A Closed-Loop Hybrid Stochastic-Robust Framework for Health-Aware PV–BESS Sizing

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Abstract

Health-aware sizing of photovoltaic (PV) and battery energy storage systems (BESS) in behind-the-meter (BTM) facilities must reconcile expected-cost efficiency with worst-case reliability. We propose a closed-loop hybrid stochastic-robust optimization (SRO) framework that fuses asynchronous PV, electricity-price, carbon-intensity, and load data via Decoupled–Recombined Sampling into typical and critical scenario sets. The framework co-optimizes economic and carbon objectives over typical scenarios while enforcing strict feasibility across critical ones, validated by a high-fidelity electrochemical simulation. On a representative case, it incurs only a 0.9% realized cost premium over stochastic programming (vs. 10.1% for robust optimization) with zero grid violations and lower cycle-induced aging.

Keywords

BESS Sizing, Stochastic-Robust Optimization, Carbon Arbitrage, Decoupled-Recombined Sampling, Out-of-Sample Validation

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1 Introduction

Modern behind-the-meter (BTM) facilities operate with substantial, volatile workloads. Integrating PV and BESS improves profitability and supports 24/7 Carbon-Free Energy targets by cutting the facility's overall carbon footprint [3].

Conventional sizing faces a tension between expected-cost efficiency and worst-case reliability. Pure Stochastic Programming (SP) optimizes expected cost but risks out-of-distribution infeasibility. Conversely, Robust Optimization (RO) enforces worst-case feasibility but systematically over-sizes storage. Both typically linearize battery degradation, ignoring its non-linear coupling with state-of-charge (SoC), depth-of-discharge (DoD), and C-rate. To close these gaps, we propose a **closed-loop hybrid stochastic-robust optimization (SRO) framework** that (i) fuses asynchronous inputs into typical and critical scenario sets [4], (ii) decouples expected-cost minimization from worst-case feasibility, and (iii) calibrates the linear aging proxy via non-linear rainflow simulations.

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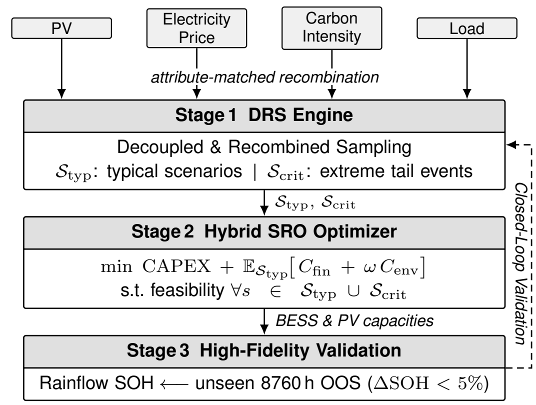

Figure 1: Three-stage closed-loop Decoupled–Recombined Sampling (DRS): From asynchronous data fusion and hybrid SRO sizing to high-fidelity validation and feedback.

2 The Closed-Loop Framework

The framework (Fig. 1) couples three fidelity-appropriate stages: statistical scenario construction, tractable Mixed-Integer Linear Programming (MILP) sizing, and electrochemical validation. Residual gaps feed back to Stage 1, closing the loop.

2.1 Stage 1: Decoupled–Recombined Sampling

To reconcile the temporal mismatch between long-horizon weather/price/carbon records and short-horizon loads, DRS synthesizes scenarios via two branches [1]. Typical scenarios ($\mathcal{S}_{\text{typ}}$) are generated by matching historical profiles with bootstrapped load traces along shared temporal attributes (e.g., winter weekday). Critical scenarios ($\mathcal{S}_{\text{crit}}$) use an attribute-constrained worst-case recombination: among admissible pairings of asynchronous days, we retain those maximizing joint net-load stress, providing empirical envelopes for robust feasibility.

2.2 Stage 2: Hybrid SRO Sizing Optimizer

$$\min_{x,\,y} C^{\text{inv}}(x) + \sum_{s\in\mathcal{S}_{\text{typ}}} \pi_s \Big[C^{\text{fin}}(y_s) + \omega\, C^{\text{env}}(y_s) \Big] \tag{1}$$

$$\text{s.t. } (x,\ y_s) \in \mathcal{F}(x, s), \quad \forall s \in \mathcal{S}_{\text{typ}} \cup \mathcal{S}_{\text{crit}} \tag{2}$$

Table 1: Benchmarking of sizing decisions, costs, and aging rates. Financial values are annualized [k€/yr]; aging rates are LP-predicted %/yr and validated in Sec. 3.3.

