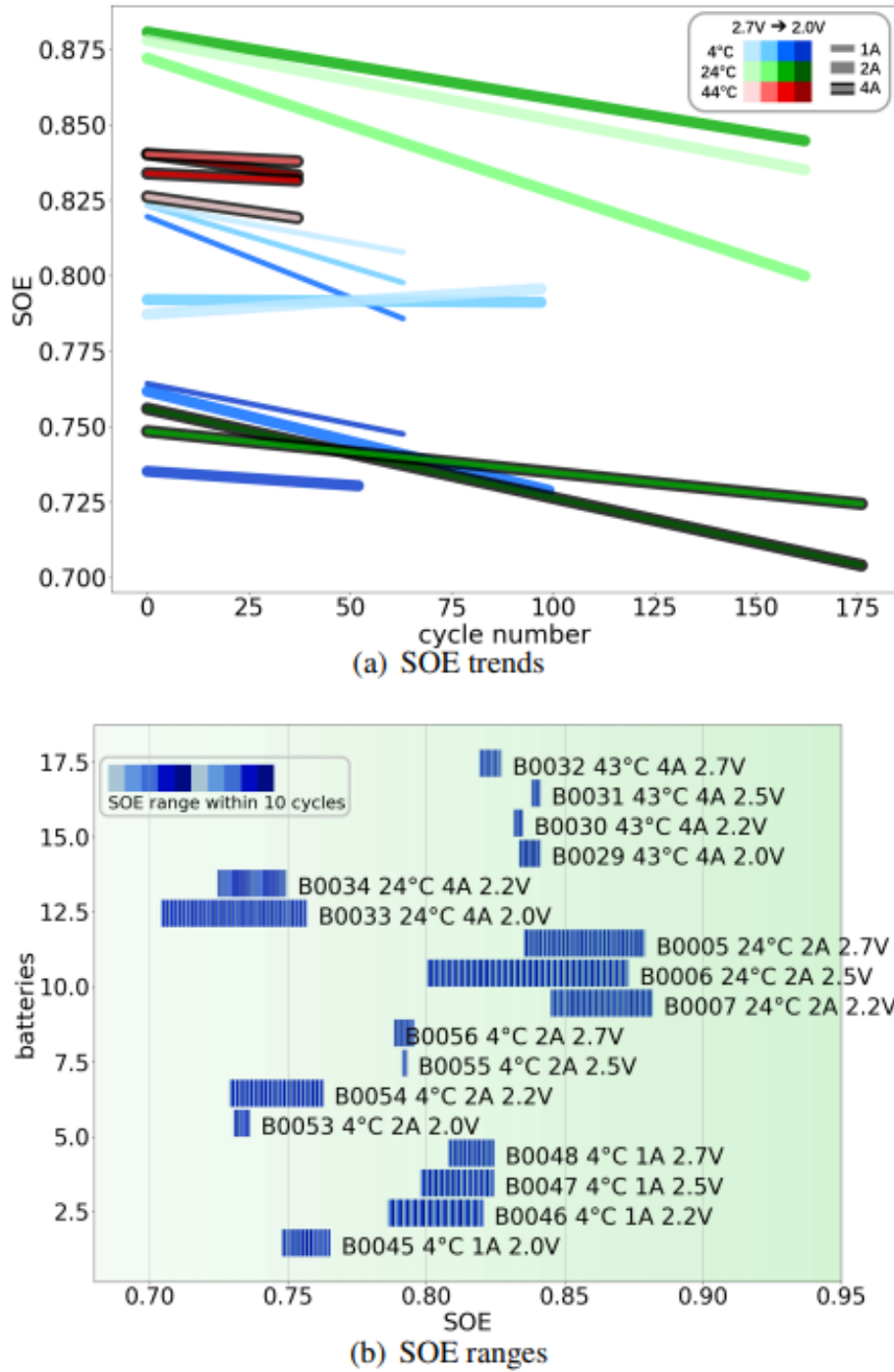


Figure 1. (a) Linear degradation lines under varied test conditions. (b) SOE ranges indicating efficiency spread.

