

Article

A Parametric LFP Battery Degradation Model for Techno-Economic Assessment of European System-Imbalance Services

Samuel O. Ezennaya *  and Julia Kowal * 

Department of Electrical Energy Storage Technology (EET), Institute of Energy and Automation, Technical University Berlin, Einsteinufer 11, 10587 Berlin, Germany

* Correspondence: samuel.ezennaya@eet.tu-berlin.de (S.O.E.); julia.kowal@tu-berlin.de (J.K.)

Abstract

Battery energy storage systems (BESSs) are increasingly deployed by European Balance Responsible Parties (BRPs) to mitigate system-imbalance exposure; yet, techno-economic assessments often represent degradation using fixed-lifetime or equivalent-full-cycle assumptions that obscure the dependence of wear on operating policy and sizing. This study develops a data-driven, parameterised degradation framework for LiFePO_4 (LFP) BESS operating under imbalance duty. Using historical imbalance datasets from five European countries spanning eight transmission system operators (TSOs), annual cycle-induced capacity loss, calendar-induced capacity loss, and total annual capacity loss at 25 °C are mapped as explicit functions of energy-to-power ratio (duration), maximum power rating, depth of discharge, state-of-charge operating bounds, and daily cycling intensity. A degree-2 Ridge specification yields compact, auditable coefficients that transfer across entities (including an out-of-time full-year hold-out for Belgium, 2025). The fitted response surfaces reveal consistent EU-wide operating regimes: cycling-dominant ageing for durations ≤ 3 h, a mixed regime for durations ≈ 3 –6 h, and calendar-dominant ageing for durations ≥ 6 h, indicating a practical compromise around ≈ 4 –5.5 h. The resulting coefficiented outputs are Techno-Economic Assessment (TEA)-ready and enable risk-aware sizing and state-of-charge policy design for imbalance-focused BESS portfolios.

Keywords: battery energy storage; lithium iron phosphate; degradation modelling; capacity loss; cyclic loss; calendaric loss; system imbalance; balancing responsible parties; techno-economic assessment; ridge regression; European TSOs



Academic Editor: King Jet Tseng

Received: 22 December 2025

Revised: 31 January 2026

Accepted: 6 February 2026

Published: 8 February 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

1.1. Background

Grid-connected battery energy storage systems (BESSs) are increasingly deployed to manage system imbalance across European transmission networks. In total, 4.9 GW of utility-scale storage was added in 2024, bringing the cumulative EU total above 13 GW [1]. In the European system-imbalance operation, Balancing Responsible Parties (BRPs) are financially responsible for deviations between nominated and realised volumes and may deploy BESS to hedge forecast-error risk. These obligations shape operating patterns, from high-SOC availability to frequent shallow cycling [2–4]. Lithium iron phosphate (LFP) is widely adopted for stationary use because of its safety, benign thermal behaviour, and strong cycle life [5]. Battery lifetime depends on both calendar and cycle ageing and is

sensitive to temperature and state of charge (SOC), motivating models that represent both mechanisms [6,7].

Consequently, battery lifetime outcomes depend on prequalified grid power ($P_{\max}$), the energy-to-power ratio (E/P , i.e., duration), the SOC window (upper and lower bounds), depth of discharge (DoD), daily cycling frequency, and temperature. A tractable annualised degradation representation that captures these drivers is needed to inform realistic techno-economic assessments and to guide dispatch and sizing for grid services [8].

Existing lifetime treatments in grid-facing models are often (i) application-agnostic linear throughput costs or fixed replacement schedules; (ii) cycle-only formulations that ignore calendar ageing and high-SOC standby; or (iii) high-fidelity electrochemical models that are too complex for long-horizon planning. Such choices can distort operational decisions and profitability: when degradation is ignored, or mis-specified, ex-post wear costs can overturn seemingly profitable trades, whereas including realistic degradation alters optimal dispatch and improves lifetime economics [9–11].

Several studies have explored parametrised ageing models for lithium-ion batteries, although relatively few have been developed in a form that is directly embeddable in techno-economic assessment and dispatch optimisation. Sui et al. conducted a long-term calendar-ageing study on commercial LiFePO_4 /graphite cells and fitted degradation parameters across temperature and SOC conditions using a two-step nonlinear regression approach, highlighting the coupled influence of thermal and SOC stressors on capacity fade [12]. Complementary contributions by Birkel and Howey, and later co-workers, used current-pulse testing and electrochemical impedance spectroscopy (EIS) with identification/fitting procedures to estimate dynamic and impedance-model parameters relevant to state-of-health tracking, with an emphasis on dynamic behaviour rather than annualised ageing response surfaces for system-level optimisation [13,14]. More broadly, O’Kane et al. reviewed mechanistic and semi-empirical degradation models and emphasised the practical difficulty of coupling multiple degradation pathways without extensive experimental datasets for parameterisation [15]. While these works demonstrate mature parameter identification and degradation modelling foundations, they typically do not provide reduced-form ageing representations tailored to techno-economic scheduling. Recent work has begun to embed ageing-aware operation directly into profit optimisation of battery energy storage systems, explicitly trading operational revenue against degradation-induced lifetime costs [16]. In this context, the remaining gap was addressed in this work by integrating a semi-empirical LFP ageing formulation within an end-to-end techno-economic framework and by providing auditable regression coefficients that map dispatch-relevant stressors (e.g., energy-to-power ratio, SOC limits, and cycling intensity) to annualised cycle- and calendar-induced capacity loss. In the absence of such a model, techno-economic results can be biased, and dispatch, sizing, and availability decisions may be systematically suboptimal, particularly under imbalance settlement, thereby constituting a critical gap addressed in this paper. Moreso, directly comparable studies at the intersection of (i) European system-imbalance operation, (ii) scenario-level parameter sweeps, and (iii) coefficientised LFP degradation response surfaces remain scarce. Accordingly, there is a clear need for simplified yet robust degradation models suitable for annual and lifecycle economic analyses of grid-scale storage.

1.2. Study Aim

This study develops and validates a simplified, parameterised, and robust annual degradation framework for LFP batteries operating in European system-imbalance services. The framework quantifies calendar (Q_{cal}), cyclic (Q_{cyc}), and total (Q_{tot}) capacity loss as explicit functions of grid and battery parameters. It is intended to enable regulators to set realistic minimum requirements and lifetime-aware performance metrics; system operators to design dispatch and availability policies that avoid unintended calendar-dominant wear; and project developers to select P_{max} , E/P , SOC limits, and DoD policies that jointly optimise profitability, compliance, and asset longevity. The resulting improvements in realism strengthen bankability assessments and reduce the risk of early capacity shortfalls.

1.3. Contribution to Knowledge

To the best of our knowledge, this paper provides the first data-driven, parameterised, and operationally interpretable LFP degradation framework explicitly tailored to the management of European system-imbalance portfolios by BRPs. Addressing a critical gap wherein investment planning has typically assumed fixed lifetimes or equivalent-full-cycle (EFC) heuristics, the study learns from historical imbalance data to produce annual Q_{cyc} , Q_{cal} , and Q_{tot} at 25 °C as explicit functions of E/P , P_{max} , DoD, $\text{SOC}_{\text{min}}/\text{SOC}_{\text{max}}$, and daily cycling intensity. The coefficientised Ridge formulation is compact and auditable, enabling risk-averse techno-economic assessment and dispatch optimisation that internalises degradation rather than assuming it, which is highly pertinent for BRPs mitigating forecast-error exposure in imbalance settlement.

Beyond accuracy and cross-entity validation (nine major European entities, including an external hold-out), the framework contributes a regime map that quantifies when Q_{tot} is cycle- versus calendar-dominated and shows how E/P , P_{max} , and DoD shift that boundary. The model thereby identifies actionable levers, notably SOC-window policy and sizing (E/P), to balance utilisation and longevity in merchant operation. Overall, the work replaces assumption-based degradation practice with calibrated, TEA-ready parametric surfaces for system-imbalance duty, establishing a transferable basis for portfolio optimisation, investment appraisal, and risk management across European TSOs.

2. Methodology

2.1. Data Collection and Case-Study Overview

To capture a diverse range of European balancing conditions, five countries were selected, each with historical imbalance price and volume data: Belgium, the Netherlands, Germany (reported per TSO control zone), Spain, and Poland. The study covers Belgium (Elia, 2020–2025), the Netherlands (TenneT NL, 2020–2023), Germany—50 Hertz (2022–2025), Germany—Amprion (2022–2025), Germany—TenneT DE (2022–2025), Germany—TransnetBW (2022–2025), Spain (REE, 2022–2025), and Poland (PSE, 2022–2025).

Historical imbalance price and volume data for Belgium were obtained from Elia's Open Data platform [17–19], while the Netherlands data were obtained directly from TenneT NL [20]. For Germany, Spain, and Poland, the datasets were sourced from the ENTSO-E Transparency Platform [21]. All time series were aligned to UTC, cleaned for missing or duplicate timestamps to ensure comparability across regions and years. The resulting dataset forms a multi-year, high-resolution record of imbalance conditions across eight European balancing zones, reflecting a wide range of grid dynamics and operational behaviours. Table 1 summarises the global scenarios used in the simulations.

Table 1. Global scenario grid applied in each zone/year.

