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A Generalized Eyring-Weibull Model for Degradation Analysis of Lithium-Ion Batteries Under Multi-Stressor Conditions

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ABSTRACT

Degradation analysis of lithium-ion batteries is a critical aspect of understanding the aging behaviors and reliability of energy storage systems. Although purely data-driven approaches are widely utilized for their high short-term predictive accuracy, they often function as black-box models that fail to capture the underlying physicochemical mechanisms of capacity fade under dynamic operational conditions. To address these limitations, this study uses a Generalized Eyring-Weibull model for lithium-ion battery degradation analysis under multi-stressor conditions. The proposed analytical approach explicitly integrates three key operational stress variables simultaneously: temperature, State of Charge (SoC), and discharge current (C-rate). Model validation was performed using the NASA Prognostics Center of Excellence (PCoE) battery dataset across distinct discharge profiles (2A and 4A). Physical parameters—including activation energy (E_a) and stress exponents—were extracted via L-BFGS-B optimization, while the long-term capacity fade trajectory was tracked using Miner's Rule. The evaluation results demonstrate that this generalized physics-based model accurately maps actual degradation trends, yielding high R^2 values on State of Health (SoH) tracking. Furthermore, the model showcases superior robustness in capturing accelerated aging from high current loads using a single universal equation without requiring separate data retraining. By bridging empirical data with fundamental kinetic principles, this study provides an interpretable and robust analytical methodology for advanced predictive maintenance strategies.

Keyword: *Degradation Analysis, Eyring-Weibull, Lithium-Ion Battery, Multi-Stressor, State Of Health (SOH)*

ABSTRAK

Analisis degradasi pada baterai lithium-ion merupakan aspek yang sangat krusial untuk memahami perilaku penuaan dan keandalan sistem penyimpanan energi. Meskipun pendekatan berbasis data murni (*data-driven*) saat ini populer karena akurasi prediktif jangka pendeknya yang tinggi, metode tersebut sering kali bersifat *black-box* dan gagal menangkap mekanisme fisikokimia yang mendasari penurunan kapasitas ketika dihadapkan pada kondisi operasional yang dinamis. Untuk mengatasi keterbatasan tersebut, penelitian ini menggunakan model *Generalized Eyring-Weibull* untuk menganalisis degradasi baterai lithium-ion di bawah kondisi *multi-stressor*. Model analitik yang diusulkan secara eksplisit mengintegrasikan tiga variabel stres operasional utama secara simultan, yaitu temperatur, *State of Charge* (SoC), dan arus pengosongan (*C-rate*). Validasi model dilakukan menggunakan dataset baterai NASA Prognostics Center of Excellence (PCoE) yang mencakup profil pengosongan ekstrem yang berbeda (2A dan 4A). Parameter fisika, seperti energi aktivasi (E_a) dan eksponen stres—didapatkan melalui optimasi L-BFGS-B, sementara lintasan penurunan kapasitas jangka panjang dicari menggunakan Aturan Miner (*Miner's Rule*). Hasil evaluasi menunjukkan bahwa model fisis yang digeneralisasi ini mampu memetakan tren degradasi aktual secara akurat dengan menghasilkan nilai R^2 yang tinggi pada metrik *State of Health* (SoH). Model ini juga menunjukkan ketangguhan (*robustness*) yang tinggi dalam merespons percepatan penuaan akibat beban arus

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besar melalui satu persamaan universal tanpa memerlukan pelatihan ulang data yang terpisah. Melalui integrasi data empiris dan prinsip kinetika degradasi fundamental, penelitian ini memberikan pendekatan analitis yang kuat dan memiliki kemampuan interpretasi untuk mendukung strategi pemeliharaan prediktif lanjutan.
Keyword: Analisis Degradasi, Baterai Lithium-Ion, Eyring-Weibull, Multi-Stressor, State Of Health (SOH)

