PhD Forum Abstract: Degradation-Aware Adaptive Design of Multi-Use Battery Energy Storage under Deep Uncertainty

Lixin Li
Institute of Electrical Engineering
Karlsruhe Institute of Technology
Karlsruhe, Baden-Württemberg, Germany
lixin.li@kit.edu

Marc Hiller
Institute of Electrical Engineering
Karlsruhe Institute of Technology
Karlsruhe, Baden-Württemberg, Germany
marc.hiller@kit.edu

Abstract

Behind-the-meter battery energy storage systems (BESS) face a tension between expected-cost efficiency and worst-case reliability, compounded by the nonlinear coupling between dispatch and cell degradation. This dissertation develops a degradation-aware, adaptive distributionally robust optimization (DRO) framework for multi-use BESS co-sizing and scheduling under deep uncertainty in load, prices, and aging. Building on a sequence of prior contributions (deterministic MILP, scenario-based SAA), it culminates in a Wasserstein DRO formulation with a physics-based piecewise-linear (PWL) aging surrogate and an explicit resilience recourse. The central claim, that operational resilience can substitute 10–20% of static capacity redundancy at comparable conditional-value-at-risk (CVaR) reliability and lower expected lifecycle cost, is under validation on 2019–2024 German market data.

Keywords

BESS sizing, degradation-aware optimization, distributionally robust optimization, operational resilience, multi-use storage

ACM Reference Format:
Lixin Li and Marc Hiller. 2026. PhD Forum Abstract: Degradation-Aware Adaptive Design of Multi-Use Battery Energy Storage under Deep Uncertainty. In *ACM Sustainability Week 2026 (ACM Sustainability Week Companion '26), June 22–25, 2026, Banff, AB, Canada.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3765611.3815014

1 Motivation and Problem Domain

Behind-the-meter facilities (industrial loads, commercial buildings, AI data centers) deploy PV+BESS for stacked objectives: cost minimization under dynamic tariffs, peak shaving, carbon arbitrage, and backup resilience. Sizing such a multi-use BESS is inseparable from dispatch and from long-horizon uncertainty in load, prices, and aging. Three gaps motivate this thesis. (G1) Sizing frameworks either optimize expected cost via sample average approximation (SAA), risking infeasibility under out-of-distribution events, or enforce worst-case feasibility on parametric uncertainty sets and over-invest; neither lets conservatism be tuned to data. (G2) Battery aging is routinely linearized as an operation-agnostic throughput proxy, decoupled from the service mix being chosen [1]. (G3) Under extreme events, operators consciously violate normal operating limits (deeper depth-of-discharge, terminal state-of-energy depletion) to keep the system running, a practice formal sizing models replace with static oversizing.

This work is licensed under a Creative Commons Attribution 4.0 International License.
ACM Sustainability Week Companion '26, Banff, AB, Canada
© 2026 Copyright held by the owner/author(s).
ACM ISBN 979-8-4007-2199-1/26/06
https://doi.org/10.1145/3765611.3815014

2 Thesis Statement

Operational resilience, the ability to consciously violate normal operating constraints under extreme scenarios while accounting for the induced degradation cost, can substitute 10–20% of static capacity redundancy at comparable CVaR-based reliability and lower expected lifecycle cost, when evaluated out-of-sample on the same reference distribution. I formalize this as a two-stage Wasserstein DRO problem in which the radius ε controls distributional uncertainty, the aging-surrogate approximation error enters the out-of-sample bound additively as a separate budget rather than being folded into ε, and the second-stage recourse adaptively switches between normal and resilient modes with an explicit aging penalty on the latter.

3 Research Progress to Date

The methodological core has been built incrementally over four years of peer-reviewed work, each stage exposing the limitation that drove the next. A deterministic MILP established the co-sizing problem without uncertainty or aging. A stochastic MPC with chance-constrained dispatch incorporated Xu's nonlinear cycle-aging model [6] but only as an offline evaluator. The next stage embedded aging in the planning objective and used CVaR on a finite scenario set, leaving tail events softly penalized. The most recent stage enforces hard feasibility on a heuristically constructed critical set $\mathcal{S}_{\text{crit}}$ while amortizing linear throughput aging and a carbon externality. Three residual weaknesses define the remaining PhD work: $\mathcal{S}_{\text{crit}}$ has no statistical coverage guarantee under the data-generating distribution; linear throughput aging is inconsistent with the underlying electrochemical model; and the terminal-state relaxation under critical scenarios is unnamed, unpriced, and unaging-penalized. Addressing all three in a single tractable framework is the PhD contribution.

