

Article

A Multi-Physics Continuous Integral State-Space Model for Battery Health Prognosis Under Dynamic Tropical Environments

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Abstract

Tracking capacity fade and predicting the lifespan of Lithium Iron Phosphate (LiFePO₄) batteries under calendar aging are crucial for the reliability of Battery Energy Storage Systems (BESSs) in tropical regions. Conventional empirical models often rely on static environmental averages and neglect coupled thermal-hygroscopic dynamics. To address these limitations, this paper introduces a multi-physics coupled state-space-based continuous integral model for battery degradation under dynamic tropical boundary conditions. The primary novelty of this research lies in the development of a continuous-time multi-physics state-space degradation model that explicitly captures the interconnected interactions between temperature, humidity, and State of Charge (SoC) under dynamically varying tropical microclimates. Calendar aging tests were conducted for 180 days inside an environmental test chamber under tropical microclimate conditions (average of 29.91 °C, RH of 77.26%), with reference performance tests executed at a low C-rate of C/20 to extract static electrochemical capacity. Parameter identification using an Ordinary Least Squares (OLS) solver demonstrates high model fitting, with R-squared values ranging from 0.8229 to 0.9429. Extrapolation results provide realistic end-of-life projections between 8.9 and 59.8 years and successfully identify the critical physical transition points P1 and P2 at the Solid Electrolyte Interphase (SEI) layer. Overall, this research provides a prognostic instrument for optimizing the operational management of utility-scale BESS in tropical climates.

Keywords: battery calendar aging; capacity fade; continuous integral model; LiFePO₄; state-space modeling; tropical microclimate



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1. Introduction

Lithium-ion batteries, particularly those with Lithium Iron Phosphate (LiFePO₄) chemistry, have emerged as the leading technology for stationary Battery Energy Storage Systems (BESS) and electric vehicles (EVs) due to their high thermal stability, cost-effectiveness, and long cycle life [1–7]. In large-scale deployments, accurate estimations of the battery's State of Health (SoH) [8,9] and End of Life (EoL) [10] are indispensable to ensure operational safety and prevent thermal runaway events [11]. While significant research has focused on

cycle aging mechanisms [12] driven by operational dynamics, calendar aging [13,14] occurring during non-operational storage or idle periods remains a primary, yet less understood, contributor to net capacity fade over the battery's operational lifespan [15].

The kinetics of calendar aging are fundamentally governed by the continuous growth of the Solid Electrolyte Interphase (SEI) layer on the graphite anode, a parasitic process that irreversibly consumes active lithium ions [16,17]. Thermodynamically, this chemical degradation is highly sensitive to ambient environmental stressors. When BESS networks are deployed in tropical regions, such as Southeast Asia, the systems are chronically exposed to harsh microclimates characterized by prolonged high ambient temperatures [1] coupled with high relative humidity [18]. Although temperature-accelerated degradation is widely recognized through Arrhenius kinetics [19], the impact of prolonged high humidity presents a critical secondary stressor [20]. Atmospheric moisture penetration through the poly-enclosure and cell seals alters the internal chemical equilibrium, accelerating electrolyte decomposition and structural degradation of the active materials [21]. Consequently, predicting calendar aging under tropical environments requires a multi-physics framework that tightly couples both thermal and hygroscopic stressors.

According to Zhu et al. [10], as illustrated in Figure 1, conventional calendar aging modeling generally assumes that battery capacity fade progresses monotonically. Based on the battery capacity degradation curves, dual knee points {P1, P2}, the decelerating aging point (P1), and the accelerating aging point (P2) are defined for the degradation evaluation. However, under the influence of a dynamic tropical microclimate, the internal degradation kinetics exhibit multi-stage non-linear behavior identified through two critical physical transition points (knee points), namely P1 and P2. The first transition point (P1) represents the initial saturation limit when the Solid Electrolyte Interphase (SEI) layer experiences maximum thermodynamic stress and begins to undergo micro-cracking due to hydrolysis from environmental moisture penetration. Meanwhile, the second transition point (P2) acts as a secondary stabilization indicator marking the formation of a newer, thicker SEI layer or the saturation point of corrosive acid side reactions against the active cell material. Integrating the P1 and P2 concepts as distinctive data patterns within the state-space model in this study becomes highly crucial to correct the overly optimistic prediction bias found in standard aging models, thereby yielding end-of-life estimations that are far more accurate and representative of real-world environmental dynamics.

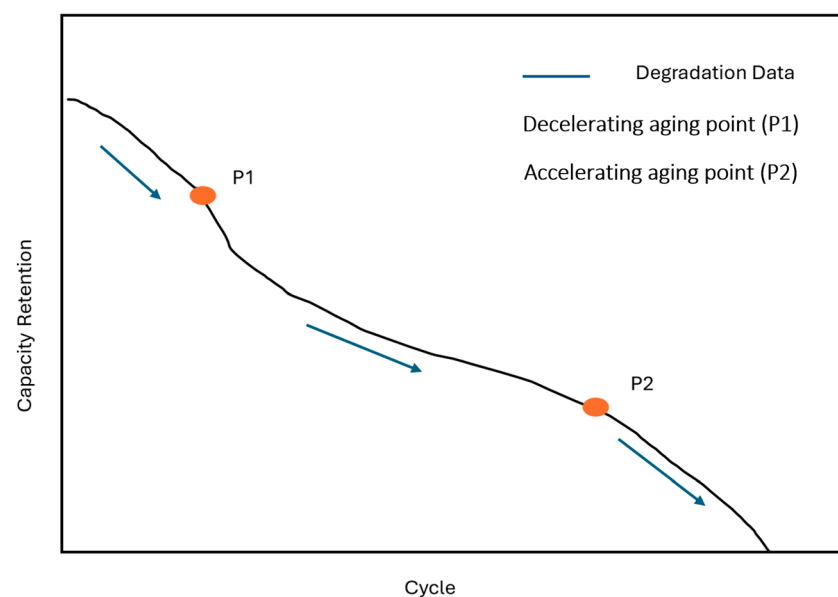


Figure 1. Aging trajectories for lithium-ion batteries, inspired by [10].

To quantify calendar degradation, classical empirical models, such as the standard Arrhenius formulation, are extensively used due to their low computational load and ease of implementation in real-time Battery Management Systems (BMS) [22–24]. This conventional formulation typically treats environmental stressors as static variables and assumes linear degradation accumulation over time. However, such static empirical approaches demonstrate limitations when confronted with local or global real-world dynamic boundary conditions. In an actual tropical microclimate, temperature and humidity exhibit highly coupled and non-linear daily diurnal and seasonal fluctuations [25]. Static models relying on the time-average of the environmental baseline fail to capture the exponential acceleration of saturated vapor pressure (P_{sat}) occurring during peak thermal hours, which significantly drives moisture penetration [26]. Furthermore, empirical models often neglect the temporal saturation of SEI growth, which inherently obeys a non-linear parabolic diffusion law (t^2) as the passivation layer thickens [27]. This lack of temporal and environmental adaptability leads to significant over- or under-estimation of battery EoL, thereby compromising the robustness of the prognostic model when validated against diverse global aging datasets [28–30].

