# Two-Stage Stochastic Optimization of Multi-Service Behind-the-Meter BESS Sizing and Scheduling

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***Abstract*—This paper presents a risk-aware co-optimization framework for the sizing and day-ahead scheduling of behind-the-meter battery energy storage systems (BESSs) under renewable and load uncertainties. For each day of a year, photovoltaic and load scenarios are generated using quantile-based forecasting, followed by Monte Carlo sampling and clustering to preserve probabilistic diversity with tractable complexity. The representative daily scenarios generated over one year are aggregated into an annual scenario set and then used in a two-stage stochastic optimization model. The first s tage determines the BESS power and energy capacities, while the second stage optimizes hourly dispatch under each scenario. A Conditional Value-at-Risk (CVaR) term is incorporated into the objective to capture rare but high-cost events, balancing expected cost and tail-risk exposure. Compared to the no-storage baseline, the optimized 16.6 kW / 33.1 kWh BESS reduces total annual cost by €4.6k (5%) while ensuring robust operation across all scenarios. The study provides a computable analytical foundation for achieving a balanced trade-off between economic performance and operational robustness in BESS design under renewable and load forecast uncertainties.**

***Index Terms*—battery energy storage, multi-service, two-stage stochastic optimization, risk-aware design**

## I. Introduction

Battery energy storage systems (BESSs) are increasingly deployed by industrial and commercial (C&I) consumers to reduce energy costs through peak shaving, time-of-use (ToU) energy arbitrage, and improved photovoltaic (PV) self-consumption [1], [2].

The techno-economic value of BESSs depends critically on optimal design that jointly considers investment and operational costs. However, conventional optimization frameworks typically determine storage capacities and dispatch schedules based on historical or deterministic data, failing to explicitly capture the influence o f f orecast u ncertainty o n d esign decisions [3]. Recently, the two-stage stochastic optimization (TSSO) framework has been applied to co-optimize BESS sizing and scheduling under uncertain renewable generation and load conditions [4], [5]. However, they typically rely on Monte Carlo–based scenario generation methods with predefined p robability d istributions, t hereby f ailing t o capture forecast-induced uncertainty and seasonal variations typically observed in practice.

Moreover, extreme events like load peaks can cause sharp increases in operating costs, highlighting the need for risk measures that capture low-probability, high-impact events. The Conditional Value-at-Risk (CVaR) offers such a framework and has been increasingly applied in power-system optimization to mitigate cost volatility [6]. Nevertheless, CVaR-based approaches for BESS sizing and scheduling are still limited.

To address these challenges, this paper develops a novel risk-aware TSSO framework for the joint sizing and scheduling of behind-the-meter (BTM) BESSs considering renewable and load uncertainties. The main contributions of this paper are summarized as follows:

1) A scenario-based TSSO model with a CVaR–based risk-averse extension is proposed to jointly optimize BESS sizing and operation, explicitly accounting for forecast uncertainties and adverse tail events.
2) Day-ahead PV and load forecast scenarios are generated directly from LightGBM-based regression models on a rolling day-ahead basis to ensure seasonal and inter-month variability.
3) By adjusting the risk-aversion parameter, the proposed framework systematically balances economic performance and robustness against extreme scenarios, providing a reliable and risk-aware tool for BESS planning.

## II. Solution Framework and Workflow

This section describes the workflow of the proposed framework, covering probabilistic forecasting, uncertainty quantification, and scenario-based stochastic optimization for joint BESS sizing and operational scheduling.

Historical PV and load data are used to train a LightGBM-based quantile regression model that provides conditional predictive distributions [7]. In a rolling day-ahead fashion, joint PV–load distributions are constructed via a copula to represent both cross-dependencies and intra-day correlations, from which Monte Carlo sampling produces daily ensembles of PV–load trajectories [8]. Each ensemble is then reduced by K-means clustering to retain a small but statistically representative set of daily scenarios [9]. These daily clusters are concatenated over the year to form the stochastic input set for the optimization.

Based on these inputs, a TSSO model is formulated to jointly determine the optimal BESS energy and power capacities as well as the corresponding daily dispatch schedules. The objective function minimizes the sum of annualized investment and expected operating costs, while an additional CVaR term can be incorporated to penalize high-cost tail realizations and enhance risk robustness.