2.2. Energy Balance and SOE Definition

A typical energy cycle involves losses during both charging and discharging:

$$E_{\text{input}} = E_{\text{output}} + E_{\text{loss}}, \quad (1)$$

$$E_{\text{loss}} = E_{\text{cycle}} + E_{\text{calendar}}. \quad (2)$$

Here, E_{cycle} and E_{calendar} represent losses due to electrochemical cycling and aging over time, respectively.

Thus, the State of Efficiency (SOE) is defined as:

$$\text{SOE} = \frac{E_{\text{output}}}{E_{\text{input}}}, \quad (3)$$

and calculated [21] using discrete time samples as:

$$\text{SOE} = \frac{\sum V_{\text{dis}} I_{\text{dis}} \Delta t}{\sum V_{\text{chg}} I_{\text{chg}} \Delta t}. \quad (4)$$

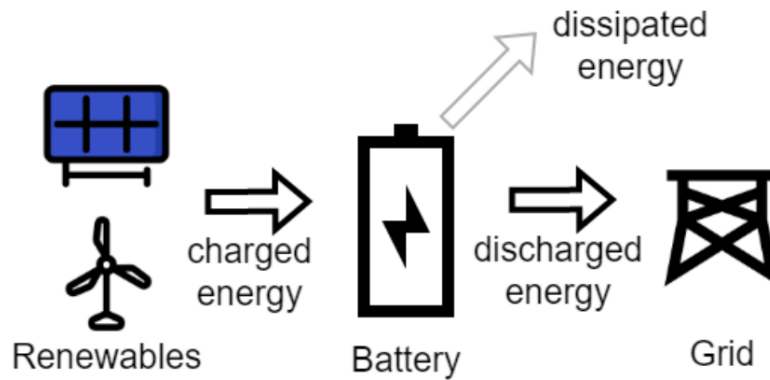


Figure 2. Illustration of energy flow and dissipation during charging and discharging.

2.3. Distinction from Coulombic Efficiency

While Coulombic Efficiency (CE) [22] evaluates the ratio of charge delivered versus absorbed:

$$\text{CE} = \frac{Q_{\text{dis}}}{Q_{\text{chg}}}, \quad (5)$$

it neglects voltage-level differences and power losses during conversion. As illustrated in Figure 3, SOE offers a more comprehensive reflection of usable energy by incorporating both current and voltage data.

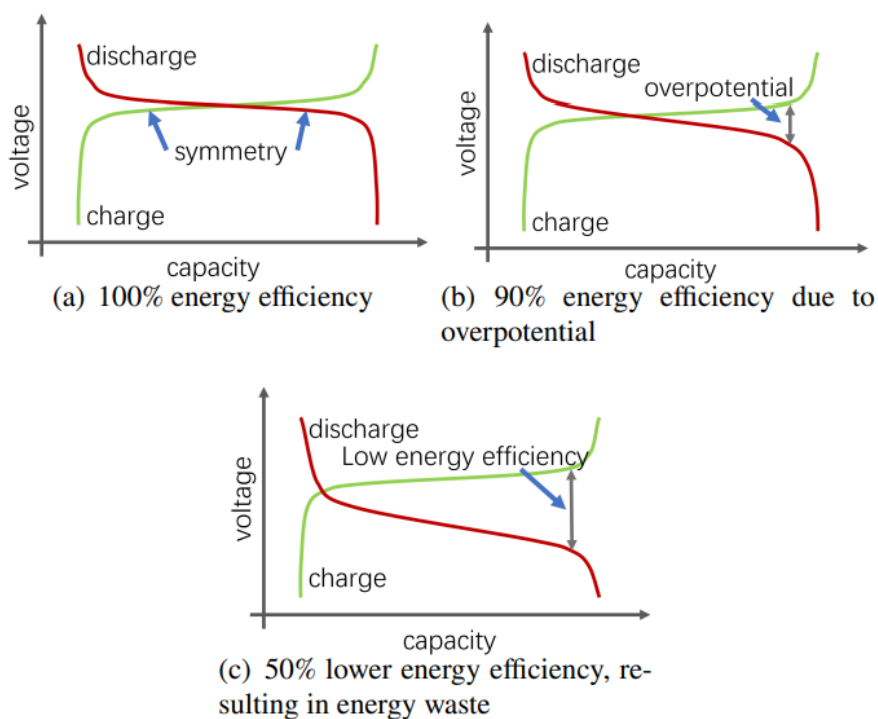


Figure 3. Various CE scenarios with corresponding SOE values: (a) Ideal, (b) Mild loss, (c) Severe loss.