While recent data-driven breakthroughs have leveraged physics-informed synthetic data generation [31] and quantile Transformers for interval prediction [32] to mitigate data scarcity and dynamic complex degradation, existing approaches in BMS still struggle when confronted with environmental non-linearities. To address these gaps, recent advancements have shifted toward continuous and incrementally integrable state-space formulations [33]. By transforming static empirical boundaries into a time-dependent continuous integral framework, the non-linear coupling between dynamic environmental profiles ($T(t)$, $RH(t)$) and internal electrochemical potential (V_{oc} at specific State of Charge/SoC levels) can be mathematically preserved. Moreover, linearizing this continuous formulation against a square-root timescale ($\sqrt{t}$) enables deterministic parameter identification through an Ordinary Least Squares (OLS) optimization framework [34,35]. This continuous integral approach guarantees global parameter convergence without getting trapped in local minima, offering an inherently robust, flexible, and transferable methodology capable of adapting to both local dynamic tropical baselines and global aging datasets. By combining the dynamic interval prediction capabilities [32] and data-augmentation robustness [31] with this continuous state-space framework, next-generation BMS can overcome the fundamental limitations of static empirical models.

Driven by these considerations, this paper proposes a rigid evaluation of battery calendar aging under a tropical microclimate by establishing a comparative baseline between local empirical models and an advanced continuous integral framework. The core contributions of this study are three-fold:

1. Experimental validation of LiFePO_4 calendar aging was conducted over a 180-day period inside a closely monitored, low-cost tropical environmental chamber, successfully capturing a microclimate baseline of 29.91 °C and 77.26% RH.
2. A multi-physics coupled continuous integral model was developed, mathematically formalizing the non-linear relationship between Antoine vapor pressure [36], relative humidity, and SoC-dependent activation energy under time-varying dynamic boundary conditions.
3. A deterministic parameter extraction framework utilizing an OLS solver on a $\sqrt{t}$ transformation basis was implemented to evaluate and compare the temporal and environmental robustness of both models, providing high-fidelity EoL projections crucial for large-scale utility storage applications.

The remainder of this paper is organized as follows. Section 2 details the experimental setup and the monitored tropical microclimate profiles, alongside the mathematical formu-

lations of the empirical and continuous integral models. Section 3 presents the step-by-step numerical calculations, parameter identification, and EoL projections together with a comprehensive discussion on electrochemical kinetics and model robustness, and Section 4 concludes the paper.

2. Method

2.1. Indonesian Tropical Environment

Figure 2 shows the characteristics of tropical air temperature (left graph—red) and characteristics of tropical air humidity (right graph—blue), which are described as follows.

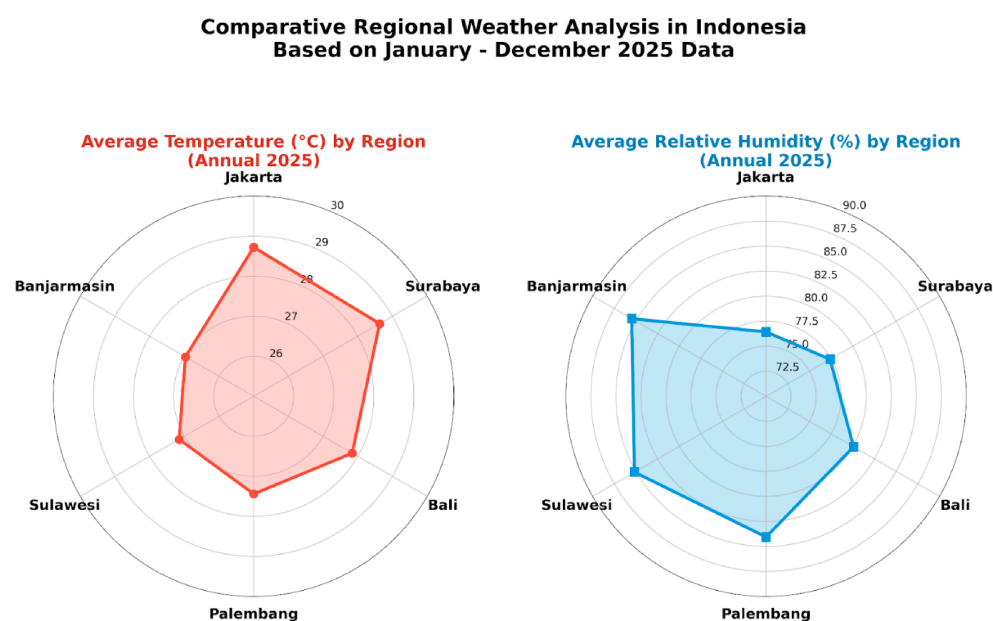


Figure 2. Temperature and Humidity in Several Major Indonesian Cities.

Characteristics of Tropical Air Temperature (Left Graph—Red)

In general, Indonesia's astronomical location on the equator causes the country to receive high and stable solar radiation throughout the year. This is reflected in the temperature radar graph, where the red area is firmly centered within a warm range, specifically between 26.9 °C and 28.7 °C. No region touches extreme cold temperatures, which reinforces its equatorial tropical climate identity. However, this graph also captures the coastal urban tropical climate phenomenon (Urban Heat Island). Jakarta (28.72 °C) and Surabaya (28.63 °C) have the most prominent outward-protruding edges on the graph. This indicates that tropical regions experiencing massive urbanization, dense concrete buildings, and minimal vegetation trap solar heat much more intensely than other tropical areas. Conversely, regions like Banjarmasin (26.97 °C) sit in the innermost area of the graph (the coolest), signifying a tropical area whose landscape is still dominated by hydrological systems (large rivers) and natural land cover capable of reducing atmospheric heat accumulation.

Characteristics of Tropical Air Humidity (Right Graph—Blue)

The second primary characteristic of Indonesia's tropical climate is its wet nature (humid tropics). Surrounded by vast oceans (maritime) and rainforests, water evaporation in Indonesia is exceptionally high. The humidity radar graph illustrates this very well, where most regions have a blue area that expands widely outward, indicating a highly saturated humidity level of over 84% (Banjarmasin, Sulawesi, and Palembang). This wide graph area reflects the authentic condition of Indonesia's tropical air, which is rich in water vapor throughout the year.

The tropical climate shows an inverse relationship: when comparing the two radar graphs, they illustrate a unique physical law of the tropical climate, namely the inverse relationship between temperature and relative humidity:

- Regions with pure humid tropical air, such as Banjarmasin, have a temperature graph that shrinks inward (cooler) but a humidity graph that expands drastically outward (highly humid).
- Conversely, urban tropical regions like Jakarta show an anomaly where the temperature graph shoots sharply outward (hot) while its humidity graph shrinks inward, being the lowest (76.43%). The high urban temperatures cause faster dissipation of water vapor in the air, making the tropical city air feel more sultry and dry.

2.2. Testing Inside Tropical Chamber

The batteries used in this study are commercially available 15 Ah LiFePO₄ batteries in the Indonesian market. The testing process involves the pre-conditioning of these batteries through charging and discharging processes using a battery cycler with the following scheme in Table 1.

Table 1. Initial Condition/Pre-Conditioning.