Finally, the optimization outputs are analyzed to quantify cost savings, peak-demand reduction, and risk-performance trade-offs across different confidence levels and risk-aversion weights. Comparative assessments against the baseline (no-storage) are performed to evaluate the economic and robustness benefits of the proposed framework.

## III. Two-Stage Stochastic Model Formulation

This section presents the modeling framework of the proposed co-optimization approach. First, a TSSO model is formulated, including BESS model, operational constraints, and objective functions. Next, a risk-averse extension incorporating CVaR is introduced to limit exposure to rare but high-cost operating outcomes. The principles of forecasting and clustering are not discussed in detail, as this paper focuses on the optimization framework.

### A. Temporal–Scenario Structure

The planning horizon is divided into days $d \in \mathcal{D} = \{1, \dots, D\}$, each day discretized into intra-day steps $h \in \mathcal{H} = \{0, \dots, H-1\}$. For each day, a finite set of forecast scenarios $s \in \mathcal{S} = \{1, \dots, S\}$ is provided with associated weights satisfying $\sum_{s \in \mathcal{S}} \omega_{d,s} = 1$. Months are indexed by $m \in \mathcal{M}$, and $D_m \subseteq \mathcal{D}$ denotes the subset of days belonging to month $m$.

### B. BESS Model and Constraints

The BESS is modeled as an energy bucket, constrained by its state-of-energy and converter power limits. The complete model is formulated as

$$E_{d,s,h} = E_{d,s,h-1} + \Delta t \big( \eta_c \, p^{\mathrm{ch}}_{d,s,h} - \eta_d^{-1} p^{\mathrm{dis}}_{d,s,h} \big), \tag{1a}$$

$$\sigma_{\min} E^{\mathrm{cap}} \le E_{d,s,h} \le \sigma_{\max} E^{\mathrm{cap}}, \tag{1b}$$

$$0 \le p^{\mathrm{ch}}_{d,s,h},\ p^{\mathrm{dis}}_{d,s,h} \le P^{\mathrm{cap}}, \tag{1c}$$

where $E_{d,s,h}$ denotes the stored energy at hour $h$ of day $d$ under scenario $s$, and $\Delta t$ is the time-step length. Equation (1a) enforces inter-temporal energy conservation, where $\eta_c$ and $\eta_d$ represent the charging and discharging efficiencies, respectively. Constraint (1b) bounds the energy state between the minimum and maximum admissible fractions $\sigma_{\min}$ and $\sigma_{\max}$ of the installed energy capacity $E^{\mathrm{cap}}$. Constraint (1c) restricts the charging and discharging power within the converter rating $P^{\mathrm{cap}}$, thus ensuring feasible converter operation. Cyclic boundary condition (2) ensures daily energy neutrality:

$$E_{d,s,0} = E_{d,s,H-1} = \theta \, E^{\mathrm{cap}}. \tag{2}$$

Finally, the design coupling (3) links the rated energy and power capacities through the C-rate bounds, restricting the feasible investment space:

$$\underline{\rho} \, P^{\mathrm{cap}} \le E^{\mathrm{cap}} \le \overline{\rho} \, P^{\mathrm{cap}}. \tag{3}$$

### C. Grid-coupling constraints

The interaction between the BTM BESS system and the utility grid is governed by the nodal power balance, which enforces instantaneous consistency among imports, exports, PV generation, load, curtailment, and BESS charging/discharging. The grid-side relations are formulated as

$$p^{\mathrm{imp}}_{d,s,h} + p^{\mathrm{dis}}_{d,s,h} + PV_{d,s,h} = LD_{d,s,h} + p^{\mathrm{ch}}_{d,s,h} + p^{\mathrm{exp}}_{d,s,h}, \tag{4a}$$

$$0 \le p^{\mathrm{imp}}_{d,s,h},\ p^{\mathrm{exp}}_{d,s,h}, \tag{4b}$$

$$p^{\mathrm{imp}}_{d,s,h} \le Y_{d,s}, \qquad \forall h \in \mathcal{H}, \tag{4c}$$

where (4a) ensures nodal power conservation at each time step, while (4b) enforces non-negativity of grid import and export power. To approximate the monthly demand charge in a computationally tractable way, a daily-peak proxy is introduced in (4c). For each day $d$ and scenario $s$, the variable $Y_{d,s}$ represents the epigraph of the daily import power, ensuring that $Y_{d,s} = \max_{h \in \mathcal{H}} p^{\mathrm{imp}}_{d,s,h}$ holds at optimality. The daily peak variables $Y_{d,s}$ are aggregated in the cost function to approximate monthly demand charges.