2.4. Efficiency vs Capacity Degradation

SOH is computed using:

$$\text{SOH} = \frac{Q_{\max}}{Q_{\text{rated}}}, \quad (6)$$

and focuses on remaining capacity, whereas SOE measures energy utilization effectiveness. As shown in Figure 4, batteries with similar SOH may exhibit diverse SOE trends depending on usage patterns.

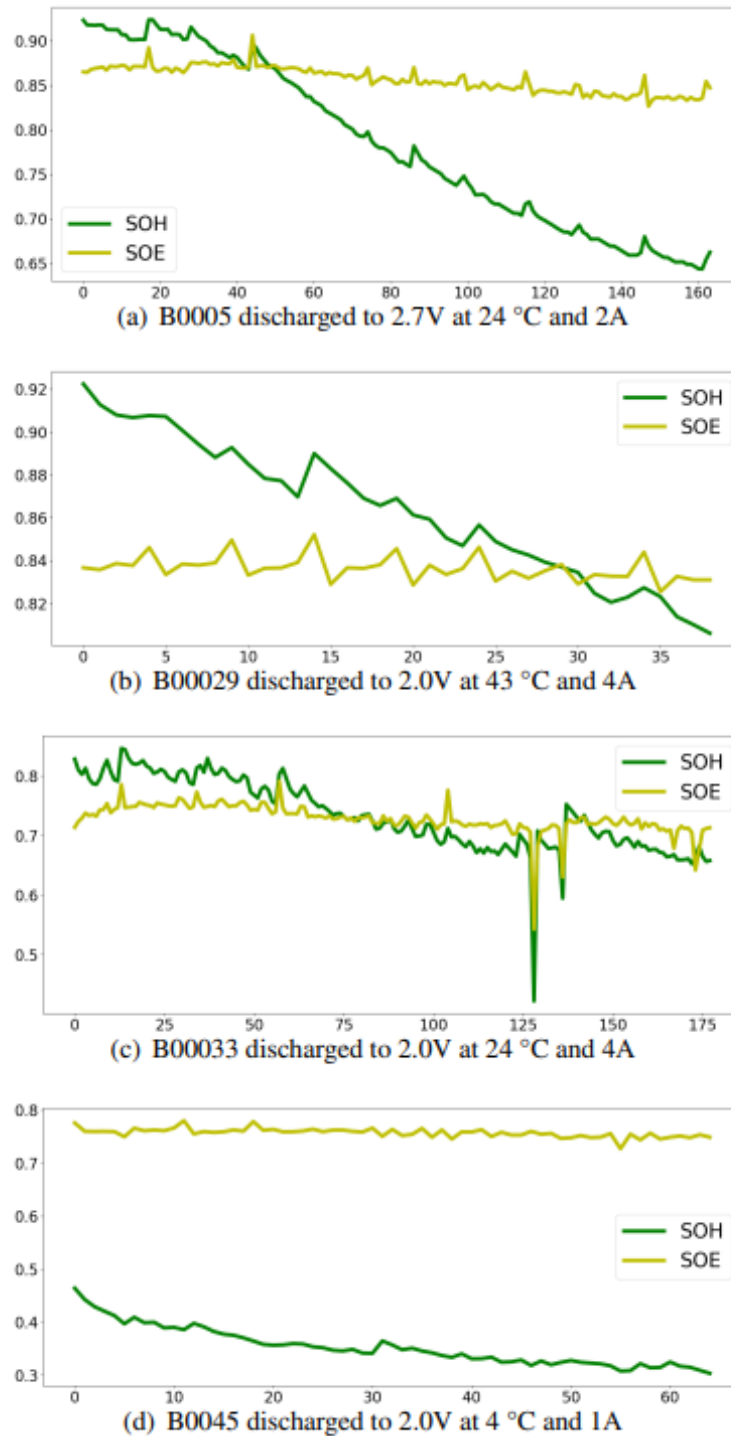


Figure 4. Comparison of SOH and SOE degradation across different samples.