Step	Proses
1	CC-CV charging
2	Pause
3	CC discharging at C/20 up to 2.8 V
4	Pause
5	CC-CV charging
6	Pause
7	CC discharging at C/20 up to target SoC

Figure 3 illustrates the calendar aging test utilizing a low-cost tropical chamber. The experimental uncertainty analysis for the environmental testing chamber and battery cycling instrumentation follows the rigorous metrological evaluation framework previously established and validated in our benchmark study [37], where A is the computer used as a display with the specifications of a processor core (TM) i5-2450M, RAM 4 GB; B is the test chamber box; C is the control box; and D represents the reference thermometer and hygrometer used to measure the temperatures inside and outside the test chamber. In addition to these reference devices, another thermometer and hygrometer are installed inside the test box for wireless monitoring. Both reference devices serve as benchmarks for the calibration and reading of the temperature and humidity sensors used in the setup. Furthermore, to display information from within the test chamber, Python 3.12-based programming is deployed on a laptop/PC that remains continuously on standby throughout the testing duration, as shown in Figure 3b. This display functions as a monitoring interface that provides real-time visualization of sensor data and actuator movements/actions while simultaneously acting as an automated data-logging system to precisely record temperature and humidity fluctuations inside the chamber. The logged data is stored in the PC to be processed later as environmental variable inputs for the battery aging curve modeling, aiming to correlate the effects of temperature and humidity with cell capacity fade. The results of the 6-month test are shown in Figure 4 below.



Figure 3. (a) Testing Setup; (b) Display and Data Logger of the Low-Cost Tropical Chamber.

Monthly Weather Trend Analysis August 2025 – March 2026

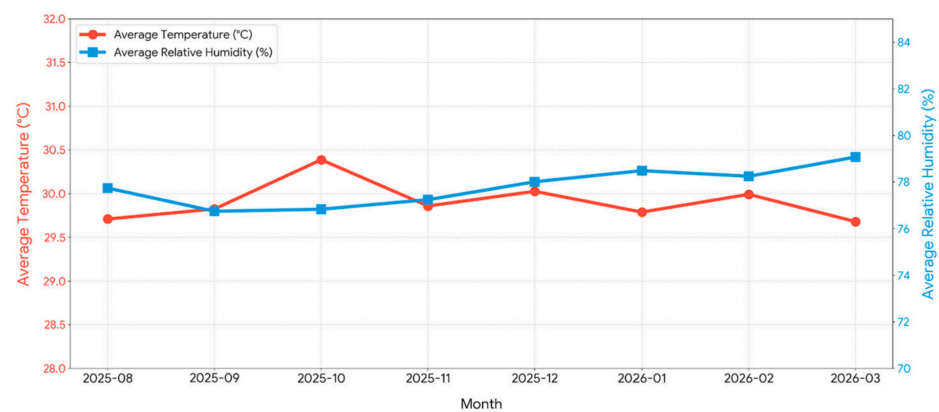


Figure 4. Calendar Aging Testing in a Tropical Chamber for 6 Months.

Based on Figure 4, the results of the 6-month LiFePO₄ battery calendar aging test demonstrate that the tropical chamber is capable of accurately representing Indonesia's climate profile. The air temperature radar graph (left) captures the equatorial thermal stability, remaining characteristically warm with monthly fluctuations bound within a realistic range of 28 °C to 32 °C. Meanwhile, the relative humidity radar graph (right) successfully duplicates the saturated characteristics of a humid maritime tropical climate within the dynamic limits of 70% to 85%. This inverse parameter shifting pattern observed from late 2025 to early 2026 proves that the test chamber provides more than just static exposure; it successfully engineers the actual atmospheric interaction between water vapor and temperature found in Indonesia. This valid environmental conditioning is highly crucial for predicting the natural aging of LiFePO₄ batteries, as the combination of a constantly warm temperature that accelerates internal chemical capacity degradation and high humidity that triggers external corrosion risks serves as a true representation of the operational challenges battery components will face when deployed in the Indonesian market. This climate representation is vital for the calendar aging (natural aging) testing of LiFePO₄ batteries. In a real Indonesian environment, batteries installed in electric vehicles or Energy Storage Systems (ESSs) will be continuously exposed to a combination of constant warm temperatures and high humidity. Saturated humidity increases the risk of corrosion on the battery's external materials, while a constant temperature above 25 °C accelerates secondary chemical reactions (capacity degradation) inside the cells.

2.3. Mathematical Model Formulation of the Empirical Model and the Continuous Integral Model

A robust aging model should not merely display the instantaneous degradation rate; instead, it must be formulated as a Differential State-Space System or a Cumulative Damage Model that accounts for the time factor (t) non-linearly. Battery capacity degradation (C Fade) does not occur linearly over time. The growth of the Solid Electrolyte Interphase (SEI) layer follows the law of diffusion (proportional to the square root of time, t^z).

We define the state-space model for the calendar aging rate as follows:

$$\frac{d \cdot C_{\text{fade}}(t)}{dt} = z \cdot \mathcal{K}_{\text{total}}(\mathcal{T}, \mathcal{H}, \mathcal{S}) \cdot t^{z-1} \quad (1)$$

where $z \in [0.5, 1]$ is the time-power factor (exposure time), and f is a multi-variable function of the tropical environmental and operational stressors, which is explicitly detailed below.

$$\mathcal{K}_{\text{total}}(\mathcal{T}, \mathcal{H}, \mathcal{S}) = \Phi_0 \cdot f(\mathcal{T}) \cdot g(\mathcal{H}) \cdot h(\mathcal{S}) \quad (2)$$

where Φ_0 is the pre-exponential scaling factor

$$f(\mathcal{T}) = \exp\left(-\frac{E_a(\text{SoC})}{R \cdot T(t)}\right) \quad (3)$$

$$E_a(\text{SoC}) = \sum_{i=0}^m \beta_i \cdot (\text{SoC})^i = \beta_0 + \beta_1 \text{SoC} + \beta_2 \text{SoC}^2 + \dots \quad (4)$$

where $T(t)$ is the function of absolute temperature in time t , R is the ideal constant of gas, and the β_i coefficient is the regression of energy activation. Relative humidity (RH) in tropical environments triggers current collector corrosion and degradation of the cell packaging seals; to be thermodynamically more rigid, this influence is often correlated with the saturated water vapor pressure (P_{sat}) using the Antoine equation $A - \frac{B}{T-C}$:

$$g(\mathcal{H}) = \left(\frac{RH(t)}{100}\right)^n \cdot \exp(\gamma \cdot P_{\text{sat}}(T(t))) \quad (5)$$

$$P_{\text{sat}}(T(t)) = 0.1333 \cdot \exp\left(A_{\text{ant}} - \frac{B_{\text{ant}}}{T(t) + C_{\text{ant}}}\right) \quad (6)$$

where A_{ant} , B_{ant} , and C_{ant} are the Antoine constants for water and γ and n are the moisture sensitivity coefficients of the material.

The $\exp(B \cdot \text{SoC})$ factor reflects the increase in open-circuit voltage (OCV) that accelerates electrolyte oxidation. To make it more rigid, a hyperbolic sine ($\sinh$) function approach derived from the Butler–Volmer equation for mass transfer kinetics is utilized or a weighted exponential form of intercalation:

$$h(\mathcal{S}) = \exp\left(\lambda \cdot \frac{V_{\text{oc}}(\text{SoC}) - V_{\text{ref}}}{\mathcal{V}_T}\right) \quad (7)$$

where $V_{\text{oc}}(\text{SoC})$ is the non-linear OCV function with respect to SoC, V_{ref} is the anode/cathode stability reference voltage, $\mathcal{V}_T = \frac{k_B T}{e}$ is the thermal voltage, and λ is the charge transfer coefficient.