Parameter	Units	Values	Notes
Strategy	—	Naïve	Always counteracts imbalance; no price-based arbitrage.
Power sweep	MW	$P_{\max} \in \{50, 100, \dots, 600\}$	Step = 50 MW (12 values).
Duration sweep	h	$E/P \in \{0.5, 1, 2, 4, 6, 8, 10\}$	Seven duration settings.
SOC windows	—	(0.50–0.50, 0.00), (0.45–0.55, 0.10), (0.40–0.60, 0.20), (0.35–0.65, 0.30), (0.30–0.70, 0.40), (0.25–0.75, 0.50), (0.20–0.80, 0.60), (0.15–0.85, 0.70), (0.10–0.90, 0.80), (0.05–0.95, 0.90), (0.00–1.00, 1.00)	Paired $\text{SOC}_{\min}$ – $\text{SOC}_{\max}$ (per-unit), with corresponding DoD (per-unit).
DoD windows	—	$\{0.0, 0.1, \dots, 1.0\}$	$\text{DoD} = \text{SOC}_{\max} - \text{SOC}_{\min}$.
Ambient temp.	°C	25	Used in calendar-ageing factors.
Time step	min	1	Data up-sampled from ISP to 1 min for integration.
Initial SOC	—	0.50	Mid-point start.

2.2. Battery Simulation Framework

An end-to-end, scenario-based simulation workflow was implemented to translate historical system-imbalance conditions into annual LFP BESS degradation indicators, as summarised in Figure 1. For each entity/year, the framework ingests system-imbalance time series (imbalance volumes and, where applicable, imbalance prices), applies harmonisation and minute-resolution resampling, and evaluates a structured scenario grid spanning power rating $P_{\max}$, duration (E/P), and SOC-window policies ($\text{SOC}_{\min}$, $\text{SOC}_{\max}$) (hence DoD). For each scenario, a physics-informed BESS operational simulation produces minute-level dispatch and SOC trajectories, including a converter/round-trip efficiency representation and an imbalance-mitigation control strategy. Cycling stress metrics are subsequently derived from the SOC trajectory using half-cycle detection (rainflow-equivalent), yielding DoC-, C-rate-, and full-equivalent-cycle (FEC) sequences. These stress metrics parameterise the semi-empirical Naumann et al. LiFePO_4 /graphite ageing model, which is accumulated in discrete time to produce scenario-level annual capacity-loss outputs Q_{cyc} , Q_{cal} , and Q_{tot} . Aggregating results across all scenarios/entities/years yields the regression dataset used to estimate compact degree-2 parametric response surfaces for Q_{cyc} and Q_{tot} (with $Q_{\text{cal}} = Q_{\text{tot}} - Q_{\text{cyc}}$), validated via within-entity splits and an external full hold-out (BE/2025). Unless otherwise stated, simulations assume a fixed ambient temperature of 25 °C and an initial SOC of 50%, consistent with controlled utility-scale container operation.

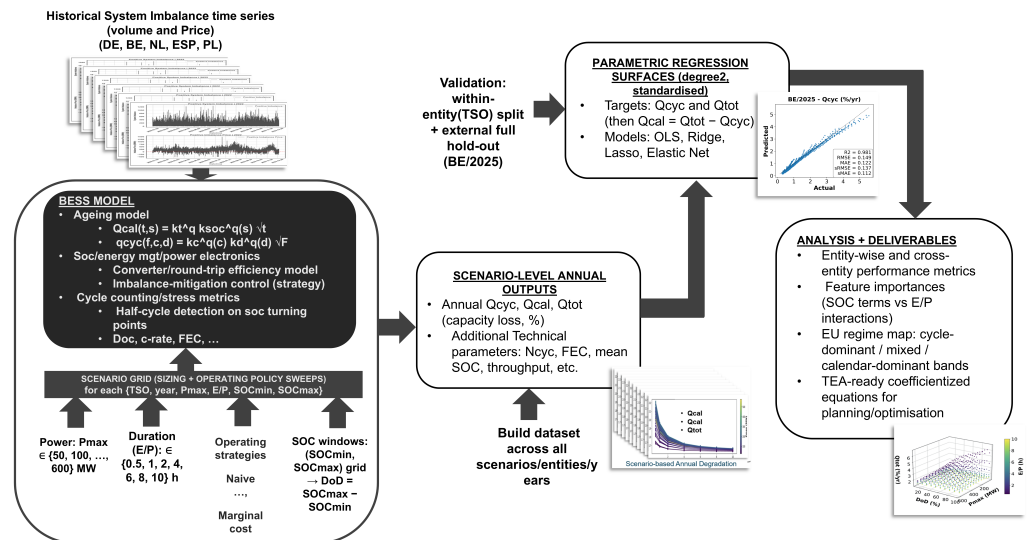


Figure 1. End-to-end framework: Historical system-imbalance datasets define scenario grids and drive minute-resolution BESS dispatch; cycle counting and Naumann-based ageing accumulation yield scenario-level annual losses (Q_{cyc} , Q_{cal} , Q_{tot}), which are then used to fit and validate degree-2 parametric regression surfaces and derive TEA-ready deliverables.

2.2.1. SOC Dynamics and Power Constraints

At discrete minute index t (time step $\Delta t = 1$ min), the system imbalance $SI(t)$ (MW; positive for surplus, negative for deficit) is mapped to battery power $P_{bat}(t)$ (MW; positive for charging, negative for discharging) subject to the converter power limit P_{max} (MW):

$$P_{bat}(t) = \begin{cases} \min\{SI(t), P_{max}\}, & SI(t) > 0 \text{ (charge)}, \\ \max\{-P_{max}, SI(t)\}, & SI(t) < 0 \text{ (discharge)}, \\ 0, & SI(t) = 0, \end{cases} \quad \text{with } |P_{bat}(t)| \leq P_{max}. \quad (1)$$

The state of charge, $SOC(t)$, is represented on a normalised scale $[0, 1]$ and is advanced each step and bounded to $[SOC_{min}, SOC_{max}]$ (both dimensionless):

$$SOC(t + \Delta t) = SOC(t) + \frac{P_{bat}(t) (\Delta t / 60)}{E_{bat}}, \quad (2)$$

where E_{bat} is the usable energy capacity (MWh) over the 0–100% SOC range and $\Delta t / 60$ converts minutes to hours. For each scenario, the energy capacity is linked to sizing via $E_{bat} = (E/P) P_{max}$, with E/P expressed in hours. Requests that would breach SOC limits are curtailed; residual imbalance beyond BESS limits is recorded.

2.2.2. Converter Efficiency Model

Round-trip efficiency depends on the instantaneous converter loading $p = 100 |P_{bat}(t)| / P_{max}$ (dimensionless, in %), where $|P_{bat}(t)|$ is the absolute battery power and P_{max} is the rated power (MW). A fitted curve $\eta_{rt}(p)$ (dimensionless fraction in $[0, 1]$) represents inverter and internal losses. The round-trip efficiency curve was parameterised from Schimpe et al.'s utility-scale measurements (cell and inverter), then compactly re-fit for the dispatcher [22].

$$\eta_{rt}(p) = \frac{-6.7843 \times 10^{-4} p^2 + 0.02723 p + 90.983 - 34.796 e^{-0.162 p}}{100}, \quad 0 \leq p \leq 100, \quad (3)$$

where e denotes the base of the natural logarithm. Efficiency is applied to energy flows (i.e., the delivered/withdrawn energy associated with $P_{\text{bat}}(t)$ is adjusted by $\eta_{\text{rt}}(p)$); dispatch remains imbalance-driven.

2.2.3. Degradation Modelling

Total degradation is represented as the superposition of calendar- and cycle-induced ageing contributions for both capacity fade and resistance growth. The functional forms follow the semi-empirical LiFePO₄/graphite ageing model of Naumann et al. [23,24]. The formulation is evaluated in discrete time and annualised at a fixed ambient temperature of 25 °C for the SOC/DoD grids considered in this work.

Calendar-induced capacity fade and resistance growth are expressed as

$$Q_{\text{cal}}(t, s) = k_T^Q k_{\text{SOC}}^Q(s) \sqrt{t}, \quad R_{\text{cal}}(t, s) = k_T^R k_{\text{SOC}}^R(s) t, \quad (4)$$

where Q_{cal} is calendar capacity loss (%), R_{cal} is calendar resistance growth (%), t is elapsed time (h), and s is the state of charge (SOC; fraction in $[0, 1]$). The factors k_T^Q and k_T^R are temperature-dependent rate terms, while $k_{\text{SOC}}^Q(s)$ and $k_{\text{SOC}}^R(s)$ are dimensionless SOC modifier functions.

The temperature factors k_T^Q and k_T^R follow Arrhenius scaling:

$$k_T = k_{\text{ref}} \exp \left[-\frac{E_A}{R_g} \left(\frac{1}{T} - \frac{1}{T_{\text{ref}}} \right) \right], \quad T_{\text{ref}} = 298.15 \text{ K}, \quad T = 25 + 273.15 \text{ K}, \quad (5)$$

where k_{ref} is the reference rate constant, E_A is the activation energy (J mol^{-1}), R_g is the universal gas constant ($\text{J mol}^{-1} \text{K}^{-1}$), T is the temperature (K), and T_{ref} is the reference temperature (K). SOC sensitivity is captured via the modifiers

$$k_{\text{SOC}}^Q(s) = 2.8575 (s - 0.5)^3 + 0.60225, \quad (6)$$

$$k_{\text{SOC}}^R(s) = -3.3903 (s - 0.5)^2 + 1.5604. \quad (7)$$

These terms impose a higher calendar-ageing rate at elevated SOC, consistent with the underlying empirical calibration reported in [23].