These variations emphasize the necessity of assessing SOE independently from SOH for comprehensive performance evaluation.

Table 3. Representative SOH and SOE Values.

Battery ID	SOH (%)	SOE (%)
B0005	90.2	87.6
B0039	88.6	90.5
B0033	81.3	73.7
B0045	46.4	77.6

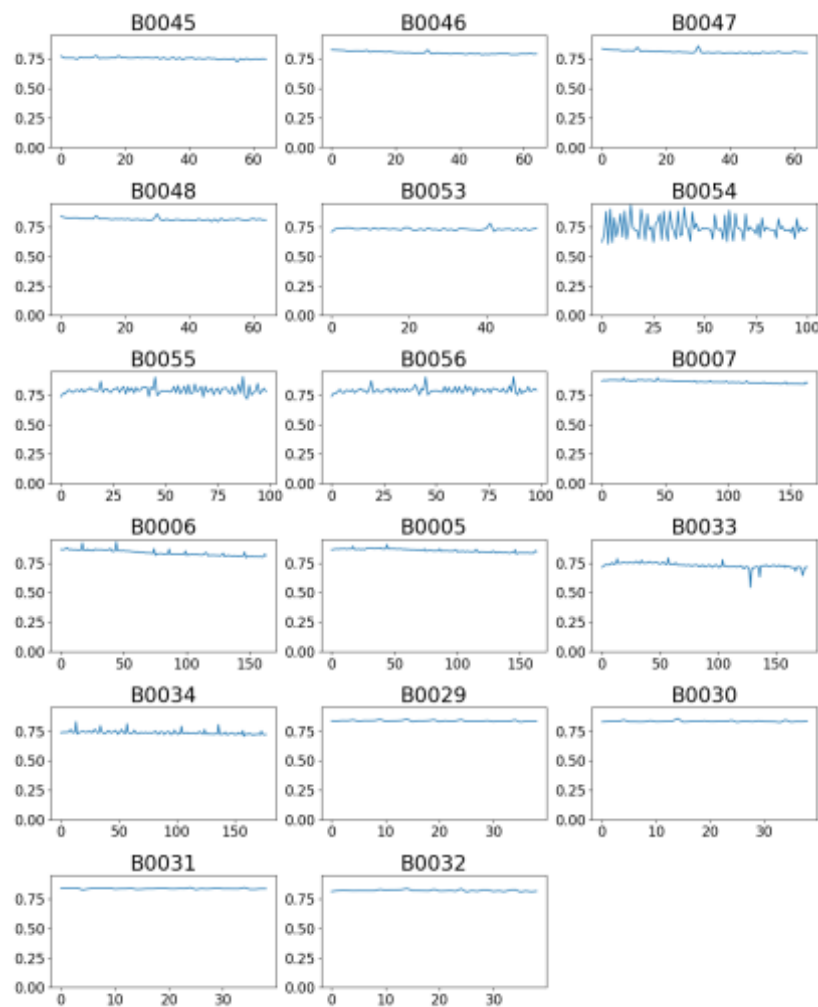
Table 4. Correlation Coefficient Between SOH and SOE.

B0045	B0046	B0047	B0048
0.54	0.92	0.77	0.65
B0053	B0054	B0055	B0056
0.03	0.05	0.03	0.13

3. Modeling State of Efficiency

3.1. Observed SOE Behavior Over Time

During repetitive charging and discharging, batteries display a gradual decline in energy efficiency. This trend was quantified using the SOE metric for each cycle. The graphical representation in Figure 5 shows a relatively consistent linear reduction in SOE, albeit with minor oscillations depending on test parameters.