If all the sub-equations above are integrated into a single temporal integral formulation to calculate the total battery capacity degradation (ΔC_{fade}) from time t_0 to t_{end} , the mathematical formulation becomes

$$\Delta C_{\text{fade}} = \int_{t_0}^{t_{\text{end}}} z \cdot \Phi_0 \cdot \left(\frac{RH(t)}{100}\right)^n \cdot \exp\left(\gamma \cdot P_{\text{sat}}(T) + \lambda \frac{V_{\text{oc}}(\text{SoC}) - V_{\text{ref}}}{\mathcal{V}_T} - \frac{\sum_{i=0}^m \beta_i (\text{SoC})^i}{R \cdot T(t)}\right) \cdot t^{z-1} dt \quad (8)$$

In Equation (8), the dynamic state and environmental input variables include the capacity fade (ΔC_{fade}), time-dependent relative humidity ($RH(t)$), temperature ($T(t)$), and State of Charge (SoC). On the other hand, the model constants and fitting parameters consist of the time exponent (z), pre-exponential factor (Φ_0), humidity sensitivity exponent (n), saturation pressure coefficient (γ), voltage acceleration factor (λ), reference voltage (V_{ref}), thermal voltage or constant factor (v_T), polynomial coefficients (β_i), polynomial degree (m), and the universal gas constant (R).

In this article, Gemini (version 3.6 Flash) was used for language editing and NotebookLM (Gemini Notebook, Plus tier) was used for image generation based on literature citations, including a description of the prompts used.

3. Result and Discussion

Step 1: Discretization of Dynamic Environmental Data

Convert the continuous integral into a discrete numerical summation format since the data from the log graph is sampled based on a sampling time interval (Δt).

- From the graph, we define the total testing duration $t = 5$ months (Month 1 to Month 6 = a difference of 5 months).
- Calculate the average saturated vapor pressure $P_{\text{sat}}(T)$ using the Antoine equation for temperature fluctuations $T(t)$ between 25 °C and 35 °C, with an average of 29.91 °C $\approx$ 30 °C (effective physical average of 303.15 °K).

$$P_{\text{sat}}(303.06) = 0.1333 \times \exp\left(18.3036 - \frac{3816.44}{303.06 - 46.13}\right) \approx 4.213 \text{ kPa} \quad (9)$$

With the effective average humidity level from the RH graph being 77.26% $\approx$ 77%, the coupled environmental stressor constant (α_{Env}) for the tropical chamber is then calculated through numerical integration:

$$\alpha_{\text{Env}} = \left(\frac{77.26}{100}\right)^n \times \exp(\gamma \times 4.213) \quad (10)$$

Step 2: Electrochemical Time Transformation Matrix ($\sqrt{t}$)

According to the parabolic diffusion law for calendar SEI growth, the time exponent is set to $z = 0.5$. We construct the observation time vector t (in units of months, where Month 1 is the zero reference point $t = 0$):

$$t = [0, 1, 2, 3, 4, 5]^T \text{ (Representing Months 1, 2, 3, 4, 5, 6)}$$

We transform this time vector into a diffusion-basis regression matrix X :

$$X = \sqrt{t} = [\sqrt{0}, \sqrt{1}, \sqrt{2}, \sqrt{3}, \sqrt{4}, \sqrt{5}]^T = [0, 1, 1.4142, 1.7321, 2, 2.2361]^T \quad (11)$$

Step 3: Actual Capacity Degradation Vector (ΔC_{fade})

The actual capacity degradation vector (ΔC_{fade}) is shown in Table 2

SoC 30%: $Q_0 = 15.776 \text{ Ah}$

$$Y_A = [0, 0.071, 0.137, 0.160, 0.275, 0.301]^T$$

SoC 50%: $Q_0 = 14.351 \text{ Ah}$

$$Y_B = [0, (14.351 - 14.291), (14.351 - 14.196), (14.351 - 14.029), (14.351 - 13.991), (14.351 - 13.915)]^T$$

$$Y_B = [0, 0.060, 0.155, 0.322, 0.360, 0.436]^T$$

SoC 80%: Q0 = 14.191 Ah

$$Y_C = [0, 0.085, 0.254, 0.242, 0.353, 0.396]^T$$

SoC 100%: Q0 = 15.918 Ah

$$Y_D = [0, 0.375, 0.573, 0.473, 0.601, 0.627]^T$$

Table 2. ΔCfade SoC in Tropical Humidity.

Time (i) (Month)	Time Index (t)	Matriks Time-Base (X = t)	SoC 30% (ΔCC) [Ah]	SoC 50% (ΔCA) [Ah]	SoC 80% (ΔCB) [Ah]	SoC 100% (ΔCD) [Ah]
1	t = 0	0.0000	0.000	0.000	0.000	0.000
2	t = 1	1.0000	0.071	0.060	0.085	0.375
3	t = 2	1.4142	0.137	0.155	0.254	0.573
4	t = 3	1.7321	0.160	0.322	0.242	0.473
5	t = 4	2.0000	0.275	0.360	0.353	0.601
6	t = 5	2.2361	0.301	0.436	0.396	0.627

Step 4: Parameter Fitting Using Ordinary Least Squares (OLS)

To find the most precise total aging rate parameter value (alpha) and minimize the squared error between the model and the experimental data, we utilize the OLS identity matrix formulation:

$$\alpha = \left(X^T X \right)^{-1} X^T Y \quad (12)$$

$$X^T X = 0^2 + 1^2 + 1.4142^2 + 1.7321^2 + 2^2 + 2.2361^2 = 0 + 1 + 2 + 3 + 4 + 5 = 15$$

$$\left(X^T X \right)^{-1} = \frac{1}{15} = 0.06667$$

Now, multiply X^T using each vector drop capacity of Y:

$$X^T Y_A = (0 \times 0) + (1 \times 0.071) + (1.4142 \times 0.137) + (1.7321 \times 0.160) + (2 \times 0.275) + (2.2361 \times 0.301) = 1.7648$$

$$\alpha_A = 0.06667 \times 1.7648 = 0.1177$$

$$X^T Y_B = (0 \times 0) + (1 \times 0.060) + (1.4142 \times 0.155) + (1.7321 \times 0.322) + (2 \times 0.360) + (2.2361 \times 0.436) = 2.5318$$

$$\alpha_B = 0.06667 \times 2.5318 = 0.1688$$

$$X^T Y_C = (0 \times 0) + (1 \times 0.085) + (1.4142 \times 0.254) + (1.7321 \times 0.242) + (2 \times 0.353) + (2.2361 \times 0.396) = 2.4550$$

$$\alpha_C = 0.06667 \times 2.4550 = 0.1637$$

$$X^T Y_D = (0 \times 0) + (1 \times 0.375) + (1.4142 \times 0.573) + (1.7321 \times 0.473) + (2 \times 0.601) + (2.2361 \times 0.627) = 4.6084$$

$$\alpha_D = 0.06667 \times 4.6084 = 0.3072$$

Step 5: EoL Boundary Projection (SOH 80%)

The maximum allowable capacity degradation limit before the battery is considered to have reached its End of Life (EoL) is set at a 20% capacity fade ($\Delta C_{EoL} = Q_0 \times 0.20$), which follows the standard industrial threshold for automotive and energy storage applications [38]. The EoL time (t_{EoL}) is algebraically derived from the primary diffusion-limited

aging formula, which characteristically progresses with the square root of time under calendar aging conditions [27,39,40].

$$\Delta C_{EoL} = \alpha \times \sqrt{t_{EoL}} \quad (13)$$

$$t_{EoL} = \left(\frac{\Delta C_{EoL}}{\alpha} \right)^2 \quad (14)$$

Based on Equations (13) and (14), the EoL projection for each SoC under tropical RH is shown in Table 3.