Cycle-induced capacity fade and resistance growth are expressed as

$$Q_{\text{cyc}}(F, c, d) = k_c^Q(c) k_d^Q(d) \sqrt{F}, \quad R_{\text{cyc}}(F, c, d) = k_c^R(c) k_d^R(d) F, \quad (8)$$

where Q_{cyc} is cyclic capacity loss (%), R_{cyc} is cyclic resistance growth (%), F is cumulative full-equivalent cycles (FEC; dimensionless), c is the effective C-rate, and d is depth-of-cycle (DoC; fraction in $[0, 1]$). The functions $k_c^Q(c)$ and $k_c^R(c)$ are dimensionless C-rate modifiers, and $k_d^Q(d)$ and $k_d^R(d)$ are dimensionless DoC modifiers. The cycle modifiers are given by

$$k_c^Q(c) = 0.0630 c + 0.0971, \quad k_c^R(c) = -0.0020 c + 0.0021, \quad (9)$$

$$k_d^Q(d) = 4.0253 (d - 0.6)^3 + 1.0923, \quad k_d^R(d) = 6.8477 (d - 0.5)^3 + 0.91882, \quad (10)$$

which encode the empirical sensitivities to effective C-rate and cycle depth described in [24]. The square-root dependence of capacity fade on F , and the linear dependence of resistance growth on F , are retained from the original model structure.

The quantities F , c , and d are obtained from the simulated SOC trajectory via half-cycle detection (rainflow-equivalent turning-point identification). For each detected half-cycle, the corresponding DoC and an effective C-rate are computed from the associated SOC excursion and power trajectory, and cumulative FEC is updated accordingly. This

procedure yields stepwise increments in F consistent with the occurrence and depth of cycling throughout the imbalance-following operation.

All simulations are performed at 1 min resolution. Let step i have duration Δt (h), time t_i , SOC s_i , and cumulative FEC F_i . Calendar increments are accumulated using the following incremental square-root (for Q_{cal}) and linear-time (for R_{cal}) forms:

$$\Delta Q_{\text{cal},i} = k_T^Q k_{\text{SOC}}^Q(s_i) (\sqrt{t_i} - \sqrt{t_{i-1}}), \quad \Delta R_{\text{cal},i} = k_T^R k_{\text{SOC}}^R(s_i) \Delta t. \quad (11)$$

Cycle increments are evaluated only when F increases between steps (i.e., when cycling is detected), using

$$\Delta Q_{\text{cyc},i} = k_c^Q(c_i) k_d^Q(d_i) (\sqrt{F_i} - \sqrt{F_{i-1}}), \quad \Delta R_{\text{cyc},i} = k_c^R(c_i) k_d^R(d_i) (F_i - F_{i-1}), \quad (12)$$

where c_i and d_i denote the effective C-rate and DoC associated with the detected cycle contribution at step i .

Annual quantities are obtained by summing increments over the full year, yielding Q_{cal} , Q_{cyc} , R_{cal} , and R_{cyc} . Total degradation is then

$$Q_{\text{tot}} = Q_{\text{cal}} + Q_{\text{cyc}}, \quad R_{\text{tot}} = R_{\text{cal}} + R_{\text{cyc}}, \quad (13)$$

where Q_{tot} and R_{tot} denote total annual capacity loss (%) and total annual resistance growth (%), respectively. The present work focuses on annual capacity loss (Q_{cal} , Q_{cyc} , Q_{tot}) as the degradation outputs used for subsequent regression and techno-economic assessment.

2.2.4. Energy Management Strategy

An imbalance-following control rule is applied at each simulation step to mitigate the realised system imbalance. A requested battery power set-point is formed directly from the imbalance signal: the BESS charges for $\text{SI}(t) > 0$ (surplus) and discharges for $\text{SI}(t) < 0$ (deficit). The request is then enforced subject to the power constraint $|P_{\text{bat}}(t)| \leq P_{\text{max}}$ and the SOC operating window $[\text{SOC}_{\text{min}}, \text{SOC}_{\text{max}}]$, with any infeasible portion curtailed and recorded as residual imbalance (see Equations (1) and (2)). Converter losses are represented via the load-dependent round-trip efficiency model in Equation (3), which is applied to energy flows (SOC evolution) while the dispatch decision remains imbalance-driven. No speculative price arbitrage is performed. Results, therefore, correspond to an ex-post replay of historical imbalance conditions at 1 min resolution.

Although the scenario dataset is generated using this imbalance-following dispatch, the fitted regression model is formulated in terms of operating stress descriptors (E/P , P_{max} , N_{cyc} , DoD, SOC_{min} , SOC_{max}) rather than dispatch logic. Consequently, alternative dispatch strategies (e.g., price-optimised or co-optimised policies) may be evaluated by computing the same descriptors from the realised annual operation and applying the coefficientised model obtained in this work.

2.3. Model Development and Parameterization

A regression modelling framework was constructed using the scenario-level dataset generated by the simulation and degradation workflow described in the preceding section. Each scenario corresponds to one entity/year and one operating-policy realisation on the parameter grid (power rating, duration, SOC window, and resulting cycling statistics). For each scenario, the simulation produces internally consistent annual degradation labels and summary operating descriptors, which are then used to fit compact parametric response surfaces for techno-economic assessment.

2.3.1. Targets

The cyclic and total annual capacity-loss components, Q_{cyc} and Q_{tot} (in % per year), are modelled directly. The calendar component is reconstructed as a residual:

$$Q_{\text{tot}} = Q_{\text{cyc}} + Q_{\text{cal}} \Rightarrow Q_{\text{cal}} = Q_{\text{tot}} - Q_{\text{cyc}}, \quad (14)$$

consistent with the additive decomposition of capacity fade in the underlying semi-empirical Naumann et al. ageing formulation and with the simulation outputs, in which Q_{cal} , Q_{cyc} , and Q_{tot} are computed coherently from the same SOC trajectory. This choice enforces the physical additivity constraint at the regression stage and avoids redundancy that can arise when fitting three separate response surfaces. Because $\hat{Q}_{\text{cal}}$ is obtained by differencing two predictions, its uncertainty reflects the combined prediction errors of $\hat{Q}_{\text{tot}}$ and $\hat{Q}_{\text{cyc}}$; therefore, robustness of the inferred calendar component is supported by the out-of-sample performance of both fitted models (including the external full-year hold-out).

2.3.2. Predictors

For each scenario, the predictor vector $\mathbf{x} \in \mathbb{R}^6$ collects the configuration and operating descriptors

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{bmatrix} = \begin{bmatrix} E/P \\ P_{\text{max}} \\ N_{\text{cyc}} \\ \text{DoD} \\ \text{SOC}_{\text{min}} \\ \text{SOC}_{\text{max}} \end{bmatrix}, \quad (15)$$

where E/P is the energy-to-power ratio (h), P_{max} is the rated power (MW), N_{cyc} is the average cycles-per-day metric derived from the simulated SOC trajectory, $\text{DoD} = \text{SOC}_{\text{max}} - \text{SOC}_{\text{min}}$ is the depth of discharge, and SOC_{min} , SOC_{max} are the lower/upper SOC bounds.

2.3.3. Standardisation and Polynomial Basis

All predictors are z-scored using the training split statistics, i.e., $x_k \leftarrow (x_k - \mu_k)/\sigma_k$. Polynomial degrees 1–4 were evaluated; degree 2 provided the best balance between complexity, accuracy, and cross-entity transfer.

2.3.4. Quadratic Model

For each target $Q \in \{Q_{\text{cyc}}, Q_{\text{tot}}\}$, the degree-2 model is written compactly as

$$\hat{Q} = a_0 + \boldsymbol{\beta}^\top \mathbf{x} + \mathbf{x}^\top \mathbf{H} \mathbf{x}, \quad (16)$$

where $a_0 \in \mathbb{R}$ is the intercept, $\boldsymbol{\beta} \in \mathbb{R}^6$ contains linear coefficients, and $\mathbf{H} \in \mathbb{R}^{6 \times 6}$ is a symmetric matrix capturing quadratic and pairwise interaction effects.

Expanding Equation (16) yields

$$\hat{Q} = a_0 + \sum_{i=1}^6 \beta_i x_i + \sum_{i=1}^6 \gamma_{ii} x_i^2 + \sum_{1 \leq i < j \leq 6} \gamma_{ij} x_i x_j, \quad (17)$$

where γ_{ii} are quadratic coefficients and γ_{ij} are interaction coefficients. The mapping to the matrix form is $H_{ii} = \gamma_{ii}$ and $H_{ij} = H_{ji} = \gamma_{ij}/2$, so that $\mathbf{x}^\top \mathbf{H} \mathbf{x}$ produces each interaction term $x_i x_j$ once (no double counting).

For each target, the training split contains n scenario observations, collected in the response vector $\mathbf{y} \in \mathbb{R}^n$. The corresponding polynomial feature expansion is assembled

in the design matrix $\Phi \in \mathbb{R}^{n \times p}$ by concatenating an intercept column, the standardised predictors, their elementwise squares, and all unique pairwise interactions:

$$\Phi = [\mathbf{1} \mid \mathbf{X} \mid \mathbf{X}^{\odot 2} \mid \{x_i x_j\}_{i < j}], \quad \theta = [a_0; \beta; \{\gamma_{ii}\}; \{\gamma_{ij}\}], \quad (18)$$

where $\mathbf{X} \in \mathbb{R}^{n \times 6}$ stacks the standardised predictor vectors row-wise, $\mathbf{X}^{\odot 2}$ denotes elementwise squaring, and $\{x_i x_j\}_{i < j}$ denotes the set of all unique pairwise products. The parameter vector $\theta \in \mathbb{R}^p$ collects the associated intercept, linear, quadratic, and interaction coefficients.

Model parameters are obtained by penalised least squares:

$$\hat{\theta} = \arg \min_{\theta} \|\mathbf{y} - \Phi \theta\|_2^2 + \mathcal{P}(\theta), \quad (19)$$

with the intercept left unpenalised; θ_{-0} denotes θ with a_0 removed.