4 Methodological Architecture

The thesis decomposes into three contributions targeted at G1–G3.

C1 (G2): a service-differentiated aging surrogate. Building on Naumann's semi-empirical calendar and cycle aging models for commercial LFP/graphite cells [4, 5], I develop a PWL surrogate $f_{\text{deg}}^{\text{PWL}}(P, \text{SoC}, \text{svc})$ whose marginal aging cost differs by service (peak shaving cycle-dominated, arbitrage calendar-dominated, carbon arbitrage adding cycling in high-emission hours). An error-propagation result bounds the NPV deviation by $K\delta$ under Lipschitz continuity, with K characterized explicitly. Validation is on LFP/graphite; generalization to NMC/LTO is a separate calibration step.

C2 (G1): a Wasserstein DRO framework. The predecessor's scenario structure is replaced by a two-stage formulation with explicit recourse:

$$\min_{x \in \mathcal{X}} C^{\mathrm{inv}}(x) + \sup_{Q \in \mathcal{P}} \mathbb{E}_Q \left[\min_{y \in \mathcal{Y}(x,\xi)} C^{\mathrm{op}}(x, y, \xi) + C^{\mathrm{deg}}_{\mathrm{PWL}}(y, \xi) \right],$$

with type-1 Wasserstein ambiguity set $\mathcal{P} = \{Q : W_1(Q, \widehat{Q}_N) \leq \varepsilon\}$ [3]. The surrogate error δ and the K-medoids scenario-reduction error do not enter ε; they appear as separate additive terms in the out-of-sample bound. The formulation reduces to the SAA predecessor as $\varepsilon \to 0$, and the radius can be adapted to the sample size and target reliability.

C3 (G3): explicit resilience recourse. Under pre-identified extreme scenarios, constraints are consciously violated (deep DoD below $\mathrm{SoC}_{\min}$, terminal depletion below $0.5\,E_{\mathrm{cap}}$) at an aging cost extrapolated from the calibrated surrogate, with sensitivity on the extrapolation. Value of Resilience (VoR) is defined under a common evaluation criterion, namely out-of-sample expected lifecycle cost on the reference distribution $P^\star$ at matched CVaR_α reliability:

$$\mathrm{VoR} = \mathbb{E}_{P^\star}\left[C(x^\star_{\mathrm{rob}}, \xi)\right] - \mathbb{E}_{P^\star}\left[C(x^\star_{\mathrm{DRO+rec}}, \xi)\right].$$

5 Current Work: Tri-Level Decomposition for the Sizing Subproblem

The immediate focus (Thesis Chapter 3, under active implementation) is a tractable algorithmic realisation of C1 combined with the degradation-aware sizing subproblem of C2 in the SAA limit ($\varepsilon = 0$), as the stepping stone to the full DRO of Chapter 4. The problem couples a year-long dispatch with a nonconvex end-of-life SOH constraint $\mathrm{SOH}_T \geq 0.80$ over a two-dimensional nominal capacity $(E_{\mathrm{nom}}, P_{\mathrm{nom}})$. A monolithic MILP is intractable; heuristic capacity sweeps forfeit optimality certificates. I adopt a three-layer decomposition; this is the architecture I use, not a uniqueness claim, and the trade-offs against flatter alternatives (penalty-based collapse, full Benders) are discussed in Chapter 3.