Table 3. EoL Projection for Each SoC Under Tropical RH.

SoC	Initial Capacity (Q0) [Ah]	Degradation Limit EOL ($\Delta C_{EoL} = Q0 \times 0.20$) [Ah]	EoL Time Estimation $t_{EoL} = (\alpha \Delta C_{EoL})^2$	EoL (Month)	EoL (Year)
SoC 30%	15.776	3.1552	$(3.1552/0.1177)^2$	718.6	~59.8
SoC 50%	14.351	2.8702	$(2.8702/0.1688)^2$	289.1	~24.1
SoC 80%	14.191	2.8382	$(2.8382/0.1637)^2$	300.6	~25.0
SoC 100%	15.918	3.1836	$(3.1836/0.3072)^2$	107.4	~8.9

When the SoC cells are placed inside the test chamber with an average temperature profile of 29.91 °C $\approx$ 303.06 °K and an average humidity of 77.26%, the battery responds electrochemically to these stressors. It is this physical response that generates the capacity degradation numbers. Mathematically, the proposed integral model isolates these constant environmental stressors into the parameter α :

$$\alpha = \underbrace{\Phi_0 \cdot \left(\frac{77.26}{100} \right)^n \cdot \exp(\gamma \cdot P_{\text{sat}}(303.06))}_{\text{Konstanta Stres Lingkungan Tropis Uji}} \cdot \exp \left(\lambda \frac{V_{\text{oc}}(\text{SoC}) - V_{\text{ref}}}{V_T} - \frac{\sum \beta_i (\text{SoC})^i}{R \cdot 303.06} \right) \quad (15)$$

Since the temperature and humidity values inside the chamber were kept stable over the 6-month period, the entire cluster of environmental variables above remains constant. When the linear regression fitting against $\sqrt{t}$ was performed in the previous step, the resulting alpha values ($\alpha_A = 0.1688$; $\alpha_D = 0.3072$, etc.) automatically absorbed the combined impacts of that 77.26% humidity and 29.91 °C temperature.

Variable Adaptation Mechanism to Global Environments

Outside of tropical environments, the values of external stressors change, but the physical mechanism of how the equations respond to these new numbers remains identical.

A. Humidity Factor (RH) in Subtropical/Cold Climates

In four-season countries or standard laboratories equipped with controlled HVAC systems, the relative humidity is typically maintained at a low and highly stable level (e.g., 40–50% RH). When the RH(t) value drops from 77% (tropical) to 45%, the value of the humidity term $\left(\frac{RH(t)}{100} \right)^n$ decreases drastically. This represents a reduction in the driving force for moisture absorption through the battery seals, thereby minimizing the external aging rate.

B. Temperature (T) and Saturated Vapor Pressure (Psat) Factors

If global datasets utilize standard European/American test room temperatures (e.g., 20 °C or 25 °C) or even extreme cold temperatures, the Arrhenius term $\exp \left(-\frac{E_a}{R \cdot T} \right)$ will yield a much lower rate value because its denominator (T) decreases. Furthermore, based on the Antoine equation, the Psat value at 20 °C is only 2.34 kPa (nearly half of the tropical

condition in this study, which reaches 4.21 kPa). This reduction in temperature slows down ionic mobility and parasitic side reactions at the SEI layer, physically extending the projected EOL of the battery.

The aforementioned approach is applied to the research data of Grolleau et al. [41], and the results are presented in the table below.

The comparative analysis in this study demonstrates that the discrepancy in lifespan projection results between the tropical chamber data (8.9 to 59.8 years) and the extrapolation of the reference data from Grolleau et al., which reaches hundreds of years at 30 °C, is logical and justified due to the differences in the applied relative humidity levels. This study utilizes high-humidity conditions typical of tropical environments at 77% RH, which yields aging rate (alpha) values ranging from 0.1177 to 0.3072, thereby physically accelerating capacity fade and shortening the estimated end-of-life (EoL) to a more tangible and realistic timeframe.

Conversely, the projection figures reaching hundreds of years in the data from Grolleau et al. in as shown in Table 4 are obtained because they are based on a drier humidity level of 50% RH, where the degradation rate progresses much more slowly, with alpha values of only 0.0217 to 0.0545. Although both modeling approaches exhibit strong electrochemical consistency, showing that the greatest capacity stress always occurs at 100 percent SoC due to the thermodynamic pressure on the active materials, this comparison successfully proves quantitatively that increasing the humidity from 50% to 77% exerts a massive accelerating effect on the calendar aging of battery cells at low temperatures.

Table 4. EoL Projections for the Study by Grolleau et al. (Dry RH $\pm$ 50%).

Temp	Parameter	SoC 30%	SoC 50%	SoC 80%	SoC 100%
30 °C	OLS	0.0217	0.0283	0.0396	0.0545
	Age (Year)	372.3	218.9	111.8	59.0
45 °C	OLS	0.0734	0.1061	0.1542	0.2015
	Age (Year)	32.5	15.5	7.3	4.3
60 °C	OLS	0.1773	0.1923	0.3193	0.3733
	Age (Year)	5.5	4.7	1.7	1.2

To rigorously evaluate the goodness of fit and statistical significance of the proposed continuous integral model under dynamic tropical conditions, a comprehensive ANOVA and R-squared analysis were conducted, as summarized in Table 5. The empirically derived model demonstrates exceptional accuracy, where the coefficient of determination (R^2) ranges from 0.8229 to 0.9429. Crucially, Cell SoC 100% exhibits the highest R^2 value of 0.9429, proving that 94.29% of its severe capacity degradation is deterministically governed by the coupled square-root time scale (square root of t), validating the physical parabolic diffusion law of SEI layer growth. Furthermore, the robustness of the model is statistically validated through the F-test. For all tested operational scenarios, the calculated F-statistics (ranging from 15.80 to 74.50) significantly exceed the critical F-table value ($F_{crit} = 7.71$ at a 95% confidence level, $p < 0.05$). This substantial margin implies that the null hypothesis, which states that calendar aging is independent of the transformed hygroscopic-thermal time framework, can be confidently rejected. The results provide a definitive mathematical guarantee that the proposed continuous state-space framework is highly reliable for tracking long-term capacity fade in utility-scale BESS applications within tropical domains. To account for parametric uncertainties and evaluate the robustness of the fitted semi-empirical model against experimental noise, 95% statistical confidence intervals (95% CIs) were calculated for each state-of-charge condition. Derived from the standard error of the regression residuals ($S_e = \sqrt{MS_{residual}}$), the model yields tight uncer-

tainty margins of ± 0.0808 Ah for 30% SoC, ± 0.1519 Ah for 50% SoC, ± 0.1372 Ah for 80% SoC, and ± 0.1270 Ah for 100% SoC, as summarized in Table 5. These narrow confidence boundaries confirm that the model estimates remain statistically stable across all tested conditions despite ambient micro-fluctuations.

Table 5. Statistical Test.