2.3.5. Regularised Estimators

The penalty term $\mathcal{P}(\cdot)$ defines the estimator:

$$\text{OLS: } \mathcal{P}(\theta) = 0, \quad (20)$$

$$\text{Ridge: } \mathcal{P}(\theta) = \alpha \|\theta_{-0}\|_2^2, \quad \alpha = 10^{-3}, \quad (21)$$

$$\text{Lasso: } \mathcal{P}(\theta) = \alpha \|\theta_{-0}\|_1, \quad \alpha = 0.1, \quad (22)$$

$$\text{Elastic Net: } \mathcal{P}(\theta) = \alpha \left[\lambda \|\theta_{-0}\|_1 + (1 - \lambda) \|\theta_{-0}\|_2^2 \right], \quad \alpha = 0.1, \lambda = 0.5. \quad (23)$$

Models are fitted separately for Q_{cyc} and Q_{tot} ; Q_{cal} is subsequently computed using Equation (14).

2.4. Training and Validation

The regression dataset was partitioned on a per-entity basis using an 80/20 random split across scenarios. Here, each observation corresponds to a complete, annualised simulation outcome for a unique operating scenario (i.e., a specific combination of E/P , P_{max} , $(\text{SOC}_{\text{min}}, \text{SOC}_{\text{max}})$ and the associated cycling descriptors), rather than minute-level time-series samples. The split, therefore, separates operating scenarios within each entity and avoids temporal leakage at the time-step level. In addition to the within-entity scenario split, an external out-of-sample test was performed by holding out an entire year of data (Belgium 2025) from training and using it exclusively for testing.

All input variables were standardised, and a second-degree polynomial expansion was applied consistently across models. Each regression model was trained separately for Q_{tot} and Q_{cyc} , after which Q_{cal} was reconstructed by difference. Model performance was evaluated using the coefficient of determination (R^2), mean absolute error (MAE), and root mean squared error (RMSE).

Comparative assessments across model types and polynomial degrees indicated that degree-2 polynomial models with the specified regularisation parameters achieved the most accurate and robust predictions across all test cases. These configurations were, therefore, selected as the final models for subsequent degradation prediction and feature-importance analysis.

3. Results and Discussion

3.1. Comparative Models: OLS, Lasso, Ridge, and Elastic Net

Table 2 summarises the cross-entity test performance of OLS, Ridge, Lasso, and Elastic Net. Ridge provides the most reliable transfer across entities, delivering the strongest overall generalisation and the highest frequency of high- R^2 outcomes while maintaining

low error. OLS attains comparable average fit but exhibits weaker stability across entities, consistent with its sensitivity to between-entity covariance shifts in the presence of multicollinearity. In contrast, Lasso and Elastic Net underperform in both accuracy and transferability, indicating that the degradation signal is not sparse but distributed across correlated quadratic and interaction terms. This aligns with the expected behaviour of ℓ_2 -regularisation (which stabilises correlated coefficients and improves transfer) versus ℓ_1 -based penalties (which tend to suppress correlated yet predictive terms), motivating the selection of Ridge for the final specification.

Table 2. Cross-entity test performance (macro-averages across nine entities).

Model	$\overline{R^2}(Q_{\text{cyc}})$	RMSE(Q_{cyc})	$\overline{R^2}(Q_{\text{tot}})$	RMSE(Q_{tot})	Entities with $R^2 \geq 0.90$ (Q_{cyc} and Q_{tot})
Ridge	0.923	0.140	0.894	0.168	7/9 and 5/9
OLS	0.923	0.140	0.894	0.149	6/9 and 4/9
Elastic Net	0.837	0.208	0.810	0.226	2/9 and 2/9
Lasso	0.777	0.245	0.751	0.262	2/9 and 2/9

Entity-wise numbers are reported in the main metrics tables/plots.

3.2. Ridge Regression: Specification, Validation, and Feature Behaviour

The final parametric Ridge equation (second degree, standardised inputs) is shown in Equation (24). For each target $Q \in \{Q_{\text{cyc}}, Q_{\text{tot}}\}$,

$$\begin{aligned}
 \hat{Q} = & a_0 + a_1(E/P) + a_2P_{\text{max}} + a_3N_{\text{cyc}} + a_4\text{DoD} + a_5\text{SOC}_{\text{min}} + a_6\text{SOC}_{\text{max}} \\
 & + a_7(E/P)^2 + a_{13}P_{\text{max}}^2 + a_{18}N_{\text{cyc}}^2 + a_{22}\text{DoD}^2 + a_{25}\text{SOC}_{\text{min}}^2 + a_{27}\text{SOC}_{\text{max}}^2 \\
 & + a_8((E/P)P_{\text{max}}) + a_9((E/P)N_{\text{cyc}}) + a_{10}((E/P)\text{DoD}) + a_{11}((E/P)\text{SOC}_{\text{min}}) \\
 & + a_{12}((E/P)\text{SOC}_{\text{max}}) + a_{14}(P_{\text{max}}N_{\text{cyc}}) + a_{15}(P_{\text{max}}\text{DoD}) + a_{16}(P_{\text{max}}\text{SOC}_{\text{min}}) \\
 & + a_{17}(P_{\text{max}}\text{SOC}_{\text{max}}) + a_{19}(N_{\text{cyc}}\text{DoD}) + a_{20}(N_{\text{cyc}}\text{SOC}_{\text{min}}) + a_{21}(N_{\text{cyc}}\text{SOC}_{\text{max}}) \\
 & + a_{23}(\text{DoD}\text{SOC}_{\text{min}}) + a_{24}(\text{DoD}\text{SOC}_{\text{max}}) + a_{26}(\text{SOC}_{\text{min}}\text{SOC}_{\text{max}}).
 \end{aligned} \quad (24)$$

where E/P [h] is the energy-to-power ratio (an effective C-rate proxy), P_{max} [MW] is the prequalified grid power, N_{cyc} [cycles/day] is the daily cycling intensity, DoD is the cycle depth, and SOC_{min} and SOC_{max} are the operating SOC bounds. Complete coefficient sets $\{a_k\}$ for Q_{tot} and Q_{cyc} are given in Appendix A.2 and Appendix A.1, respectively.

Equation (24) is a second-order parametric response-surface model calibrated to the scenario-level simulation dataset. Quadratic and interaction terms are retained to capture nonlinearities and joint effects among operational levers (e.g., SOC-window policy, duration, and power) that improve predictive fidelity and cross-entity transfer. Accordingly, individual coefficients, particularly interaction terms such as $\text{SOC}_{\text{min}}\text{SOC}_{\text{max}}$, should be interpreted as empirical sensitivities within the studied operating domain, rather than as direct electrochemical causal parameters. Interpretation is, therefore, emphasised at the level of predicted response surfaces, regime boundaries, and policy-relevant trends, not coefficient-level mechanistic attribution.

Feature Importance and Behaviour

Normalised importances exhibit a stable hierarchy across targets. SOC-window terms dominate: $\text{SOC}_{\text{min}}^2$ is the strongest contributor (Q_{cyc} : 0.4104; Q_{tot} : 0.4178), followed by $\text{SOC}_{\text{min}}\text{SOC}_{\text{max}}$ (0.1459; 0.1437), the linear bounds (SOC_{min} : 0.1363 for Q_{cyc} and 0.1372 for Q_{tot} ; SOC_{max} : 0.1363 for Q_{cyc} and 0.1372 for Q_{tot}), and $\text{SOC}_{\text{max}}^2$ (0.0756; 0.0757). The next tier comprises E/P and $E/P \times \text{SOC}$ terms: $(E/P)\text{SOC}_{\text{max}}$ (0.0334; 0.0322), E/P (0.0243;

0.0229), $(E/P) SOC_{\min}$ (0.0213; 0.0163), and $(E/P)^2$ (0.0044; 0.0043). This indicates that sizing (duration versus power) modulates the effective C-rate and high-voltage dwell. DoD-related effects are present but modest relative to SOC and E/P (e.g., $DoD(\%) SOC_{\min}$: 0.0061; 0.0064). Overall, the ranking identifies the SOC policy, especially $SOC_{\min}$ and window width, as the primary operational lever for both Q_{cyc} and Q_{tot} , with E/P and its SOC interactions providing the next-most influential controls. A table of top feature importances is provided in Appendix B.

3.3. Performance Validation Across Countries/TSOs

Table 3 summarises the test performance of the Ridge model for Q_{cyc} and Q_{tot} . All reported test/hold-out results compare surrogate predictions against the annual degradation outputs generated by the end-to-end simulation-and-ageing workflow. These refer to the within-entity 20% hold-out set from the 80/20 split across operating scenarios. In addition, BE/2025 is an out-of-sample evaluation year: a full year of Belgian imbalance inputs held out from training and used exclusively for external testing. Overall, the model maintains high explanatory power across most TSOs, with the external Belgian full hold-out (BE/2025) tracking the in-sample level, evidence of transferability. Performance is consistently strong for Belgium, the Netherlands, and Amprion/50 Hertz/TenneT, while Spain, Poland, and TransnetBW exhibit comparatively larger errors but preserve overall trend fidelity. The corresponding parity panels (Figures 2 and 3) visually corroborate the table: predictions cluster tightly around the 45° line, with mild dispersion at higher degradation levels in the more challenging entities. Collectively, Table 3 and Figures 2 and 3 indicate that the Ridge formulation provides robust cross-entity accuracy without systematic bias.