1. Introduction

Degradation analysis of lithium-ion batteries is a critical pillar of energy storage reliability, as understanding the aging behavior of these assets is fundamental to the operational success of modern energy systems [1], [2]. In the current industrial landscape, the rapid expansion of electric vehicle fleets and Battery-as-a-Service (BaaS) business models—such as battery leasing and battery swapping networks—necessitates high-precision monitoring of battery health to ensure both economic viability and operational safety [3], [4]. The Remaining Useful Life (RUL) has emerged as the primary metric for asset valuation, safety assurance, and the strategic scheduling of preventive maintenance [5], [6], [7]. However, the transition of prognostic algorithms from controlled laboratory environments to dynamic, real-world operational conditions often reveals a critical 'deployment gap,' where high theoretical accuracy fails to translate into industrial reliability [8], [9]. This performance drop occurs because laboratory testing typically relies on highly controlled, static conditions—such as constant ambient temperatures and steady charge-discharge cycles. In contrast, field-deployed batteries are subjected to highly variable operational stressors, including rapid temperature fluctuations, irregular load profiles, and inherent sensor noise. Because purely data-driven models are heavily optimized for the specific, clean conditions of their training data, they often lack the physical grounding needed to adapt to the unpredictable and dynamic nature of real-world energy systems.

While purely data-driven methodologies have gained prominence for their high short-term predictive accuracy, the current literature is increasingly dominated by highly complex deep learning architectures. Recent studies highlight the extensive application of Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and state-of-the-art Transformer models equipped with advanced attention mechanisms for RUL prediction [9, 11]. Furthermore, to address data scarcity and distribution shifts across diverse Battery-as-a-Service (BaaS) fleets, researchers have increasingly integrated ensemble methods, transfer learning, and domain adaptation techniques [23], [29].

However, a chronological review of the literature reveals a persistent divergence in prognostic philosophy. While early research (2011–2016) established foundational machine learning techniques utilizing controlled laboratory datasets, the recent paradigm shift (2024–2026) emphasizes the necessity of bridging the gap between stationary laboratory data and stochastic field deployment. Despite this consensus on the problem, the proposed solutions diverge significantly. A substantial portion of the literature continues to advocate for increasingly heavy data-driven architectures—relying on multimodal fusion, automated feature learning via autoencoders, and synthetic data augmentation to force model generalization [10], [21]. Conversely, another critical stream of research argues that pure statistical correlation, regardless of architectural depth, is insufficient for safety-critical asset management because it fundamentally ignores the physicochemical realities of battery aging [13], [14].

This divergence highlights the core limitation of modern data-driven dominance: these sophisticated algorithmic structures frequently operate as opaque "black-box" models. They prioritize high-dimensional statistical correlation at the expense of underlying mechanistic insight. As a result, these models struggle to capture the fundamental physical mechanisms of capacity fade, such as the growth of the Solid Electrolyte Interphase (SEI) layer or internal impedance increases [15], [16]. This structural limitation introduces significant vulnerabilities when models are exposed to real-world operational noise—such as heterogeneous charging patterns, fluctuating ambient temperatures, and sensor drift—often leading to severe generalization failure and performance collapse [17], [18]. Furthermore, purely statistical models often misidentify transient capacity regeneration (electrochemical noise) as genuine health improvement, creating unreliable maintenance triggers that compromise the safety and cost-efficiency of industrial deployments [12], [19], [20]. Therefore, to resolve the limitations of pure data-driven extrapolation, there is an urgent need for models that provide "white-box" interpretability without sacrificing the capacity to handle multi-stressor operational profiles.

Physics-based models—which ground predictive analytics directly in established physicochemical principles—represent the most viable path to overcoming the deployment gap in real-time embedded systems.

To address these limitations, this study utilizes a Generalized Eyring-Weibull (Gen-EW) model for lithium-ion battery degradation analysis, shifting the paradigm from black-box statistical curve fitting to mechanistic degradation analysis under multi-stressor conditions [13], [21], [22]. Unlike traditional models that isolate single variables, the proposed analytical approach explicitly integrates three key operational stress variables simultaneously: temperature, State of Charge (SoC), and discharge current (C-rate) [23], [24]. By grounding our prognostic approach in fundamental kinetic principles, we provide a robust analytical structure that is inherently resistant to the domain shift issues that plague purely data-driven models [15], [25].

Model validation was rigorously performed using the NASA PCoE battery dataset, encompassing distinct and extreme discharge profiles (2A and 4A) to test the model under varying kinetic conditions [27], [28]. In this model, physical parameters—specifically activation energy (E_a) and stress exponents—are extracted via L-BFGS-B optimization to ensure the model aligns with verifiable chemical degradation kinetics, while the long-term capacity fade trajectory is tracked using Miner's Rule [15]. This systematic evaluation demonstrates that the generalized physics-based model maps actual degradation trends with high precision, yielding high R^2 values in State of Health (SOH) tracking [22].