Metric	Pure SP	Pure RO	Proposed
A. In-sample sizing			
BESS capacity E_{cap} [kW h]	373.4	1663.4	**493.4**
Grid contract P_{con} [kW]	720.8	742.1	**717.5**
Oversizing ratio vs. SP	1.0×	4.5×	**1.3×**
Total predicted cost	541.5	1203.4	**543.6**
B. Out-of-sample performance			
Realized total cost	495.9	546.0	**500.1**
Cost premium vs. SP	—	+10.1%	**+0.9%**
Grid-contract violations [h]	0	0	**0**

To internalize environmental impacts, we adopt a dual-track objective weighting financial cost C^{fin} against carbon externality C^{env} via ω. Let x denote investment decisions with annualized CAPEX $C^{\text{inv}}(x)$ and y_s decisions in scenario s with probability π_s. Equation (1) minimizes expected financial-plus-carbon cost on typical scenarios, while (2) enforces hard feasibility against physical limits $\mathcal{F}(x, s)$ on the union of both sets—cleanly separating where to average (cost) from where to guarantee (feasibility), and thereby inheriting SP's cost efficiency and RO's robustness without paying RO's full conservatism tax.

2.3 Stage 3: Out-of-Sample High-Fidelity Validation

The optimal capacities $[C^*_{\text{pv}}, C^*_{\text{bess}}, P^*_{\text{con}}]$ from Stage 2 are re-simulated over a 10-year horizon under a high-fidelity non-linear aging model resolving SOH degradation as a joint function of SoC, DoD, and C-rate. The gap between LP-predicted and simulation-realized degradation quantifies proxy fidelity and is fed back to Stage 2 for calibration, closing the loop.

3 Methodological Validation

3.1 Value of Dual-Track Optimization

Compared to a grid-only baseline, internalizing carbon externalities ($\omega > 0$) activates joint price-carbon arbitrage. This transforms the BESS from a reactive buffer into an active multi-service asset, reducing total annualized costs by 12.6% and CO_2 emissions by 23.3%.

3.2 Algorithmic Benchmarking

Table 1 benchmarks Pure SP, Pure RO, and the proposed framework, first in-sample and then out-of-sample (OOS) over 1 000 unseen scenarios. Because SP's sampling happens to cover most critical realizations in this dataset, its realized OOS cost closely tracks ours; the advantage lies in the guarantees. Tactical oversizing (1.3× BESS vs. SP) costs a negligible 0.4% in-sample and only 0.9% realized OOS—against 10.1% for RO—yet the $\mathcal{S}_{\text{crit}}$-based feasibility constraints eliminate all OOS grid-contract violations, matching RO without paying its 4.5× over-sizing tax.

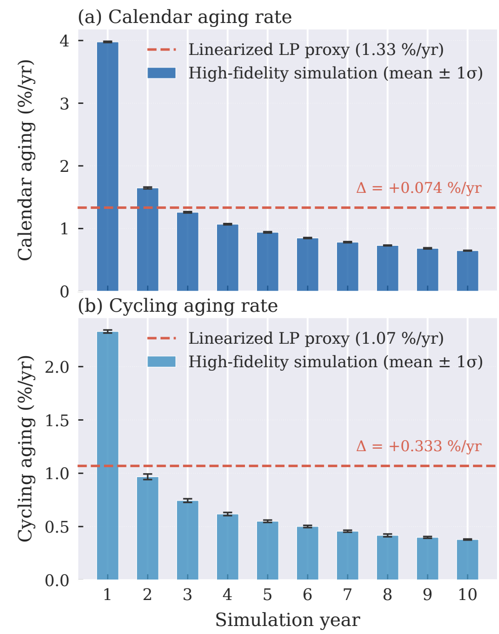

Figure 2: Validation of the linearized aging proxy against high-fidelity SimSES simulations. (a) Calendar and (b) cycling degradation rates over 10 years.

3.3 Physical Fidelity of the Aging Proxy

Fig. 2 validates the LP aging rates against a 10-year high-fidelity SimSES simulation on the same %/yr basis [2]. The proxy deviates by only 0.41%/yr (0.07 calendar, 0.33 cycling) and is strictly conservative: it slightly over-estimates degradation, embedding a safety margin against under-provisioning. SimSES exceeds the proxy only in a Year-1 electrochemical formation transient; from Year 2 onward the empirical trajectory stabilizes well within the proxy's envelope.

4 Conclusion and Future Work

The framework attains near-SP cost efficiency (0.9% OOS premium) and near-RO robustness (zero violations) with only 1.3× BESS oversizing, maintaining high physical fidelity. Future work includes semi-empirical non-linear aging models resolving SoC/DoD/C-rate, multi-year epoch-recursion, and distributionally robust ambiguity sets to harden tails.

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