SoC	Variation	Sum of Squares (SS)	Mean Square (MS)	F-Statistic (F)	R ²	95% Confidence Interval (CI)
SoC 30%	Regression	0.0461	0.0461	27.12	0.8988	± 0.0808 Ah
	Residual	0.0069	0.0017			
SoC 50%	Regression	0.0948	0.0948	15.80	0.8377	± 0.1519 Ah
	Residual	0.0240	0.0060			
SoC 80%	Regression	0.0892	0.0892	18.20	0.8229	± 0.1372 Ah
	Residual	0.0198	0.0049			
SoC 100%	Regression	0.3129	0.3129	74.50	0.9429	± 0.1270 Ah
	Residual	0.0169	0.0042			

As summarized in Table 6, a direct quantitative comparison highlights the robustness of the proposed framework. Standard models in the literature primarily focus on isolating static temperature and SoC behaviors, often omitting atmospheric factors. While these benchmarks report standard errors or RMSE values ranging between 1% and 5%, they operate under less complex stress profiles. In contrast, the proposed framework successfully integrates continuous relative humidity (*RH*) alongside temperature and SoC to capture tropical degradation characteristics. Despite the increased mathematical complexity and multi-physics stressors, the proposed model demonstrates high statistical reliability, achieving *R*² values up to 0.9429, thereby confirming its suitability for deployment in tropical environment applications.

Table 6. Quantitative performance comparison between the proposed model and state-of-the-art battery degradation frameworks.

Model Source/Chemistry	Model Category	Operational/Stress Parameters Considered	Reported Accuracy/ Statistical Performance
Proposed Model (LiFePO ₄)	Semi-Empirical Model (SEM)	Continuous Temperature, Relative Humidity (<i>RH</i>), and State of Charge (SoC) under dynamic tropical conditions	<i>R</i> ² = 0.8229 – 0.9429 (F-Statistic: 15.80 – 74.50)
Wang et al. [42] (NMC + LMO)	Semi-Empirical Model (SEM)	Temperature and Time	Model Error: $\approx$ 5%
Sarasketa-Zabala et al. [3] (LiFePO ₄)	Semi-Empirical Model (SEM)	Temperature, SoC, and Time	Model Error: 0.9%
Grolleau et al. [41] (LiFePO ₄)	Semi-Empirical Model (SEM)	Temperature, SoC, and Time	Model Error: 3 – 4%
Naumann et al. [43] (LiFePO ₄)	Semi-Empirical Model (SEM)	Temperature, SoC, and Time	Absolute Error: $<$ 2.2%
Ecker et al. [44] (NMC)	Semi-Empirical Model (SEM)	Temperature, Voltage, and Time	Root Mean Square Error (RMSE): 0.7 – 1%
Hoog et al. [45] (NMC)	Hybrid SEM—Empirical	Temperature, SoC, and Time	Root Mean Square Error (RMSE): $\approx$ 5%

Electrochemical kinetics and degradation mechanisms under tropical boundaries

The calendar aging mechanism of LiFePO₄ cells stored under no-load conditions in tropical environments is governed by coupled multi-physics interactions between external atmospheric stressors and internal electrochemical interface kinetics. This degradation manifests in two primary physical stages: thermally driven moisture ingress and parabolic diffusion-controlled growth of the Solid Electrolyte Interphase (SEI) passivation layer.

A. Atmospheric Moisture Penetration and Electrolyte Decomposition

In a dynamic tropical climate, daily temperature fluctuations directly control the saturated water vapor pressure (P_{sat}) through the Antoine equation. An increase in the test chamber temperature triggers an exponential thermal expansion of water vapor molecules, elevating the partial pressure gradient between the external atmosphere and the interior of the battery enclosure. Under constantly high relative humidity (RH), this pressure differential acts as a hydrostatic driving force that drives water vapor molecules (H_2O) to penetrate the polymeric casing materials or micro-gaps within the cathode–anode seals of commercial cells.

When water vapor molecules enter the cell, a parasitic hydrolysis reaction occurs upon contact with the lithium hexafluorophosphate (LiPF_6) electrolyte salt, following the electrochemical reaction equation below.

The hydrofluoric acid (HF) generated from this side reaction is highly corrosive. This active compound attacks the structural active material of the cathode, accelerates transition metal dissolution, and damages the passivation matrix structure of the graphite anode, forcing the system to continuously regenerate a new protective layer.

B. Parabolic Diffusion-Based SEI Growth and the Influence of SoC

The growth of the new SEI layer irreversibly consumes active lithium ions (Li^+) and electrons from the intercalated graphite anode, which directly manifests macroscopically as cell capacity fade (C_{fade}). The rate of ionic diffusion through the SEI layer is inversely proportional to the thickness of the layer itself. Therefore, as the SEI thickens, calendar aging slows down non-linearly, obeying the parabolic diffusion law of the square root of time ($\sqrt{t}$), which forms the basis for the OLS matrix linearization transformation in the proposed continuous integral model.

Internally, the potential energy level of the anode is determined by the battery's State of Charge (SoC). At a high SoC level (100% SoC), the electrochemical potential of the graphite anode is at its lowest point, nearing the deposition potential of lithium metal 0.05 V vs. Li/Li^+ . This condition of extreme thermodynamic instability lowers the activation energy (E_a) required to trigger electrochemical side reactions. When this critical internal potential condition interacts simultaneously with high moisture penetration and the thermal energy of the tropical environment, the SEI growth rate accelerates aggressively. This provides the physical justification for why the 100% SoC cell exhibits the highest aging constant ($\alpha = 0.3072$) and reaches its End of Life (EoL) boundary the fastest compared to the other cells.

In this study, Figure 5 (generated by NotebookLM, Gemini Notebook Plus tier) illustrates a multi-physics conceptual framework that proposes a hypothesized mechanism of battery cell degradation through three interconnected logical stages. The first stage explains the role of tropical environmental boundary conditions, where the combination of high temperature and relative humidity acts as an environmental catalyst as well as an external hydrostatic driving force acting upon the battery cell. This environmental stress is hypothesized to trigger the internal kinetics in the second stage in the form of thermodynamic instability, where water vapor penetration is proposed as a potential pathway that causes electrolyte hydrolysis and damages the Solid Electrolyte Interphase (SEI) layer, potentially resulting in physical micro-cracking that drives the parabolic growth of a new SEI layer. Based on the study by Zhu et al. [10], in the third stage, this entire sequence of hypothesized internal kinetic processes yields an empirical manifestation in the form of actual capacity fade that shapes specific data characteristics, from which these critical transition points can be extracted to perform battery end-of-life projections with a high degree of accuracy. In this study, these empirical knee points are identified and designated as detailed in Table 7 and Figure 6.