Note that the complementarity constraints for power exchanges between grid import/export and BESS charging/discharging are inherently satisfied under the cost-minimization objective, as discussed in [10].

### D. Cost Function Formulation

The annualized total cost consists of investment cost, electricity cost, and peak demand charges. All monetary quantities are expressed on an annual-equivalent basis.

*1) Annualized Investment Cost:* The annualized capital expenditure (CAPEX) for the installed energy and power capacities, including fixed operation and maintenance (O&M) costs, is given by

$$C_{\mathrm{inv}} = \mathrm{CRF}\, c_E \, E^{\mathrm{cap}} + \mathrm{CRF}\, c_P \, P^{\mathrm{cap}} + f_{\mathrm{om}} \big( c_E E^{\mathrm{cap}} + c_P P^{\mathrm{cap}} \big), \tag{5a}$$

$$\mathrm{CRF} = \frac{r(1+r)^n}{(1+r)^n - 1}, \tag{5b}$$

where $c_E$ and $c_P$ denote the specific investment costs for energy and power components, and $f_{\mathrm{om}}$ represents the annual fixed O&M ratio. The capital recovery factor (CRF) (5b) converts the total investment into annual equivalents, where $r$ denotes the annual discount rate and $n$ represents the economic lifetime in years.

*2) Electricity Cost:* For each day $d$ and scenario $s$, the daily cost of energy exchange (purchases minus export revenues) is defined as

$$L_{d,s} = \sum_{h \in \mathcal{H}} \big( p^{\mathrm{buy}}_{d,h} \, p^{\mathrm{imp}}_{d,s,h} - p^{\mathrm{sell}}_{d,h} \, p^{\mathrm{exp}}_{d,s,h} \big) \, \Delta t. \tag{6}$$

The expected annual electricity cost is

$$\mathbb{E}[C_{\mathrm{en}}] = \kappa \sum_{d \in \mathcal{D}} \sum_{s \in \mathcal{S}} \omega_{d,s} \, L_{d,s}, \tag{7}$$

where $\kappa$ denotes the annual scaling factor, which equals 1 in this study since the full year (365 days) is explicitly modeled. $\omega_{d,s}$ denotes the probability weight of scenario $s$ on day $d$.

*3) Approximate Peak-Demand Cost:* To represent the monthly demand charge in a tractable way, the daily-peak variables $Y_{d,s}$ are employed as proxy samples for monthly maxima. For each month $m$, the expected peak-demand cost is approximated by the weighted average of daily peaks:

$$\mathbb{E}[C_{\text{peak}}] = \sum_{m\in\mathcal{M}} c_{\text{peak}} \sum_{d\in D_m} \sum_{s\in\mathcal{S}} \bar{\omega}_{m,d,s}\, Y_{d,s}, \tag{8}$$

where $\bar{\omega}_{m,d,s}$ denotes the normalized scenario weights within each month:

$$\bar{\omega}_{m,d,s} = \frac{\omega_{d,s}}{\sum_{s\in\mathcal{S}} \sum_{d'\in D_m} \omega_{d',s}}. \tag{9}$$

The daily-peak sampling method is an engineering approximation of the true monthly maximum import, consistent with the day-ahead forecast structure that yields independent daily scenarios. This method offers substantial computational simplification while retaining the demand-charge sensitivity to high-import days.

## E. Baseline Two-Stage Optimization

The optimization problem naturally decomposes into design and operation layers. First-stage (investment) variables comprise the BESS energy and power capacities $(E^{\text{cap}}, P^{\text{cap}})$. Second-stage (operational) variables are compactly represented by $x_{d,s}$, encompassing the hourly dispatch and daily-peak decisions for each day $d$ and scenario $s$, i.e.,

$$x_{d,s} = \{p^{\text{imp}}_{d,s,h}, p^{\text{exp}}_{d,s,h}, p^{\text{ch}}_{d,s,h}, p^{\text{dis}}_{d,s,h}, E_{d,s,h}, Y_{d,s}\}_{h\in\mathcal{H}}.$$