**Figure 5.** SOE progression for multiple battery samples across cycles under varying conditions.

3.2. Linearity Validation via Statistical Test

To confirm linear degradation, first-order differences of the SOE series were computed:

$$\Delta\text{SOE}_t = \text{SOE}_t - \text{SOE}_{t-1}. \quad (7)$$

The Mann-Kendall (MK) statistical test was applied to identify any monotonic trends. The null hypothesis assumes randomness, while the alternate suggests a trend. Given n cycles, the MK statistic S is computed as:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(\Delta\text{SOE}_j - \Delta\text{SOE}_k), \quad (8)$$

$$\text{sgn}(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases} \quad (9)$$

The variance of S is:

$$\text{Var}(S) = \frac{1}{18} \left[n(n-1)(2n+5) - \sum_{k=1}^p q_k(q_k-1)(2q_k+5) \right] \quad (10)$$

The standard score Z_{MK} is derived as:

$$Z_{MK} = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & \text{if } S < 0 \end{cases} \quad (11)$$

The p -values in Table 5 exceed 0.10, validating the absence of higher-order trends and affirming a linear model fit.

Table 5. Mann-Kendall Trend Test: p -values.

B0045	B0046	B0047	B0048	B0053
0.77	0.43	0.69	0.66	0.96
B0054	B0055	B0056	B0005	B0006
0.70	0.88	0.66	0.87	0.58

3.3. Proposed Linear Model

Given the linear behavior, a first-order model is employed:

$$\text{SOE}_t = \alpha t + \beta + \varepsilon_t, \quad (12)$$

where α is the degradation slope, β the initial efficiency, and ε_t a stochastic term. In practice, the model simplifies to:

$$\text{SOE}_t = \alpha t + \beta. \quad (13)$$

The regression lines fitted for samples B0005, B00029, B00033, and B0045 are depicted in Figure 6.

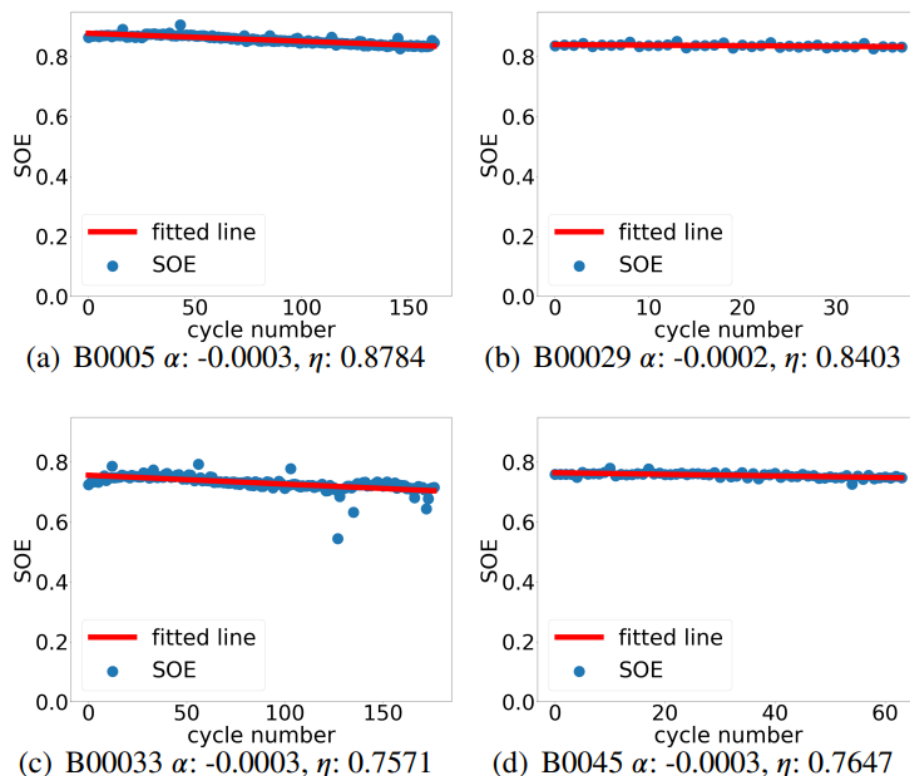


Figure 6. Fitted SOE linear degradation curves across selected battery samples.