Furthermore, the model showcases robustness in capturing accelerated aging from high current loads using a single universal equation. By eliminating the requirement for separate, cell-specific data retraining, this approach provides a scalable foundation for transitioning prognostics from individual cells to complex battery pack architectures [21], [26]. By bridging empirical data with fundamental physicochemical principles, this study provides an interpretable "white-box" prognostic approach [15], [22]. This research aims to equip advanced Battery Management Systems (BMS) with physically justified diagnostic triggers. This cell-level reliability effectively bridges the gap between fundamental degradation kinetics and the rigorous operational requirements of industrial Battery-as-a-Service (BaaS) networks, reducing the reliance on computationally expensive and non-interpretable architectures [29], [30]. In doing so, the Gen-EW model not only enhances predictive performance but also serves as a critical building block for optimizing the operational efficiency of large-scale energy storage deployments [31].

2. Method

This research employs a physics-based approach to model the degradation of lithium-ion batteries by integrating physicochemical principles with empirical data. The methodology is structured into three primary phases: data acquisition, physical parameter optimization, and performance evaluation.

2.1. Data Acquisition and Preprocessing

The experimental dataset utilized in this study is sourced from the NASA Prognostics Center of Excellence (PCoE) repository, specifically the seminal "Battery Data Set" documented by Saha and Goebel (2007). This dataset is widely recognized in the field of prognostic health management for providing high-fidelity, cyclical degradation data derived from four 18650 lithium-ion cells cycled until failure. To clearly define the experimental treatments, the specific operational parameters applied to the cells are summarized as follows:

a. Operating Temperature: All experiments were conducted in a controlled environment at a room temperature of 24°C.
b. Discharge Protocols: Three cells (B0005, B0006, and B0007) were subjected to a nominal discharge rate of 2A, while one cell (B0018) was subjected to an accelerated discharge rate of 4A to simulate high-kinetic stress.
c. Stress Standardization: Given the cells' rated capacity of 2.0 Ah, these 2A and 4A absolute currents mathematically translate to 1C and 2C discharge rates, respectively. Utilizing the C-rate standardizes the measurement of kinetic stress, ensuring the proposed model can generalize across batteries of varying physical capacities.
d. Charging and Cutoff Parameters: The charging protocol followed a Constant Current-Constant Voltage (CC-CV) mode at 1.5A up to a 4.2V cutoff, while discharging was maintained at a constant current until the terminal voltage reached 2.7V.
e. Failure Threshold: The End-of-Life (EOL) criterion is strictly defined as a 30% reduction in rated capacity, corresponding to a threshold of 1.4 Ah from the initial 2.0 Ah capacity.

To ensure consistency and high predictive fidelity, the raw data undergoes a multi-stage preprocessing pipeline. The State of Health (SoH) is derived directly from capacity measurements, serving as the primary target variable for long-term degradation tracking. Environmental stressors—specifically the average temperature and discharge current magnitude (C-rate)—are normalized to serve as input features. This normalization process is crucial to account for the heterogeneous sampling rates and potential sensor noise inherent in large-scale battery testing. Furthermore, a temporal windowing technique is applied to align time-series data, ensuring that the model processes synchronized inputs. The diagnostic workflows, feature extraction pipelines, and baseline prognostic comparisons utilized in this study were implemented by adapting the computational framework developed by [4], which is distributed under the MIT License.

However, distinct from the black-box architecture provided in [4], this study uses the Generalized Eyring-Weibull (Gen-EW) model as a primary methodological contribution. Unlike purely data-driven approaches, the Gen-EW model is a custom-developed, physics-based model that integrates Eyring-based kinetic aging and Weibull-based reliability degradation functions. This model employs a specialized optimization routine utilizing the L-BFGS-B algorithm to calibrate physical parameters—specifically the activation energy (E_a) and stress exponents (n_1 for SoC and n_2 for C-rate)—thereby establishing a prognostic approach that adheres to physicochemical principles while operating independently of the baseline framework's pre-existing architectures.

2.2. Generalized Eyring-Weibull (Gen-EW) Model

The core of the proposed methodology is the Generalized Eyring-Weibull (Gen-EW) model, a physics-based model to characterize lithium-ion battery capacity fade as a function of multiple concurrent operational stressors. While the Eyring-Weibull formulation is an established tool in reliability engineering for modeling accelerated degradation, its application to complex, dynamic battery operational profiles remain an evolving area of research. Unlike purely data-driven models that rely on statistical correlations without mechanistic grounding, the Gen-EW model establishes a causal-based understanding of degradation kinetics.