For compactness, all second-stage decisions are jointly denoted as $x = \{x_{d,s}\}_{d\in\mathcal{D}, s\in\mathcal{S}}$. The risk-neutral objective minimizes the sum of the annualized investment cost, the expected electricity cost, and the expected peak-demand charge:

$$\begin{aligned} \min_{E^{\text{cap}}, P^{\text{cap}}, x} \quad & C_{\text{inv}} + \mathbb{E}[C_{\text{en}}] + \mathbb{E}[C_{\text{peak}}], \\ \text{s.t.} \quad & \text{BESS model and constraints (1)}, \\ & \text{Boundary constraints (2)}, \\ & \text{Design constraints (3)}, \\ & \text{Grid-coupling constraints (4)}. \end{aligned} \tag{10}$$

This two-stage framework enables a coordinated design and operational planning, where the first stage addresses long-term investment decisions and the second stage focuses on short-term operational strategies under multiple scenarios under the assumption of risk neutrality.

## F. Risk-Averse Extension with CVaR

While (10) minimizes the expected total cost, it does not limit exposure to rare but high-cost realizations, typically arising from simultaneous high imports and low PV generation. To address this, a CVaR term is introduced to penalize the upper tail of the monthly operating cost distribution. A monthly operating cost proxy is constructed based on the daily-peak approximation:

$$T_{m,d,s} \;=\; n_m\, L_{d,s} \;+\; c_{\text{peak}}\, Y_{d,s}, \tag{11}$$

where $T_{m,d,s}$ represents the aggregated monthly cost sample for day $d \in D_m$, scenario $s$, and month $m$; $n_m$ scales daily costs to the monthly equivalent. This proxy does not represent a physically continuous month-long trajectory but a statistically weighted estimate of possible monthly billing outcomes.

For each month, the CVaR operator is linearized by introducing an auxiliary Value-at-Risk (VaR) variable $z_m$ and nonnegative slack variables $\xi_{m,d,s}$:

$$\xi_{m,d,s} \geq T_{m,d,s} - z_m, \qquad \xi_{m,d,s} \geq 0, \tag{12a}$$

$$\text{CVaR}_m = z_m + \frac{1}{1-\alpha} \sum_{d\in D_m} \sum_{s\in\mathcal{S}} \bar{\omega}_{m,d,s}\, \xi_{m,d,s}. \tag{12b}$$

Here, $\alpha \in (0,1)$ is the confidence level that determines the tail probability considered in the risk evaluation. The total annual CVaR ist accumulated through the whole year:

$$\text{CVaR}_{\text{total}} = \sum_{m\in\mathcal{M}} \text{CVaR}_m. \tag{13}$$

The final risk-averse optimization problem combines the deterministic investment cost, the expected operational cost, and the CVaR-based tail penalty:

$$\begin{aligned} \min_{E^{\text{cap}}, P^{\text{cap}}, x} \quad & C_{\text{inv}} + \mathbb{E}[C_{\text{en}}] + \mathbb{E}[C_{\text{peak}}] + \lambda\, \text{CVaR}_{\text{total}}, \\ \text{s.t.} \quad & (1), (2), (3), (4), \\ & \text{CVaR termin (12)}, \end{aligned} \tag{14}$$

where $\lambda \geq 0$ is the risk-aversion coefficient balancing expected performance and downside-risk mitigation. Setting $\lambda = 0$ recovers the risk-neutral formulation (10), while higher $\lambda$ values yield designs and operational schedules more robust against unfavorable high-cost scenarios.

Alternatively, all samples $(m, d, s)$ can be aggregated into a single annual CVaR with one VaR variable $z_{\text{ann}}$, using weights normalized across the full annual sample set. This yields a single $\text{CVaR}_{\text{ann}}$ in (14) replacing $\text{CVaR}_{\text{total}}$.

# IV. Case Study

## A. Data Sources

Weather forecasts are obtained from the ICON-D2 numerical model operated by the German Weather Service (DWD), accessed through the Open-Meteo interface [11]. These forecasts are paired with ground-truth PV power measurements over a three-year period, in which the first two years are used for model training and the third year (May 2022–April 2023) is reserved for validation and stochastic optimization input. Similarly, load data from a university campus building in Germany is partitioned into a one-year training set and a one-year validation set over the same period. Both PV and load forecasts are generated one day in advance with an hourly resolution, providing 24-step ahead probabilistic trajectories used as input to the scenario-based optimization framework.