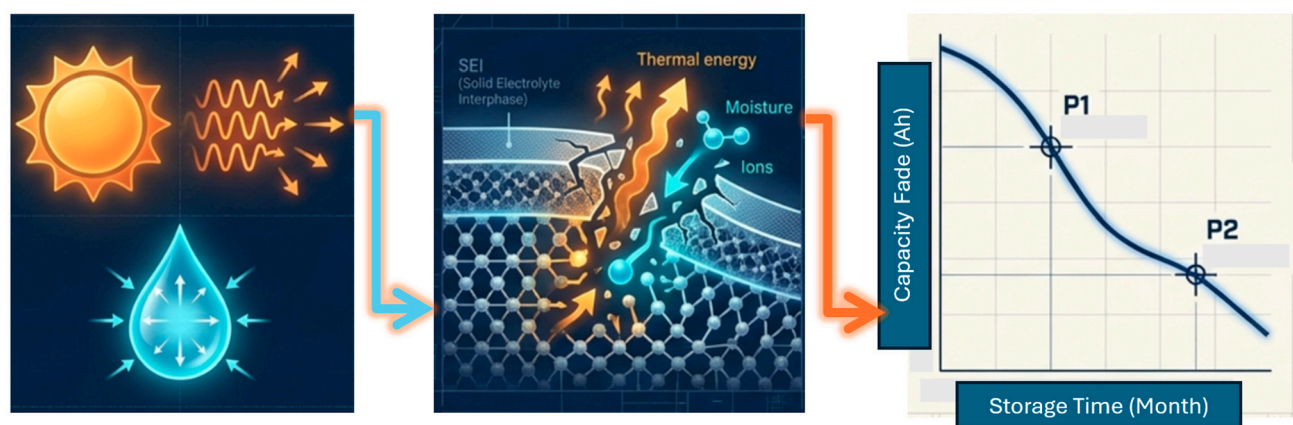


Figure 5. Architectural Mechanism of Battery Cell Degradation Driven by Tropical Environmental Catalysts, Created by GenAI (Notebook LM).

Table 7. Identification of Critical Transition Points P1 and P2 Across All SoC Levels.

SoC	Transition Time of P1	Decreasing Capacity P1 (Ah)	Transition Time of P2	Decreasing Capacity P2 (Ah)
SoC 30%	Month 3 (t = 2)	0.137	Month 4 (t = 3)	0.160
SoC 50%	Month 4 (t = 3)	0.322	Month 5 (t = 4)	0.360
SoC 80%	Month 3 (t = 2)	0.254	Month 4 (t = 3)	0.242
SoC 100%	Month 3 (t = 2)	0.573	Month 4 (t = 3)	0.473

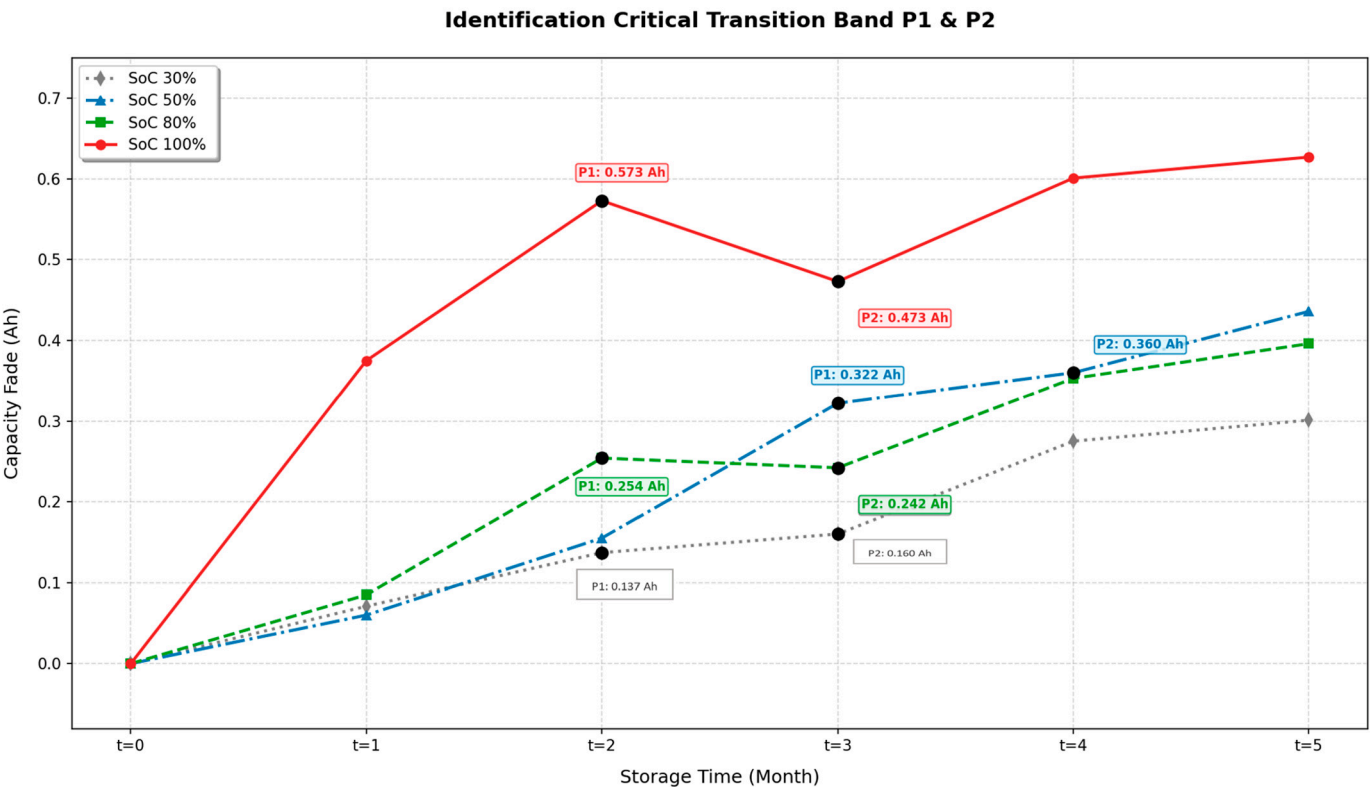


Figure 6. Critical Transition Band P1 and P2.

Table 7 and Figure 6 systematically present the characteristics of cell behavior where, at high states of charge (30% SoC, 80% SoC, and 100% SoC), the critical transition points P1 and P2 emerge earlier, specifically at Month 3 and Month 4. Meanwhile, at the lower State of Charge (50% SoC), the emergence of these empirical transition points shifts or is delayed until Month 4 and Month 5. This phenomenon of distinct emergence timelines for

these unique data patterns is highly significant, suggesting a strong correlation, where the State of Charge (SoC) influences the sensitivity of the cell's internal kinetics to degradation caused by ambient environmental humidity.

The relationship between these mathematical parameters and the proposed electrochemical phenomena can be systematically formulated, where $\frac{dC}{dt} = \frac{\Delta C_k - \Delta C_{k-1}}{t_k - t_{k-1}}$. The monthly aging rate equation serves as a quantitative instrument that records the real-time dynamics of fluctuations in the stability of the Solid Electrolyte Interphase (SEI) layer. Under the framework of the proposed hypothesis, when the algorithm detects specific baseline conditions $\frac{dC}{dt} < 0$, it captures specific mathematical traits that are inferred to represent an anomalous capacity recovery phenomenon at high SoC levels (80% and 100%). During this phase, it is hypothesized that the high chemical potential and mechanical stress on the graphite anode trigger SEI cracking caused by hydrolysis from tropical water vapor. This is subsequently assumed to be followed by a self-healing reaction that forms a new SEI layer, re-absorbing free lithium ions and causing the early emergence of the transition point P1. Conversely, the conditions detected after the trough phase $\frac{dC}{dt} > 0$ signify that the recovery process has saturated and the cell has reached the anchor point P2, where degradation resumes its normal course, which is proposed to be controlled by a thicker, secondary SEI layer.