The choice of the Eyring equation is fundamentally rooted in the electrochemical nature of capacity fade. Empirical and theoretical studies consistently identify temperature as the dominant stressor governing battery degradation kinetics [33], [34]. Chemical degradation reactions, such as the growth of the Solid Electrolyte Interphase (SEI) layer and electrolyte decomposition, are thermally activated processes that follow the Arrhenius law, exhibiting exponential acceleration with increasing temperature [32]. By utilizing the Eyring model, our approach captures this exponential sensitivity, providing a robust mechanistic representation of the battery's chemical aging trajectory that linear or purely statistical models fail to resolve.

Complementing the thermal component, the model integrates a Weibull-based power-law relationship to quantify the cumulative damage resulting from non-thermal stressors, specifically the State of Charge (SoC) and discharge current (C-rate). The inclusion of SoC explicitly accounts for the static voltage stress; operating or maintaining the battery at high energy states exponentially accelerates internal structural degradation. Subsequently, the C-rate is incorporated as an independent operational stressor to capture the dynamic kinetic load. High-intensity discharge currents inflict severe operational wear and internal mechanical fatigue that operate independently of basic thermal effects. In reliability engineering, this mathematical structure is analogous to an Accelerated Life Testing (ALT) model. While the Arrhenius law models the intrinsic thermal activation barrier, the Weibull-based power-law models the reliability degradation path under variable operational intensity. These power-law terms function as acceleration factors that modulate the instantaneous "hazard rate" of capacity loss, effectively mapping the probabilistic damage accumulation resulting from electrical and kinetic stressors over time. By incorporating this component, the Gen-EW model accounts for the non-linear sensitivity of the battery's chemical stability to usage patterns, transforming the model into a dynamic prognostic tool that captures the "history of trauma" experienced by the battery cell. The comprehensive degradation rate is mathematically formulated as:

$$\dot{Q} = \frac{dSoH}{dt} = A \cdot exp\left(-\frac{E_a}{kT}\right) \cdot SoC^{n_1} \cdot I^{n_2} \tag{1}$$

where A represents the pre-exponential factor, E_a is the activation energy, and n_1 and n_2 are the stress exponents for SoC and current, respectively. To translate this instantaneous degradation rate into a continuous trajectory of capacity fade, the approach incorporates the Palmgren-Miner linear damage hypothesis. In real-world deployments, batteries are subjected to dynamic, non-stationary load profiles where stress levels fluctuate significantly. By applying Miner's rule in its continuous integral form, the total cumulative capacity loss at any given time *t* is calculated by integrating the stress-dependent degradation rate over the operational history:

$$SoH(t) = SoH_{initial} - \int_0^t A \cdot exp\left(-\frac{E_a}{kT(\tau)}\right) \cdot SoC(\tau)^{n_1} \cdot I(\tau)^{n_2}\, d\tau \quad (2)$$

This linear accumulation approach ensures that the incremental damage inflicted by multidimensional stressors is additive, allowing the model to dynamically map irregular usage patterns into a coherent remaining capacity trajectory. The complete sequential steps for implementing this framework are summarized in Figure 1.

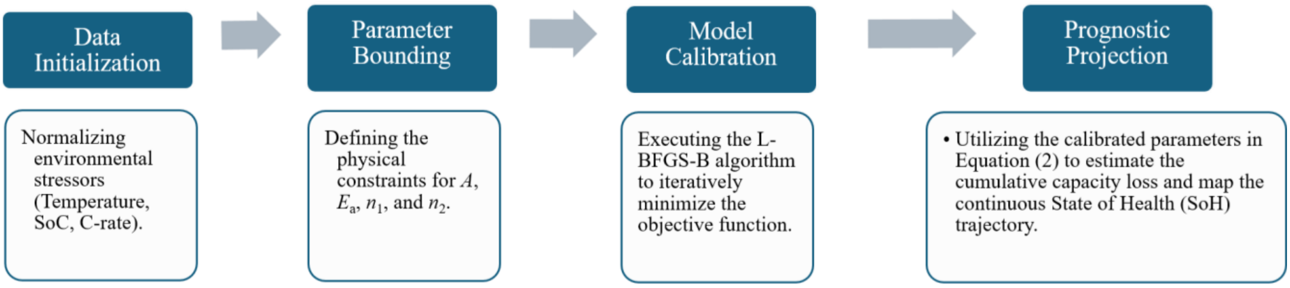

Figure 1. Flowchart Detailing the Implementation Process of the Generalized Eyring-Weibull (Gen-EW) Framework