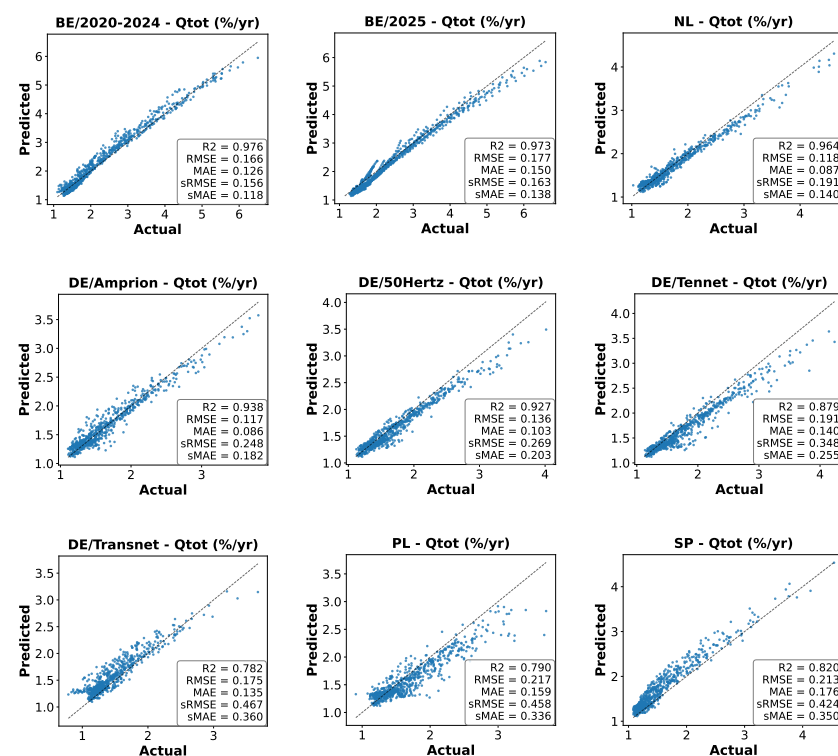


Figure 2. Predicted-actual parity plots for total capacity loss (Q_{tot}) under the Ridge model across all entities. Tight alignment with the 1:1 line indicates strong fidelity and transfer. Belgium, the Netherlands, and Amprion exhibit the closest agreement; TenneT and 50 Hertz remain solid, while Spain and TransnetBW show modest upper-tail dispersion consistent with their higher RMSE. Insets report entity-level R^2 /MAE/RMSE/sMAE/sRMSE.

Table 3. Entity-wise test performance for Ridge (degree 2).

Entity	$R^2(Q_{cyc})$	RMSE(Q_{cyc})	$R^2(Q_{tot})$	RMSE(Q_{tot})
BE/2020–2024	0.9812	0.1460	0.9758	0.1660
BE/2025	0.9811	0.1492	0.9734	0.1769
NL	0.9738	0.0984	0.9637	0.1181
DE/Amprion	0.9710	0.0799	0.9385	0.1170
DE/Tennet	0.9432	0.1273	0.8788	0.1909
DE/50 Hertz	0.9419	0.1212	0.9274	0.1365
DE/Transnet	0.9005	0.1201	0.7823	0.1752
PL	0.8432	0.1826	0.7898	0.2168
SP	0.7700	0.2392	0.8201	0.2131

Metrics are computed on the within-entity test split; BE/2025 is an external hold-out. Parity and residual panels are shown in Figures 2 and 3.

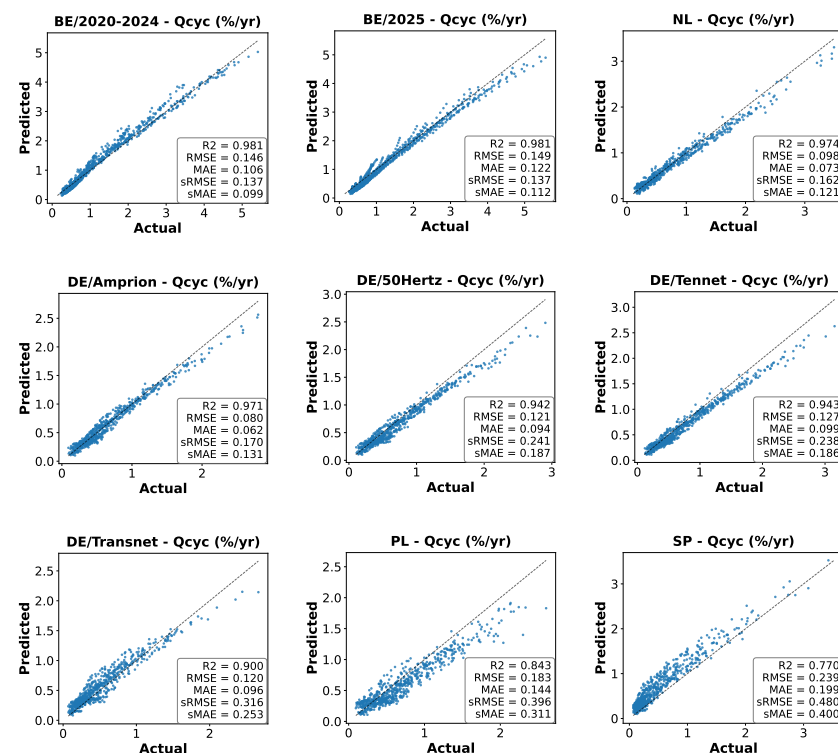


Figure 3. Predicted–actual parity plots for cyclic capacity loss (Q_{cyc}) under the Ridge model across BE (Elia, Belgium), NL (TenneT NL, Netherlands), PL (PSE, Poland), SP (REE, Spain), and the four German TSOs (50 Hertz, Amprion, TenneT DE, TransnetBW). Tight clustering around the 1:1 line indicates strong fidelity. Agreement is closest for Belgium, the Netherlands, and Amprion; 50 Hertz and TenneT DE remain solid, while Spain and Poland (and, to a lesser extent, TransnetBW) exhibit upper-tail dispersion consistent with higher RMSE. Insets report entity-level R^2 /MAE/RMSE/sMAE/sRMSE.

3.4. Cross-Behaviour Analysis of Degradation and Regime Balance

This section synthesises, for each TSO, the behaviour of the annual cycle and calendar capacity loss, Q_{cyc} and Q_{cal} , as a function of the E/P . Figure 4 compares Q_{cyc} , Q_{cal} , and the total loss Q_{tot} for system-imbalance portfolio operation across all countries/TSOs as functions of P_{max} , DoD, and E/P . From the empirical Q_{cyc} – Q_{cal} – E/P panels, three operating bands are delineated: cycle-dominant, mixed/balanced, and calendar-dominant, with the corresponding TSO-level regime boundaries summarised in Table 4. Here, “dominant” denotes a clear separation in magnitude, whereas the mixed band reflects comparable contributions. The reported ranges are approximate and are read from stable visual patterns

along the surface perimeters; the accompanying notes summarise how higher DoD and $P_{\max}$ shift these thresholds.

Table 4. Country/TSO-level balance between cyclic and calendar degradation.

TSO (Country)	$Q_{\text{cyc}}\text{-dom.}$ E/P Band	Mixed/ Balanced	$Q_{\text{cal}}\text{-dom.}$ E/P Band	Sensitivity (DoD/ $P_{\max}$)
Elia (BE)	≤ 3 h	3–6 h	≥ 6 h	Higher DoD and $P_{\max}$ extend Q_{cyc} dominance by ~ 0.5 –1 h.
TenneT NL (NL)	≤ 3 h	3–6 h	≥ 6 h	Similarly to BE; the mixed band widens at high DoD.
PSE (PL)	≤ 3.5 –4 h	~ 4 –6.5 h	≥ 6.5 h	Most right-shifted thresholds; heavy cycling sustains Q_{cyc} at larger E/P .
REE (ES)	≤ 3 h	3–6 h	≥ 6 h	Mixed band broad at high DoD; otherwise near the canonical 3/6 h split.
50 Hertz (DE)	≤ 3 h	3–6 h	≥ 6 h	Canonical split; small right shift under high DoD/ $P_{\max}$.
Amprion (DE)	≤ 3.5 –4 h	~ 4 –6.5 h	≥ 6.5 h	Similarly to PL: prolonged Q_{cyc} dominance to higher E/P .
TenneT DE (DE)	≤ 3 h	3–6 h	≥ 6 h	Near-canonical; thresholds are slightly elastic with DoD.
TransnetBW (DE)	≤ 3 h	3–6 h	≥ 6 h	Near-canonical; minimal shift.

At the European level (all TSOs aggregated), regime boundaries are remarkably consistent, with predictable elasticity under heavier cycling (higher DoD and $P_{\max}$). Table 5 condenses the operating bands, typical behaviours, and design implications.

Table 5. EU-level operating bands (all TSOs aggregated).

E/P Band (h)	Dominant	Typical Behaviour
≤ 3 h (up to ~ 3.5 –4 h under heavy cycling)	Q_{cyc}	High throughput; Q_{cyc} is large (≈ 1.5 –4) and Q_{cal} is low (≈ 0.9 –1.1).
~ 3 –6 h	Mixed	Q_{cyc} decreases with E/P while Q_{cal} increases modestly; magnitudes are comparable (balance region).
≥ 6 h ($\gtrsim 6$ –6.5 h under heavy cycling)	Q_{cal}	Low cycling; $Q_{\text{cal}} \approx 1.1$ –1.3 dominates, while $Q_{\text{cyc}} \approx 0$ –1.