- **Outer layer.** Bayesian optimisation over $(E_{\mathrm{nom}}, P_{\mathrm{nom}})$, justified by the noisy and non-smooth dependence of the inner optimal value on capacity (induced by successive convex approximation and scenario sampling), which makes gradient/subgradient cuts unreliable in this two-dimensional setting.
- **Middle layer.** Bisection search for the Lagrange multiplier λ on the EOL-SOH inequality, with the shadow-price interpretation following He et al. [2] and KKT complementarity.
- **Inner layer.** Successive convex approximation (SCA) MILP over K-medoids representative days with weights w_d. All aging quantities are unified in life-fraction units ($L = Q_{\mathrm{loss}}/0.20$). Annual cycle and calendar aging are aggregated as weighted sums across representative days; the resulting aggregation error is quantified in Chapter 3 by comparing against a chronological 52-week schedule on a benchmark instance.

A residual value $\mathrm{RV} = \mathrm{CAPEX} \cdot \max(0, \mathrm{SOH}_T - 0.80)/0.20$ is embedded in NPV to prevent systematic undersizing. A 10-year engineering horizon with inequality SOH constraint is adopted. Convergence of the overall three-layer scheme is established empirically; a weak convergence argument under noiseless inner solves is sketched in Chapter 3.

6 Planned Work and Open Questions

Chapter 4 replaces the inner SCA-MILP's fixed scenario set with the type-1 Wasserstein ball of C2 and integrates the resilience recourse of C3. Because the mode-switching recourse introduces binary second-stage variables, strong duality fails in general; I adopt Column-and-Constraint Generation following the integer-recourse extensions of Hanasusanto and Kuhn, benchmarked against a linear decision rule approximation as fallback. A degradation-aware acceleration pre-computes active PWL breakpoints in the worst-case subproblem, reducing subproblem size by roughly 40% on Chapter 3 instances. Chapter 5 quantifies VoR on a 2019–2024 German benchmark (factory load, KIT PV, EPEX spot, Electricity Maps carbon intensity), handling the 2022 energy-crisis regime shift through stratified evaluation with 2022 as an out-of-sample stress test.

Open questions on which feedback is particularly sought:

(1) In the out-of-sample bound, the statistical term $L\varepsilon$, the surrogate term $K\delta$, and the scenario-reduction term enter additively. How can their magnitudes be identified from data, so the design budget is allocated across ε, δ, and the reduction tolerance rather than by judgment?
(2) Does the tri-level architecture persist under alternative ambiguity sets (moment-based, ϕ-divergence), or is it specific to the transport structure of Wasserstein?
(3) VoR is defined here as an expected-cost difference at matched CVaR reliability, but it lacks an axiomatic basis comparable to coherent risk measures. What properties (monotonicity in tail thickness, subadditivity across services, invariance under cost reparameterization) should a well-defined Value of Resilience satisfy, and is resilience recourse meaningful when the tail itself is only partially known?

References

[1] Nils Collath, Martin Cornejo, Veronika Engwerth, Holger Hesse, and Andreas Jossen. 2023. Increasing the lifetime profitability of battery energy storage systems through aging aware operation. *Applied Energy* 348 (2023), 121531.
[2] Guannan He, Soummya Kar, Javad Mohammadi, Panayiotis Moutis, and Jay F Whitacre. 2020. Power system dispatch with marginal degradation cost of battery storage. *IEEE Transactions on Power Systems* 36, 4 (2020), 3552–3562.
[3] Peyman Mohajerin Esfahani and Daniel Kuhn. 2018. Data-driven distributionally robust optimization using the Wasserstein metric: Performance guarantees and tractable reformulations. *Mathematical Programming* 171, 1 (2018), 115–166.
[4] Maik Naumann, Michael Schimpe, Peter Keil, Holger C Hesse, and Andreas Jossen. 2018. Analysis and modeling of calendar aging of a commercial LiFePO4/graphite cell. *Journal of Energy Storage* 17 (2018), 153–169.
[5] Maik Naumann, Franz B Spingler, and Andreas Jossen. 2020. Analysis and modeling of cycle aging of a commercial LiFePO4/graphite cell. *Journal of Power Sources* 451 (2020), 227666.
[6] Bolun Xu, Jinye Zhao, Tongxin Zheng, Eugene Litvinov, and Daniel S Kirschen. 2017. Factoring the cycle aging cost of batteries participating in electricity markets. *IEEE Transactions on Power Systems* 33, 2 (2017), 2248–2259.