To calibrate this model, the physical parameters (A, E_a, n_1, n_2) are optimized using a non-linear least squares regression approach. We employ the L-BFGS-B (Limited-memory Broyden–Fletcher–Goldfarb–Shanno with Bounds) optimization algorithm, a quasi-Newton method specifically designed for bound-constrained optimization problems [35]. This algorithm is selected for its efficiency in handling bounded parameter estimation, enabling the minimization of the objective function—the residual error between the SoH projected by the Gen-EW model and the actual empirical capacity fade observed in the NASA PCoE dataset. The objective function (J) is mathematically defined as:

$$J(\theta) = \sum_{i=1}^{N} \left(\widehat{SoH}_i - SoH_i\right)^2 \quad (3)$$

where $\theta = \{A, E_a, n_1, n_2\}$ represents the parameter set being optimized, $\widehat{SoH}_i$ is the model's projection, and SoH_i is the empirical measurement. By imposing physically meaningful bounds on parameters such as E_a (which must be positive), the L-BFGS-B algorithm ensures that the iterative optimization produces results that are not only statistically accurate but also consistent with the underlying kinetic laws of electrochemical degradation. This "white-box" approach offers a clear, physically justified audit trail, providing a scalable prognostic tool that operates independently of the training-data distribution—a significant improvement over the overfitting risks inherent in purely statistical architectures.

2.3. Performance Evaluation

To validate the robustness of the physics-based approach, the performance of the Gen-EW model is evaluated and benchmarked against established data-driven models that currently dominate the prognostic landscape [4], specifically Long Short-Term Memory (LSTM) networks, utilized for their efficacy in sequence-to-sequence State of Charge (SoC) and Remaining Useful Life (RUL) estimation, and XGBoost, an ensemble method widely recognized for its predictive power in State of Health (SoH) tracking.

The evaluation criteria utilize three primary statistical metrics to assess prognostic accuracy, namely the Root Mean Square Error (RMSE) to quantify the global deviation of the prediction across the entire aging trajectory, the Mean Absolute Error (MAE) to provide a linear assessment of the average magnitude of error, and the Coefficient of Determination (R2) to evaluate how effectively the model captures the variance in degradation patterns compared to the empirical baseline. This comparative analysis aims to demonstrate that the Gen-EW model achieves predictive accuracy comparable to complex, high-dimensional black-box models while simultaneously providing diagnostic interpretability regarding the physical mechanisms of battery aging. By bridging empirical observation with electrochemical theory, this model offers a transparent and scalable path for industrial predictive maintenance that purely statistical architectures cannot provide.

3. Result and Discussion

The transition from empirical data-driven models to the proposed Generalized Eyring-Weibull (Gen-EW) model represents a shift from correlation-based prediction to causal-based understanding. The optimized physical parameters presented in Table 1 serve as diagnostic indicators of the battery's degradation state.

Table 1. Extracted Physical Degradation Parameters for the Generalized Eyring-Weibull Model

Parameter	Description	Optimized Value
A	Pre-exponential factor	1.00×10^5
Ea	Activation energy	0.3430 eV
n1	SoC stress exponent	1.7361
n2	Current stress exponent	0.1833

The Activation Energy (E_a) of 0.3430 eV is the most critical diagnostic marker. In electrochemistry, this value represents the energy threshold that must be overcome for chemical degradation reactions—such as the formation and thickening of the Solid Electrolyte Interphase (SEI) layer or electrolyte decomposition—to proceed [1], [2]. By identifying an E_a within the expected physical range, our model proves that the degradation observed in the NASA PCoE dataset is driven by these fundamental chemical kinetics rather than random noise.