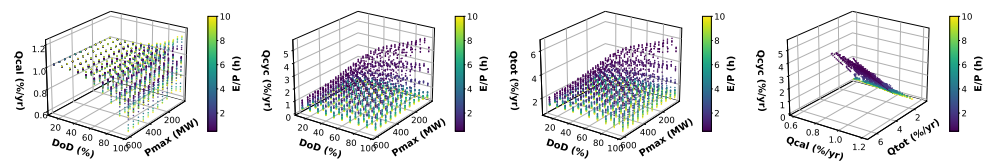
Across TSOs, $E/P \approx 3$ h marks the onset of a mixed regime from a Q_{cyc} -dominated one; $E/P \approx 6$ h marks the transition to Q_{cal} -dominated behaviour. Depth of discharge and $P_{\max}$ reshape these boundaries: higher DoD and $P_{\max}$ (a) raise Q_{cyc} monotonically, most strongly at low E/P (high effective C-rate), and (b) shift the E/P thresholds right by ~ 0.5 –1 h (most visible for PL and DE–Amprion), because heavier cycling keeps Q_{cyc} relevant at longer duration. In contrast, Q_{cal} is nearly insensitive to $P_{\max}$, increases only mildly with DoD, and grows with E/P owing to longer dwell at elevated SOC; thus at $E/P \gtrsim 6$ –8 h with DoD $\lesssim 40$ –50% and moderate $P_{\max}$, Q_{cal} typically exceeds Q_{cyc} .

Quantitatively, three planning envelopes at 25°C summarise cross-entity behaviour:

- Cycling-leaning ($E/P \leq 3$ h; DoD $\geq 70\%$; $P_{\max}$ high): $Q_{\text{cal}} \approx 1.0$ –1.3%/yr, $Q_{\text{cyc}} \approx 2.0$ –4.0%/yr (up to $\sim 6.5\%$ /yr in the most severe corner), $Q_{\text{tot}} \approx 3.0$ –5.0 + %/yr.
- Balanced-regime ($E/P \approx 4$ –6 h; DoD ≈ 50 –70%): $Q_{\text{cal}} \approx 1.0$ –1.4%/yr, $Q_{\text{cyc}} \approx 0.8$ –1.8%/yr, $Q_{\text{tot}} \approx 1.8$ –3.2%/yr.
- Calendar-leaning (E/P high; DoD moderate/low; $P_{\max}$ moderate): $Q_{\text{cal}} \approx 1.0$ –1.5%/yr, $Q_{\text{cyc}} \approx 0.4$ –1.0%/yr, $Q_{\text{tot}} \approx 1.5$ –2.5%/yr.

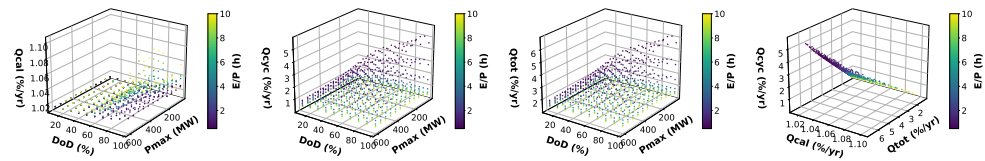
For imbalance management, sizing purely for high availability to cover volatile deviations pushes designs to larger E/P , improving coverage but moving assets into calendar-dominated ageing; sizing too small (low E/P) maximises cycling opportunity but risks coverage shortfalls and shifts wear towards Q_{cyc} . A portfolio-level compromise of $E/P \sim 4$ –5.5 h sits squarely in the EU-wide balance region; operators can then steer the dominant wear mode via operational DoD while maintaining availability without a step change in lifetime drivers.

Elia - Belgium (2020-2024)



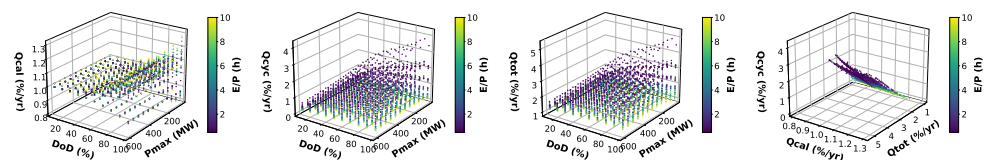
(a)

Elia - Belgium (2025)



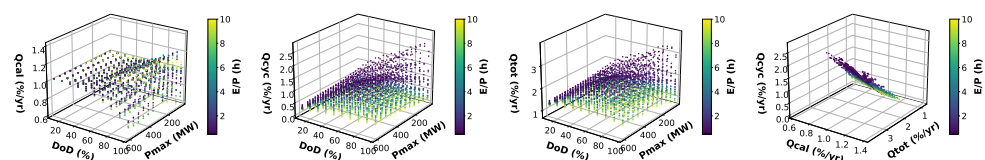
(b)

TenneT - Netherlands



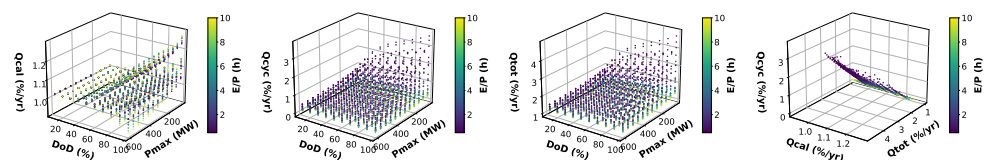
(c)

PSE - Poland



(d)

Red Elctrica - Spain



(e)

Figure 4. Cont.

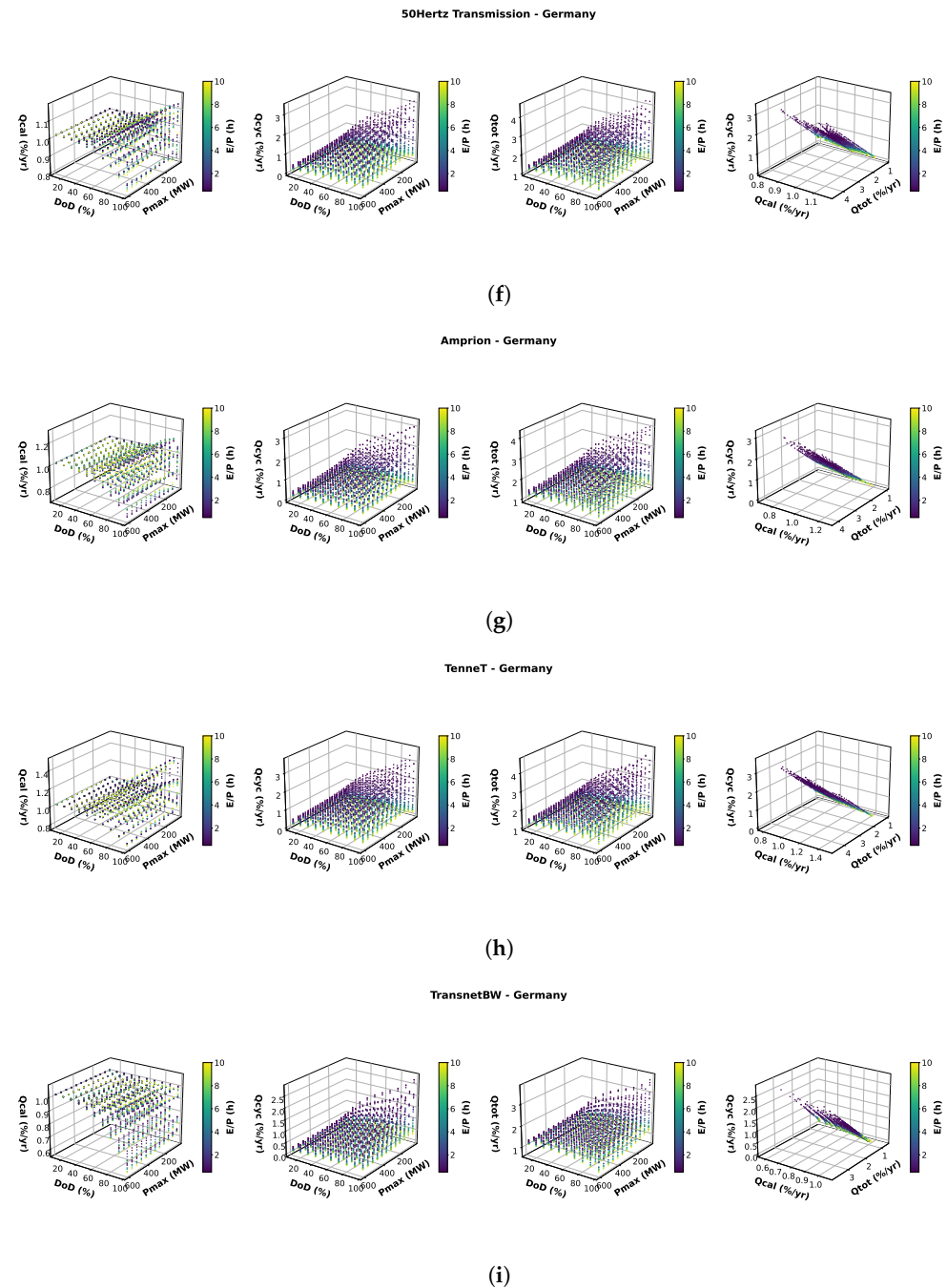


Figure 4. (a–e) Cross-behaviour of Q_{cal} , Q_{cyc} , and Q_{tot} versus P_{max} , depth of discharge (DoD), and E/P (non-German entities). Panels: (a) Belgium—Elia (2020–2024); (b) Belgium—Elia (2025, hold-out); (c) Netherlands—TenneT NL; (d) Poland—PSE; (e) Spain—REE. Each panel shows Q_{cal} , Q_{cyc} , and Q_{tot} (left to right), with colour indicating E/P . (f–i) Cross-behaviour of Q_{cal} , Q_{cyc} , and Q_{tot} versus P_{max} , depth of discharge (DoD), and E/P (German TSOs). Panels: (f) Germany—50 Hertz; (g) Germany—Amprion; (h) Germany—TenneT DE; (i) Germany—TransnetBW.