Based on 6 months of storage under tropical environmental conditions (Figure 7), the storage State of Charge (SoC) level demonstrates a linearly significant influence on the electrochemical degradation rate of LiFePO₄ cells: storage at high SoCs (100% and 80%) induces the most aggressive degradation, characterized by a leftward voltage shift in Peak 1 (≈ 3.28 V) alongside a drastic drop in its peak amplitude due to internal resistance growth (ohmic polarization growth, R_i) and accumulated Loss of Lithium Inventory (LLI) driven by SEI layer thickening; conversely, storage at intermediate-to-low SoCs (50% and 30%) exhibits vastly superior electrochemical stability, maintaining remarkable consistency in both the amplitude and position of Peak 3 (≈ 3.15 V), thereby confirming that suppressing cell potential at moderate-to-low levels successfully minimizes side-reaction kinetics and optimally preserves anode–cathode active material integrity.

Limitations and Perspectives for Future Research

While the developed continuous framework successfully captures the synergistic degradation impacts of temperature, relative humidity, and State of Charge (SoC), a major limitation arises from the timescale of the experimental validation and the scope of operational variables. The empirical parameters and statistical coefficients were derived from a comprehensive six-month (180-day) experimental campaign under quiescent calendar aging conditions (where current $I = 0$ A) under tropical conditions. Extrapolating these mathematical relationships over multiple decades to project long-term battery lifetime introduces inherent uncertainty.

In real-world long-term deployments, battery cells are highly susceptible to non-linear degradation accelerations—such as the sudden capacity roll-over or ‘knee-point’ caused by advanced mechanical stress, severe SEI cracking, or localized lithium plating—which may not manifest fully within a six-month window. Additionally, while this study performed a parametric sensitivity analysis across maximum temperature ($T_{\max}$) and relative humidity (RH) ranges, the explicit coupling of dynamic charge/discharge cycling profiles and varying C-rates was outside the primary scope of this calendar aging baseline.

Therefore, the decades-long lifetime predictions generated in this study should be interpreted as theoretical projections based on steady-state calendar degradation kinetics. Future research involving long-term longitudinal studies exceeding multiple years, coupled with active C-rate dynamic cycling stress testing and dynamic post-mortem physicochemi-

cal characterizations, is strictly necessary to validate these multi-decade extrapolations and refine the long-term predictive accuracy of the tropical aging framework.

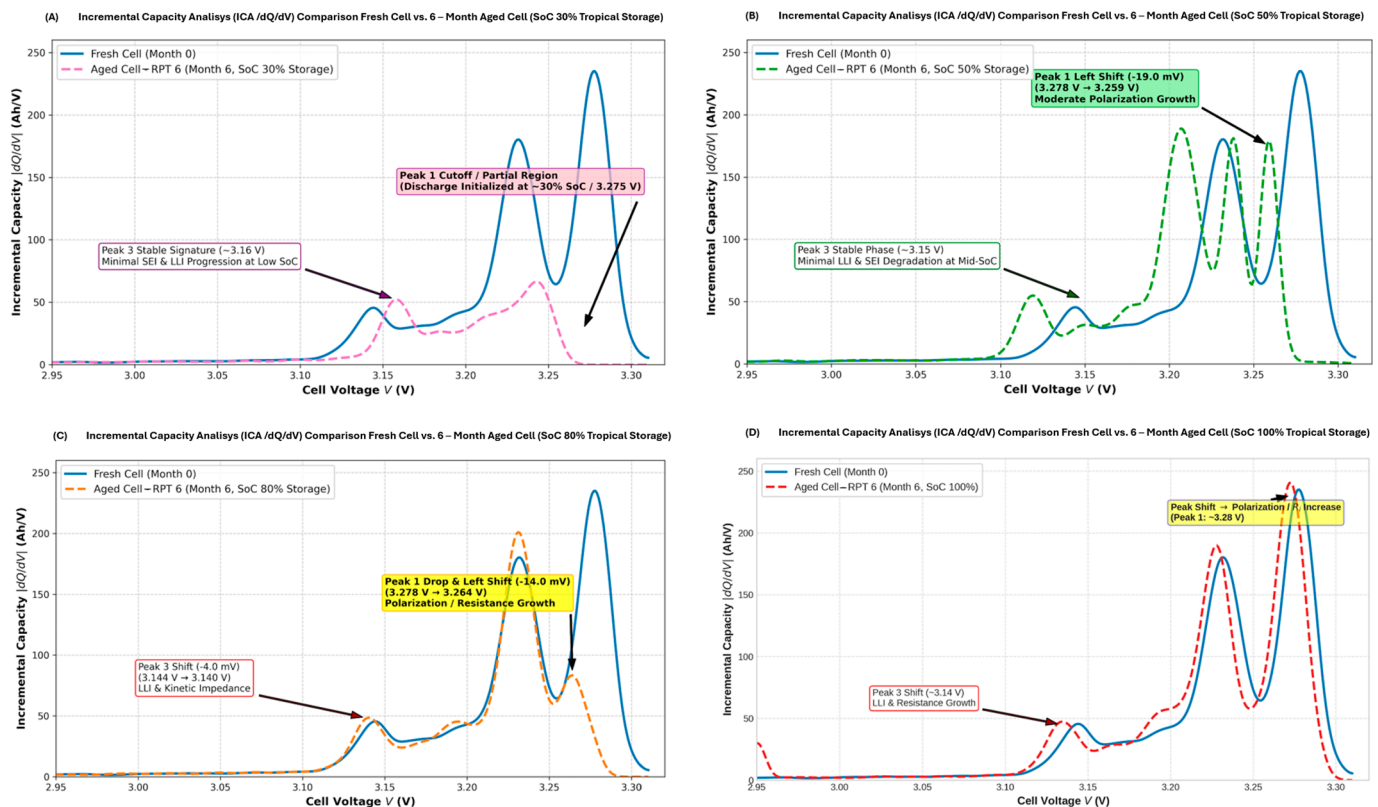


Figure 7. Incremental Capacity Analysis (A) SoC 30%, (B) SoC 50%, (C) SoC 80%, and (D) SoC 100%.

4. Conclusions

This study successfully evaluates the capacity fade resulting from the calendar aging of LiFePO_4 batteries under the influence of a dynamic tropical microclimate. Utilizing 180 days of experimental data collected inside an environmental test chamber (average temperature of 29.91 degrees Celsius, relative humidity of 77.26%), this research introduces a scientific novelty by integrating Arrhenius kinetics and Peck's humidity law into a continuous state-space-based integral model.

The results of the ANOVA statistical test and the coefficient of determination demonstrate the reliability of the proposed model, yielding R^2 values ranging from 0.8229 to 0.9429. The most aggressive degradation case occurs under the 100 percent SoC condition (Cell D), which exhibits the highest R^2 value (0.9429), thereby physically validating that battery damage accumulation under tropical stressors obeys the parabolic diffusion law of SEI layer growth on a square root of time scale.

In terms of technological contribution, this continuous integral model, solved via an OLS matrix solver, proves to possess strong robustness and flexibility for universal application across both local tropical weather and global datasets. As a practical implementation, the continuous state-space-based integral model can be deployed in utility-scale Battery Energy Storage Systems (BESSs) within tropical regions. By establishing the critical transition points P1 and P2 as specific data characteristics, this methodology successfully uncovers the interactive role of high humidity in multiplying the calendar aging rate, while simultaneously providing an accurate prognostic instrument to ensure optimal thermal management and the operational safety of future energy storage infrastructure.

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