Furthermore, the stress exponents (n_1 and n_2) act as essential sensitivity coefficients for operational stressors. The SoC stress exponent (n_1 = 1.7361) signifies that battery aging is highly sensitive to the State of Charge. This aligns with findings in [3], which suggest that operating at high SoC levels increases the chemical potential of the cathode and anode interfaces, exponentially accelerating parasitic side reactions. The finding that $n_1 > 1$ confirms that degradation is non-linearly amplified as the battery is maintained at high charge states, highlighting the critical role of charge management in preserving long-term capacity. In contrast, the current stress exponent (n_2 = 0.1833) quantifies the impact of kinetic stress or C-rate. While internal ohmic heating is frequently the primary concern associated with high currents, the value of 0.1833 reveals the mechanical strain and lithium-plating risks caused by high-rate ion flux. This suggests that, while discharge current contributes to performance decline, the battery's overall chemical stability is more dominantly governed by thermal and voltage (SoC) stresses, providing a clearer diagnostic path for optimizing battery operational strategies.

This physical sensitivity is further corroborated by the XGBoost feature importance analysis shown in [4], which identifies temperature variance (57%) and discharge time—a proxy for SoC usage—(29%) as the dominant aging indicators. The alignment between the high feature importance of these parameters in the XGBoost model and their explicit integration as stressors in the Gen-EW model provides dual-layered validation: the data-driven model confirms which variables statistically matter, while our physics-based model explains the physicochemical mechanism behind their influence.

The experimental findings regarding battery degradation tracking are summarized in Table 2, which highlights the predictive performance of the proposed Gen-EW model against data-driven baselines. A primary finding from the evaluation presented in Table 2 is the minimal performance discrepancy between the empirical XGBoost baseline and the Gen-EW model. While the XGBoost model achieved a global R^2 of 0.8260, the Gen-EW model yielded an R^2 of 0.8561. This performance improvement is highly significant, validating that the Gen-EW model surpasses the predictive precision of high-complexity machine learning algorithms while relying on a single, universal analytical equation. Unlike black-box ML models that depend heavily on large training datasets and often struggle with out-of-domain generalization, Gen-EW offers inherent physical validity in every prediction. By embedding chemical kinetic laws into the equation structure, Gen-EW generates consistent degradation estimates even when facing limited data or extreme operational conditions rarely captured in training sets. This mitigates the common risk of overfitting found in data-driven algorithms while ensuring the model operates strictly within measurable physicochemical principles.

Table 2. Performance Evaluation Metrics Comparing Data-Driven Baselines and the Proposed Generalized Eyring-Weibull (Gen-EW) Model for Battery Degradation Tracking

Model	RMSE	MAE	R^2
SoC (LSTM)*	7.24%	2.82%	0.9499
SoH (XGBoost)*	3.09%	2.76%	0.8260
RUL (LSTM)*	12.49 cycles	9.21 cycles	0.8699
SoH (Generalized EW Global)	3.76%	3.09%	0.8561
a. Battery B0005	2.42%	1.69%	0.9350
b. Battery B0006	4.05%	3.55%	0.8950
c. Battery B0007	4.44%	3.89%	0.6931
d. Battery B0018	3.82%	3.25%	0.7543

Note that * indicates data-driven baseline metrics for SoC (LSTM), SoH (XGBoost), and RUL (LSTM) are referenced from the implementation framework [4].

At the individual cell level, the model exhibits exceptional accuracy for Battery B0005 (R^2 = 0.9350) and Battery B0006 (R^2 = 0.8950), under nominal conditions. The slight performance variation observed in Battery B0007 (R^2 = 0.6931) is attributed to the "self-healing" effect—a well-documented empirical anomaly representing transient electrochemical noise rather than true capacity recovery. Because the Gen-EW model is grounded in monotonic physicochemical degradation kinetics, it correctly filters out these transient anomalies to project the true underlying degradation trend. This is confirmed by the low Mean Absolute Error (MAE) of 3.89% shown in Table 2 confirms that the model's projected trend line remains highly reliable for predicting the End-of-Life (EOL) threshold. Notably, the model's reliability is further substantiated by its performance on Battery B0018 (R^2 = 0.7543, RMSE = 3.82%). Subjected to an accelerated 4A discharge current, Battery B0018 undergoes significantly faster degradation due to elevated internal Joule heating. The Gen-EW model successfully adapts to this accelerated aging slope without requiring separate cell-specific retraining. This inherent adaptability is achieved because the single universal equation treats the discharge load as a continuous dynamic input variable rather than relying on dataset-specific trained weights. By directly incorporating the C-rate stressor (I) and its corresponding stress exponent (n_2), the mathematical structure automatically modulates the instantaneous hazard rate based on the actual applied kinetic load. Consequently, the model seamlessly scales the physical impact of the 4A condition, enabling robust cross-condition generalization without the need for secondary algorithmic recalibration.