4. Conclusions and Context-Specific Recommendations

This work develops a compact, coefficientised degradation model for utility-scale LFP BESS operated under European system-imbalance conditions at 25 °C. The principal contribution is an auditable, scenario-parameterised representation of annual capacity loss that yields Q_{cyc} , Q_{cal} , and Q_{tot} as explicit functions of E/P , P_{max} , DoD, daily cycling intensity N_{cyc} , and SOC bounds (SOC_{min} , SOC_{max}). By expressing degradation in coefficient form, the proposed model is directly usable as a transparent benchmark for

system-imbalance techno-economic assessment and planning across EU jurisdictions where detailed electro-thermal telemetry is unavailable.

A second-degree polynomial specification with standardised inputs was evaluated across multiple linear estimators. Ridge regression ($\alpha = 10^{-3}$) provided the most reliable generalisation across entities, consistent with a degradation signal distributed across correlated quadratic and interaction terms. Cross-entity testing (Table 2) confirms robust transferability across TSOs, and a full-year external hold-out (Belgium, 2025) provides an additional out-of-sample validation of the fitted response surfaces.

Beyond predictive performance, the fitted surfaces reveal consistent regime-level structure across countries and TSOs. Cycling-induced loss Q_{cyc} intensifies at low E/P (high effective C-rate), higher P_{max} , and deeper DoD, whereas calendar-induced loss Q_{cal} increases with sustained SOC dwell and is therefore promoted by higher E/P and elevated SOC operation. Consequently, Q_{tot} transitions from cycling-dominant behaviour at low E/P to calendar-dominant behaviour at high E/P , with an intermediate mixed regime. At the EU level, this yields a practical sizing interpretation: $E/P \lesssim 3$ h is predominantly cycling-driven, $E/P \approx 3\text{--}6$ h is mixed, and $E/P \gtrsim 6$ h is predominantly calendar-driven, with the boundaries shifting with stress intensity (DoD and P_{max}).

Actionable Recommendations

- (a) Size within the mixed regime where possible: For stand-alone imbalance duty, $E/P \approx 4\text{--}5.5$ h provides a balanced operating region in which availability is improved without a step change toward calendar-dominant ageing. Selections of $E/P \geq 6$ h should be justified by explicit availability requirements, whereas $E/P \leq 3$ h should be supported by portfolio-level coverage of large excursions.
- (b) Prioritise disciplined SOC policy: The SOC window is a dominant operational lever. Avoid high-SOC dwell and excessively wide windows; favour mid-SOC parking in the absence of events and maintain a conservative SOC_{min} consistent with the required discharge headroom.
- (c) Manage cycling stress under sustained deviations: Limit prolonged deep cycling by constraining effective DoD and moderating P_{max} during extended imbalance events. Where feasible, distribute correction through more frequent shallow actions rather than infrequent deep cycles to reduce Q_{cyc} .
- (d) Use the coefficientised model as a TEA benchmark: Techno-economic studies for imbalance services should represent both cycle and calendar ageing. Where detailed duty-cycle or thermal data are not available, the coefficientised outputs provided here can be applied as a transparent benchmark for annual degradation, using Q_{cyc} , Q_{tot} , and $Q_{\text{cal}} = Q_{\text{tot}} - Q_{\text{cyc}}$.

The framework is TEA-ready: the coefficientised equations support scenario screening, sizing studies, and SOC-policy design for BRP imbalance portfolios, and they can be embedded in optimisation workflows that balance availability, revenue, and lifetime cost. Feature-importance results (Appendix B) confirm SOC-window terms as dominant drivers, followed by E/P and its SOC interactions, with throughput-related interactions becoming more relevant under high-stress operation.

Two scope limitations remain. First, temperature is fixed at 25 °C, reflecting the common assumption that utility-scale, containerised BESS employ thermal-management systems to maintain operation near a nominal setpoint; future work may extend the framework to explicitly quantify deviations from this assumption. Second, while cross-entity generalisation is strong for imbalance duty, validation for other duty types (e.g., peak shaving and reserves) is left for future work. A focused next step is to embed the

degradation model in a techno-economic optimisation that jointly prices cycle and calendar ageing and quantifies the marginal cost of availability across historical imbalance traces.

Author Contributions: Conceptualization, S.O.E.; methodology, S.O.E.; software, S.O.E.; validation, S.O.E. and J.K.; formal analysis, S.O.E.; investigation, S.O.E.; resources, S.O.E. and J.K.; data curation, S.O.E.; writing—original draft preparation, S.O.E.; writing—review and editing, S.O.E. and J.K.; visualisation, S.O.E.; supervision, J.K.; project administration, S.O.E. and J.K. All authors have read and agreed to the published version of the manuscript.

Funding: We acknowledge support by the German Research Foundation and the Open Access Publication Fund of TU Berlin.

Data Availability Statement: The data presented in this study are available from the corresponding author upon reasonable request.

Acknowledgments: During the preparation of this work, the authors used ChatGPT (OpenAI; GPT-5.1) in order to assist with drafting, refining language, and improving clarity of presentation. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations and symbols are used in this manuscript:

BRP	Balancing Responsible Party
BESS	Battery Energy Storage System
LFP	Lithium Iron Phosphate
TEA	Techno-Economic Assessment
TSO	Transmission System Operator
ENTSO-E	European Network of Transmission System Operators for Electricity
EBGL	Electricity Balancing Guideline
ISP	Imbalance Settlement Period
UTC	Coordinated Universal Time
SI	System Imbalance
OLS	Ordinary Least Squares
LASSO	Least Absolute Shrinkage and Selection Operator
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
R^2	Coefficient of determination
sMAE	Scaled mean absolute error
sRMSE	Scaled root mean squared error
E/P	Energy-to-power ratio (duration proxy)
$P_{\max}$	Maximum (prequalified) power
N_{cyc}	Daily cycling intensity (cycles/day)
DoD	Depth of discharge
SOC	State of charge
$\text{SOC}_{\min}$	Lower SOC bound
$\text{SOC}_{\max}$	Upper SOC bound
Q_{cyc}	Annual cyclic capacity loss
Q_{cal}	Annual calendar capacity loss
Q_{tot}	Annual total capacity loss

BE	Belgium
NL	Netherlands
DE	Germany
PL	Poland
ES	Spain
Elia	Belgium TSO
TenneT NL	Netherlands TSO
PSE	Poland TSO (Polskie Sieci Elektroenergetyczne)
REE	Spain TSO (Red Eléctrica de España)
50 Hertz	German TSO
Amprion	German TSO
TenneT DE	German TSO
TransnetBW	German TSO

Appendix A. Ridge Coefficients and Closed-Form Models

All models use standardized inputs and a degree-2 polynomial basis. The intercept is not penalized. In this appendix N_{cyc} denotes cycles per day. Calendar loss is reported via the residual definition

$$\hat{Q}_{cal} = \hat{Q}_{tot} - \hat{Q}_{cyc}. \quad (A1)$$

Appendix A.1. Cyclic Loss Model $\hat{Q}_{cyc}$

Table A1. Ridge coefficients for the cyclic loss model $\hat{Q}_{cyc}$ (degree-2).

Symbol	Term	Value
a_0	Intercept	0.43370504
a_1	E/P	-0.037743268
a_2	P_{max}	3.9176498×10^{-5}
a_3	N_{cyc}	0.001487032
a_4	DoD	0.0010598648
a_5	SOC_{min}	-0.21197298
a_6	SOC_{max}	0.21197298
a_7	$(E/P)^2$	0.0068779559
a_8	$(E/P) P_{max}$	2.3831506×10^{-5}
a_9	$(E/P) N_{cyc}$	-0.00033347328
a_{10}	$(E/P) DoD$	-0.00057625259
a_{11}	$(E/P) SOC_{min}$	-0.033087238
a_{12}	$(E/P) SOC_{max}$	-0.052017935
a_{13}	P_{max}^2	$-5.4467615 \times 10^{-7}$
a_{14}	$P_{max} N_{cyc}$	$-8.8147812 \times 10^{-7}$
a_{15}	$P_{max} DoD$	$-8.4894949 \times 10^{-8}$
a_{16}	$P_{max} SOC_{min}$	0.00015575948
a_{17}	$P_{max} SOC_{max}$	2.4021368×10^{-5}
a_{18}	N_{cyc}^2	$-1.5267926 \times 10^{-6}$
a_{19}	$N_{cyc} DoD$	2.0586156×10^{-5}

Table A1. *Cont.*

Symbol	Term	Value
a_{20}	$N_{\text{cyc}} \text{SOC}_{\text{min}}$	0.00321675
a_{21}	$N_{\text{cyc}} \text{SOC}_{\text{max}}$	0.0017971117
a_{22}	DoD^2	5.6723442×10^{-6}
a_{23}	$\text{DoD} \text{SOC}_{\text{min}}$	0.0094170521
a_{24}	$\text{DoD} \text{SOC}_{\text{max}}$	0.00079726299
a_{25}	$\text{SOC}_{\text{min}}^2$	−0.63844033
a_{26}	$\text{SOC}_{\text{min}} \text{SOC}_{\text{max}}$	−0.22689383
a_{27}	$\text{SOC}_{\text{max}}^2$	0.11757815

Appendix A.2. Total Loss Model $\hat{Q}_{\text{tot}}$ **Table A2.** Ridge coefficients for the total loss model $\hat{Q}_{\text{tot}}$ (degree-2).