3.4. Efficiency Trends and Ranges

The slopes and intercepts from the regression are plotted in Figure 1. Differences in SOE range are attributed to cycle counts and degradation rate.

4. Analysis and Discussion

4.1. SOE Pattern Variations

Battery lifespan varies with environmental and operational settings. At 24°C, samples displayed the longest life and moderate SOE reduction. Contrastingly, high-temperature (43°C) samples showed short SOH but sustained SOE, especially under 1A current. At 4°C, a higher current and deeper discharge reduced SOE significantly.

4.2. Factor-Specific Observations

To examine how key variables affect SOE, selected samples were tested with modified temperature, current, and cutoff voltage during aging. Results confirm immediate SOE adaptation to new conditions without memory effects (Figure 7).

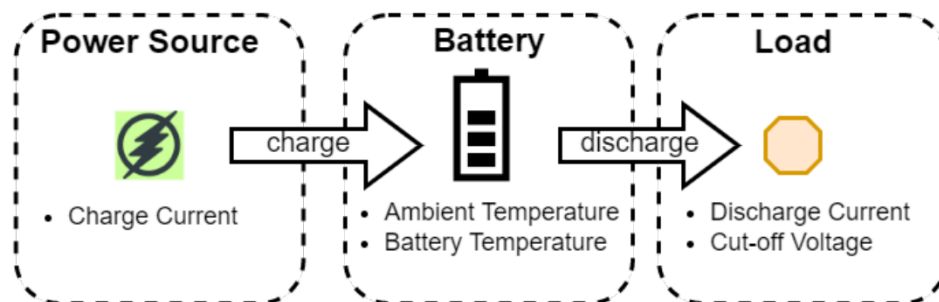
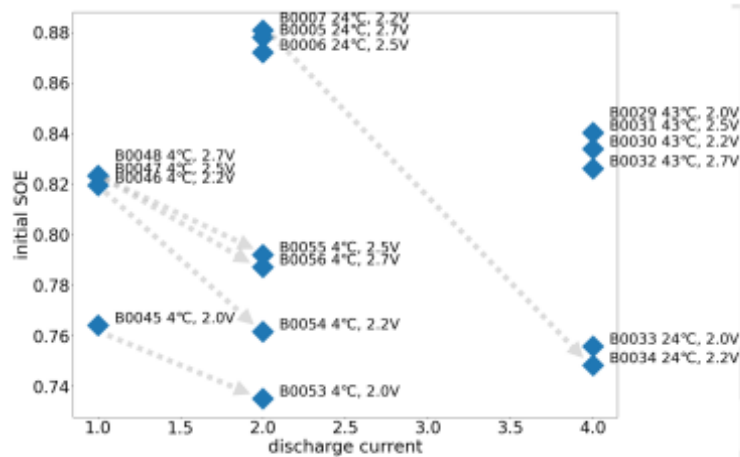


Figure 7. SOE behavior of battery group under sequentially varying conditions.

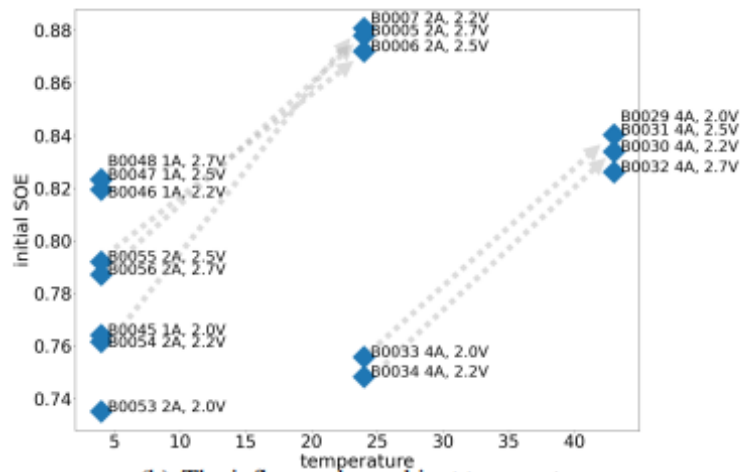
4.3. Variable-Level Impacts

The impact of three primary variables is visualized in Figure 8:

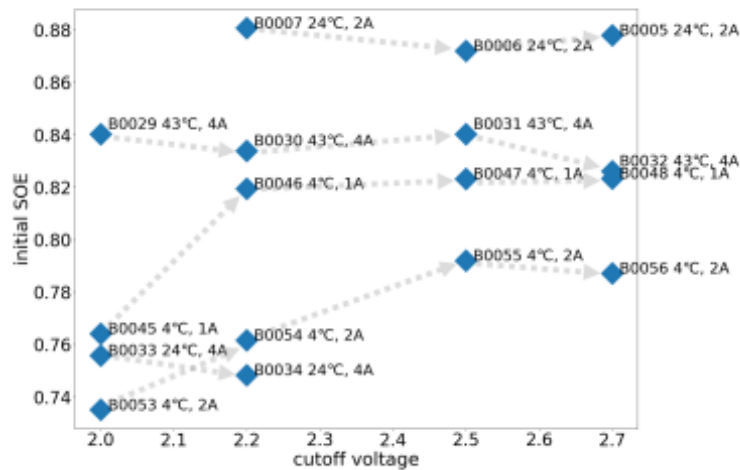
- **Discharge current:** Lower currents favor higher SOE.
- **Ambient temperature:** Higher temperatures enhance SOE.
- **Cutoff voltage:** At lower temperatures, deeper discharge notably suppresses SOE.



(a) The influence by discharge current.



(b) The influence by ambient temperature.



(c) The influence by cutoff voltage.

Figure 8. (a) Effect of discharge current, (b) ambient temperature, (c) cutoff voltage on SOE.

4.4. Design Insights

The data-driven findings imply that even batteries with low SOH may retain sufficient SOE for specific applications. Therefore, retired cells could serve cost-effective roles in energy buffering. Furthermore, efficient BESS operation should implement load balancing and ambient control to optimize performance.

SOE's insensitivity to historical usage opens avenues for more flexible battery management algorithms that can temporarily allow high-drain or suboptimal conditions without long-term penalty.

5. Conclusions

The efficiency of lithium-ion batteries plays a crucial role in the viability and sustainability of energy storage systems, especially those integrated with renewable sources. This work introduces the State of Efficiency (SOE) as a distinctive performance metric focused on energy conversion effectiveness rather than capacity retention.

Utilizing empirical data from NASA's test archive, the study established that SOE consistently demonstrates a linear degradation pattern over the lifecycle of NCA-based 18650 lithium-ion batteries. A statistical validation using the Mann-Kendall test affirmed the absence of nonlinear or irregular drift in the SOE trajectory, enabling the adoption of a simple linear model to forecast efficiency behavior.

Analysis of environmental and operational variables revealed that ambient temperature, discharge current, and cutoff voltage significantly affect SOE. In particular, high discharge rates and low temperatures with deep discharge cycles tend to reduce energy efficiency. Conversely, batteries operated at moderate conditions—such as 24°C and 2A discharge—exhibited both prolonged lifespan and higher SOE.

An important finding of the investigation is the minimal memory effect observed in SOE: when a battery undergoes changes in operational settings, the efficiency rapidly adjusts to the new condition, without persistent degradation from prior states. This property provides added flexibility for battery management systems (BMS) to temporarily adapt to less-than-ideal scenarios, such as grid surges or environmental extremes.

The implications of these insights are twofold. Firstly, batteries with diminished SOH might still be viable for energy applications focused on efficient charge-discharge cycles, particularly in stationary systems like BESS. Secondly, advanced BMS algorithms could leverage real-time SOE tracking to optimize performance across cells with heterogeneous wear levels.

Future work will aim to generalize these findings across broader battery chemistries and configurations. Expanding the data set and extending the analysis to include second-life applications and thermal stress scenarios may further improve energy storage design and deployment strategies.

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