Beyond cell-level diagnostics, these findings carry profound managerial implications for the Battery-as-a-Service (BaaS) and leasing industry. By utilizing the Gen-EW model, fleet managers can transition from generic, time-based maintenance schedules to "degradation-aware" operational strategies. Since the model explicitly quantifies the non-linear impact of SoC (n_1 = 1.7361) and C-rate (n_2 = 0.1833) on battery life, leasing companies can implement dynamic pricing models that penalize aggressive charging behaviors or reward users who maintain batteries within optimal chemical stability ranges. Furthermore, the model's scalability—demonstrated by its ability to project the End-of-Life (EOL) of various cells without individual retraining—provides a foundational tool for the automated valuation of used battery packs. For investors and operators, this "white-box" interpretability minimizes financial risk by providing a clear, physically justified audit trail of asset health, ultimately extending the economic lifecycle of battery assets in large-scale energy storage and electric vehicle fleets. This capability confirms that the explicit inclusion of the C-rate stressor is the key to achieving a truly generalizable prognostic approach, suitable for real-world Battery Management Systems (BMS) where operational profiles are highly dynamic.

This robustness is visually illustrated in Figure 2, where the continuous SOH degradation trajectories for all four cells are compared. As observed in Figure 2(a), (b), and (c), the Generalized Eyring-Weibull (Gen-EW) model accurately captures the fundamental degradation trends of the cells operating under a nominal 2A discharge current, filtering out localized measurement noise. Furthermore, any minor initial deviation observed between the empirical data and the model's projection during the early cycles is physically attributed to the Solid Electrolyte Interphase (SEI) stabilization phase. During this initial break-in period, the battery experiences rapid, non-linear capacity fluctuations as the SEI layer dynamically forms and stabilizes on the anode, before eventually settling into the monotonic chemical degradation trajectory that the Gen-EW equation accurately captures. Notably, Figure 2(d) highlights the model's capability under accelerated aging conditions. Despite the significantly higher 4A discharge current applied to Battery B0018, the model successfully projects the aggressive degradation slope. Ultimately, these results validate the hypothesis that a multi-stressor physics-based model can effectively bridge empirical data with fundamental physicochemical principles to outperform empirical black-box models in both interpretability and operational versatility.