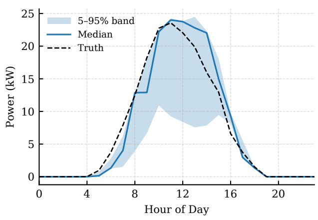
TABLE I: Summary Optimization Setup

| Objects | Parameters | Values | Units |
|---|---|---|---|
| Profiles | Electrical load | 217.2 | MWh |
| | PV generation | 37.6 | MWh |
| | Average electricity price[1] | 0.32 | €/kWh |
| | Electricity feed-in price | 0.06 | €/kWh |
| BESS | Energy specific price | 200 | €/kWh |
| | Power specific price | 200 | €/kW |
| | Fixed O&M | 8 | €/kW-a |
| | Life year | 10 | a |
| | RTE $\eta^2$ | $0.95^2$ | - |
| | Electrical SoE limit | [0.1, 0.9] | - |
| Optimization | Simulation time span | 1 | a |
| | Sampling time $\Delta t$ | 1 | h |
| | Initial electrical SoE | 0.5 | - |

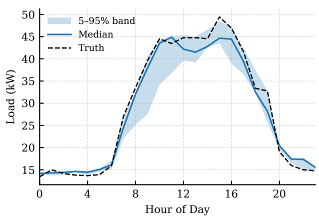
[1] Dynamic electricity price contracts can be obtained from providers such as *GP JOULE* [12]. The real-time electricity price equals the EPEX market price plus a base price.

### B. Forecasting Reults

Figure 1 compares the probabilistic forecasting results for PV generation and load demand for one day (October 11, 2022), using quantile-based predictions. The 5th to 95th percentile prediction intervals for both variables exhibit satisfactory coverage, with the median forecasts closely tracking the realized trajectories throughout the day. Figure 2 illustrates the first three representative scenarios derived for PV and load, respectively, along with their associated probabilities. The dominant PV scenario (with a weight of 0.8) captures the overall shape of the observed output, while the remaining scenarios reflect variability stemming from morning and afternoon weather fluctuations, thereby preserving the diversity of the distribution. In contrast, the load scenarios display a more concentrated distribution, consistent with the lower inherent volatility of demand profiles.

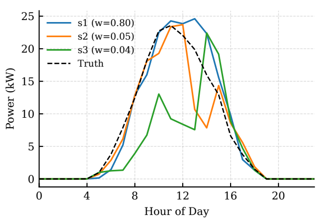



**(a)** PV predictive band and truth.

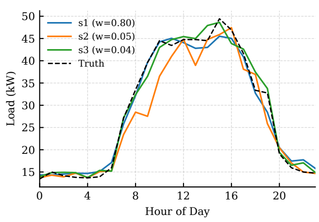



**(b)** Load predictive band and truth.

Fig. 1: Predictive bands of PV and load profiles for a representative day.




**(a)** PV representative scenarios and truth.




**(b)** Load representative scenarios and truth.

Fig. 2: Representative scenarios of PV and load profiles for a day.

### C. Results Analysis

The no-storage case yields a total annual cost of €89.4k, consisting of approximately €79.2k in electricity charges and €10.2k in peak-demand costs. The optimization results at confidence level $\alpha = 0.95$ are summarized in Table II and Fig. 3. As $\lambda$ increases, annualized CAPEX rises, while expected electricity cost decreases and peak-demand cost remains almost unchanged. These opposing trends nearly offset each other, resulting in a stable total cost.

TABLE II: Sizing and cost results at $\alpha = 0.95$ for different $\lambda$ values. The total cost comprises annualized CAPEX, expected electricity cost, and expected peak-demand cost.

| Metric | 0.00 | 0.05 | 0.10 | 0.15 | 0.20 | 0.25 |
|---|---|---|---|---|---|---|