Symbol	Term	Value
b_0	Intercept	1.417728
b_1	E/P	−0.035978105
b_2	P_{max}	6.6073963×10^{-5}
b_3	N_{cyc}	0.0015216873
b_4	DoD	0.0010786251
b_5	SOC_{min}	−0.21572504
b_6	SOC_{max}	0.21572501
b_7	$(E/P)^2$	0.0067200451
b_8	$(E/P) P_{\text{max}}$	1.8052712×10^{-5}
b_9	$(E/P) N_{\text{cyc}}$	−0.00038919497
b_{10}	$(E/P) \text{DoD}$	−0.00057379236
b_{11}	$(E/P) \text{SOC}_{\text{min}}$	−0.025563053
b_{12}	$(E/P) \text{SOC}_{\text{max}}$	−0.050574177
b_{13}	P_{max}^2	$-5.9769256 \times 10^{-7}$
b_{14}	$P_{\text{max}} N_{\text{cyc}}$	$-1.0815026 \times 10^{-6}$
b_{15}	$P_{\text{max}} \text{DoD}$	1.8252497×10^{-8}
b_{16}	$P_{\text{max}} \text{SOC}_{\text{min}}$	0.00022469141
b_{17}	$P_{\text{max}} \text{SOC}_{\text{max}}$	4.8399153×10^{-5}
b_{18}	N_{cyc}^2	-1.58117×10^{-6}
b_{19}	$N_{\text{cyc}} \text{DoD}$	2.0749117×10^{-5}
b_{20}	$N_{\text{cyc}} \text{SOC}_{\text{min}}$	0.0035044117
b_{21}	$N_{\text{cyc}} \text{SOC}_{\text{max}}$	0.001826607
b_{22}	DoD^2	5.6479658×10^{-6}
b_{23}	$\text{DoD} \text{SOC}_{\text{min}}$	0.010020273
b_{24}	$\text{DoD} \text{SOC}_{\text{max}}$	0.00080428759
b_{25}	$\text{SOC}_{\text{min}}^2$	−0.65694676
b_{26}	$\text{SOC}_{\text{min}} \text{SOC}_{\text{max}}$	−0.22591869
b_{27}	$\text{SOC}_{\text{max}}^2$	0.11900439

Appendix B. Feature-Importance Analysis

Normalised permutation/GINI importances indicate that SOC-window terms dominate both targets, followed by E/P and $E/P \times \text{SOC}$ interactions; throughput-related terms (e.g., interactions involving daily cycling intensity) are present but secondary. Tables A3 and A4 report the top-10 features for Q_{cyc} and Q_{tot} , respectively.

Table A3. Top-10 normalised feature importances for Q_{cyc} .

Rank	Feature	Importance
1	SOC_{min}^2	0.4104
2	$SOC_{min}SOC_{max}$	0.1459
3	SOC_{min}	0.1363
4	SOC_{max}	0.1363
5	SOC_{max}^2	0.0756
6	$(E/P) SOC_{max}$	0.0334
7	E/P	0.0243
8	$(E/P) SOC_{min}$	0.0213
9	$DoD (\%) SOC_{min}$	0.0061
10	$(E/P)^2$	0.0044

Table A4. Top-10 normalised feature importances for Q_{tot} .

Rank	Feature	Importance
1	SOC_{min}^2	0.4178
2	$SOC_{min}SOC_{max}$	0.1437
3	SOC_{min}	0.1372
4	SOC_{max}	0.1372
5	SOC_{max}^2	0.0757
6	$(E/P) SOC_{max}$	0.0322
7	E/P	0.0229
8	$(E/P) SOC_{min}$	0.0163
9	$DoD (\%) SOC_{min}$	0.0064
10	$(E/P)^2$	0.0043

References

- European Commission, Directorate-General for Energy. Key Facts on Energy Storage. European Commission—Energy. 2025. Available online: https://energy.ec.europa.eu/topics/research-and-technology/energy-storage/key-facts-energy-storage_en (accessed on 5 August 2025).
- European Parliament and the Council of the European Union. Regulation (EU) 2019/943 of 5 June 2019 on the internal market for electricity (recast). *Off. J. Eur. Union* **2019**, *158*, 54–124.
- European Commission. Commission Regulation (EU) 2017/2195 of 23 November 2017 establishing a guideline on electricity balancing (EBGL). *Off. J. Eur. Union* **2017**, *312*, 6–53.
- ENTSO-E; EFET; ebIX. *The Harmonised Electricity Market Role Model*; Version 2020-01; ENTSO-E: Brussels, Belgium, 2020.
- Chen, T.; Li, M.; Bae, J. Recent Advances in Lithium Iron Phosphate Battery Technology: A Comprehensive Review. *Batteries* **2024**, *10*, 424. <https://doi.org/10.3390/batteries10120424>.
- Yarimca, G.; Cetkin, E. Review of Cell Level Battery (Calendar and Cycling) Aging Models: Electric Vehicles. *Batteries* **2024**, *10*, 374. <https://doi.org/10.3390/batteries10110374>.
- Lam, V.N.; Cui, X.; Stroebel, F.; Uppaluri, M.; Onori, S.; Chueh, W.C. A decade of insights: Delving into calendar aging trends and implications. *Joule* **2025**, *9*, 101796. <https://doi.org/10.1016/j.joule.2024.11.013>.
- García-Miguel, P.L.C.; Alonso-Martínez, J.; Arnaltes Gómez, S.; García Plaza, M.; Asensio, A.P. A review on the degradation implementation for the operation of battery energy storage systems. *Batteries* **2022**, *8*, 110. <https://doi.org/10.3390/batteries8090110>.
- Wankmüller, F.; Thimmapuram, P.R.; Gallagher, K.G.; Botterud, A. Impact of battery degradation on energy arbitrage revenue of grid-level energy storage. *J. Energy Storage* **2017**, *10*, 56–66. <https://doi.org/10.1016/j.est.2016.12.004>.
- Schade, C.; Egging-Bratseth, R. Battery degradation: Impact on economic dispatch. *Energy Storage* **2024**, *6*, e588. <https://doi.org/10.1002/est2.588>.
- Reniers, J.M.; Mulder, G.; Ober-Blöbaum, S.; Howey, D.A. Improving optimal control of grid-connected lithium-ion batteries through more accurate battery and degradation modelling. *arXiv* **2018**, arXiv:1710.04552v3.
- Sui, H.; Zhang, X.; Qin, Y.; Chen, L.; Liu, L. The degradation behavior of $LiFePO_4/C$ batteries during long-term calendar aging. *Energies* **2021**, *14*, 1732. <https://doi.org/10.3390/en14061732>.
- Birkel, C.R.; Howey, D.A. Model identification and parameter estimation for $LiFePO_4$ batteries. In Proceedings of the IET Hybrid and Electric Vehicles Conference 2013, London, UK, 6–7 November 2013. <https://doi.org/10.1049/cp.2013.1889>.

14. Alavi, B.N.; Birkel, C.R.; Howey, D.A. Time-domain fitting of battery electrochemical impedance models. *J. Power Sources* **2015**, *288*, 345–352. <https://doi.org/10.1016/j.jpowsour.2015.04.099>.
15. O’Kane, S.E.J.; Ai, W.; Madabattula, G.; Alonso-Alvarez, D.; Timms, R.; Sulzer, V.; Edge, J.S.; Wu, B.; Offer, G.J.; Marinescu, M. Lithium-ion battery degradation: How to model it. *Phys. Chem. Chem. Phys.* **2022**, *24*, 7909–7922. <https://doi.org/10.1039/D2CP00417H>.
16. Collath, M.; Cornejo, A.; Engwerth, S.; Hesse, H.C.; Jossen, A. Increasing the lifetime profitability of battery energy storage systems through aging aware operation. *Appl. Energy* **2023**, *348*, 121531. <https://doi.org/10.1016/j.apenergy.2023.121531>.
17. Elia Group. *Imbalance Prices Per Quarter-Hour (Historical Data—Up to 22/05/2024)*; Dataset ID: Ods047; Elia Open Data Portal: Brussels, Belgium, 2025.
18. Elia Group. *Imbalance Prices Per Quarter-Hour (Historical Data as of 22/05/2024)*; Dataset ID: Ods134; Elia Open Data Portal: Brussels, Belgium, 2025.
19. Elia Group. *Imbalance Prices Per Quarter-Hour (Near Real-Time)*; Dataset ID: Ods162; Elia Open Data Portal: Brussels, Belgium, 2025.
20. TenneT TSO B.V. *Settlement Prices—Imbalance Prices Per Balancing Time Unit (API)*; TenneT Developer Portal: Arnhem, The Netherlands, 2025.
21. ENTSO-E Transparency Platform. *Balancing → Imbalance (Price and Components; Total Imbalance)—Interactive Data View*; ENTSO-E AISBL: Brussels, Belgium, 2025.
22. Schimpe, M.; Truong, C.N.; Naumann, M.; Jossen, A.; Hesse, H.C.; Reniers, J.M.; Howey, D.A. Marginal costs of battery system operation in energy arbitrage based on energy losses and cell degradation. In Proceedings of the 2018 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), Sarajevo, Bosnia and Herzegovina, 21–25 October 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6.
23. Naumann, M.; Schimpe, M.; Keil, P.; Hesse, H.C.; Jossen, A. Analysis and modeling of calendar aging of a commercial LiFePO₄/graphite cell. *J. Energy Storage* **2018**, *17*, 153–169.
24. Naumann, M.; Spingler, F.B.; Jossen, A. Analysis and modeling of cycle aging of a commercial LiFePO₄/graphite cell. *J. Power Sources* **2020**, *451*, 227666.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.