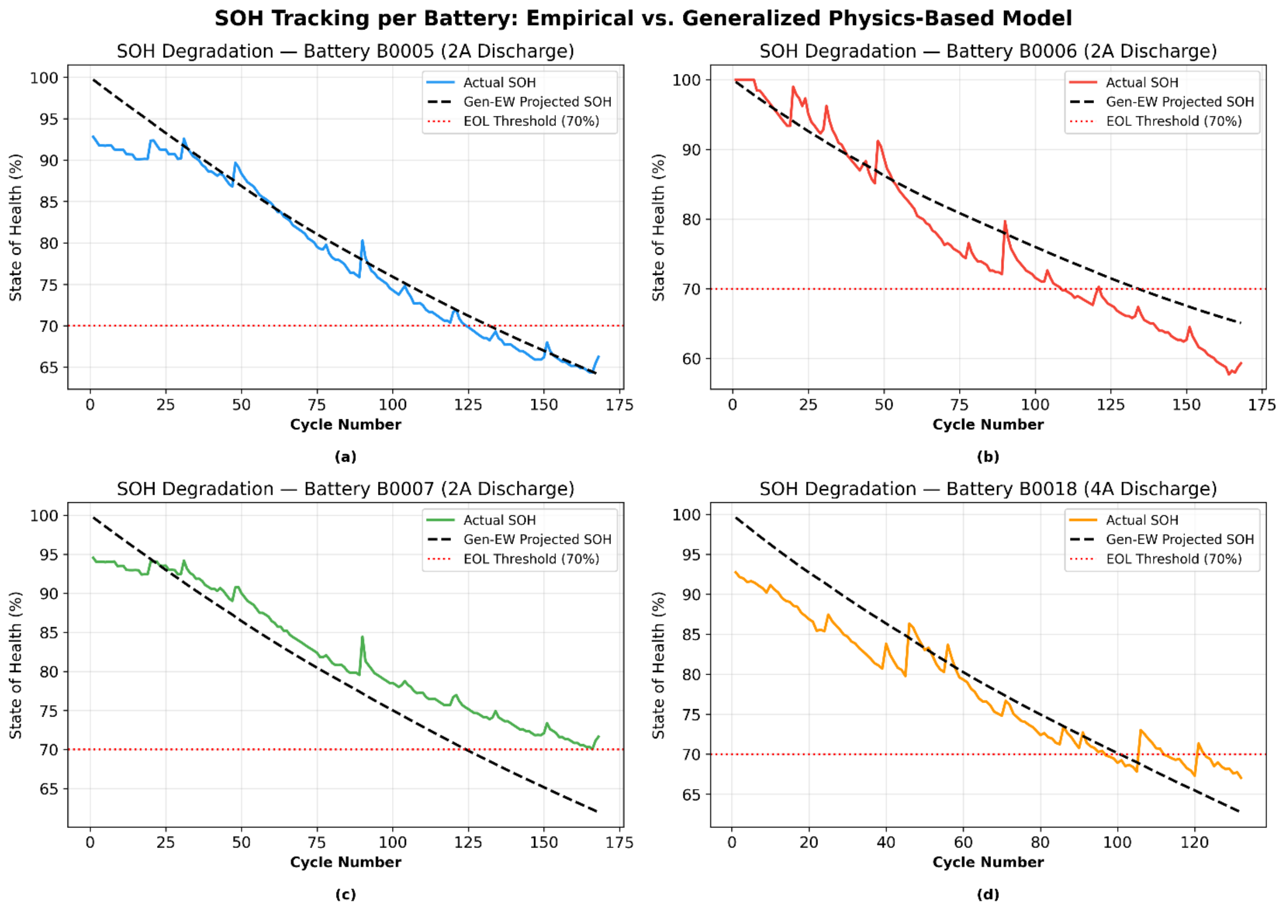

Figure 2. State of Health (SOH) degradation tracking comparing empirical data and the Generalized Eyring-Weibull (Gen-EW) model projections for: (a) Battery B0005; (b) B0006; (c) B0007 under a nominal 2A discharge current; and (d) Battery B0018 under an accelerated 4A discharge condition. The red dotted line indicates the 70% End-of-Life (EOL) threshold

4. Conclusion

This research has successfully developed and validated a Generalized Eyring-Weibull (Gen-EW) model for lithium-ion battery health prognosis. By integrating temperature, State of Charge (SoC), and discharge current (C-rate) as concurrent stressors, the proposed model bridges the gap between empirical observation and electrochemical degradation kinetics. The findings confirm that the physics-based Gen-EW model outperforms established data-driven baselines, evidenced by a global R^2 of 0.8561 compared to the 0.8260 achieved by the XGBoost model. More importantly, the model's white-box nature provides diagnostic interpretability, where the extracted Activation Energy (E_a = 0.3430 eV) and stress exponents (n_1 = 1.7361, n_2 = 0.1833) offer a quantitative understanding of the degradation mechanisms—specifically SEI layer growth and kinetic strain—without requiring cell-specific retraining. The results validate the hypothesis that a multi-stressor analytical model can effectively capture aggressive capacity fade under dynamic operational profiles, such as the 4A accelerated discharge condition observed in Battery B0018. Consequently, the Gen-EW model offers a robust, computationally efficient, and physically interpretable alternative to black-box machine learning algorithms.

Despite these advancements, this study has certain limitations. First, the current model assumes a deterministic relationship between stress factors and degradation, which may not fully account for the stochastic nature of real-world battery usage or manufacturing inconsistencies. Second, the model's validation is restricted to specific discharge profiles in the NASA PCoE dataset, potentially limiting its immediate applicability to battery chemistries with significantly different aging characteristics, such as LiFePO4 (LFP) or high-nickel NMC batteries. Future research will focus on two key areas. First, we plan to integrate Bayesian inference to quantify prediction uncertainty, allowing the model to provide confidence intervals that are crucial for safety-critical maintenance decisions. Second, we aim to extend the Gen-EW model to incorporate transfer learning techniques, enabling the model to adapt its stress exponents dynamically when deployed in heterogeneous BaaS fleets with varying battery ages and usage histories. This research provides a foundational tool for the next generation of intelligent Battery Management Systems (BMS), enabling more accurate End-of-Life (EOL) predictions and smarter, degradation-aware charging strategies for real-world applications.

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