P E A E E T

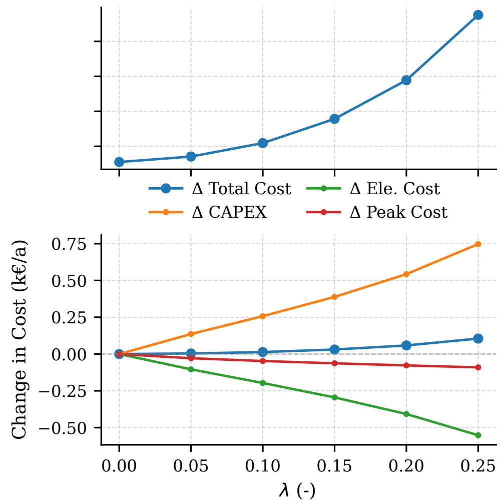



Fig. 3: Cost variations at $\alpha = 0.95$ with varying $\lambda$. The trade-off between increasing BESS CAPEX and decreasing electricity and peak-demand costs results in a nearly unchanged total cost.

To determine an appropriate risk-aversion weight $\lambda$, Fig. 4 illustrates the Pareto front between annualized CAPEX and annual operational CVaR for different $\lambda$ values. Increasing $\lambda$ leads to higher investment and lower CVaR, shifting the optimal design from low-investment/high-risk to high-investment/low-risk configurations. A knee point is observed, where additional investment significantly reduces operational risk up to this point, but offers diminishing benefits thereafter. This Pareto front indicates that a suitable choice of $\lambda$ achieves a balanced trade-off between CAPEX and operational risk. Compared to the benchmark case, the optimized configuration at $\alpha = 0.95$ and $\lambda = 0.05$ yields a 16.6 kW / 33.1 kWh BESS, lowering the total annual cost to €84.8k (–5.0%) and resulting in annual savings of €4.6k per year. These results confirm a cost-effective and risk-aware design.

Detailed operation is illustrated in Fig. 5, which depicts the system power flows and the BESS SoE trajectory on the day with the highest total cost under $\alpha = 0.95$ and $\lambda = 0.05$. During the morning (06:00–10:00) and evening

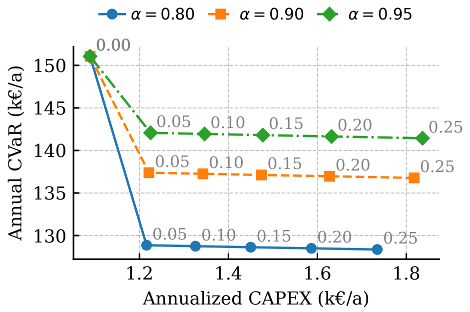



Fig. 4: Pareto front between annualized CAPEX and annual CVaR under varying confidence levels $\alpha$ and risk weights $\lambda$. The orange dotted line indicates the selected use case.

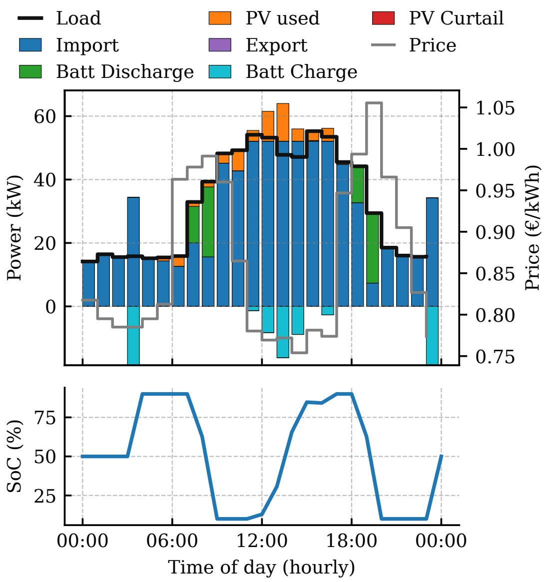



Fig. 5: Power profiles and BESS (16.6 kW / 33.1 kWh) SoE on the highest-cost day. The BESS discharges during morning and evening price peaks and charges from midday PV surpluses.

(18:00—19:00) periods, high electricity prices coincide with low PV generation, prompting the BESS to discharge and reduce grid imports. In contrast, between 11:00 and 17:00, abundant PV generation covers the load and charges the battery. The results demonstrate that the CVaR-based optimization enables the BESS to operate effectively under adverse conditions, maintaining cost-efficient and robust performance even on the most expensive day.

## V. Conclusion

This study establishes a computable analytical framework for designing BTM BESSs that balance economic performance and operational robustness under uncertainties in renewable generation and load forecasts. The framework integrates quantile-based scenario generation with a two-stage stochastic formulation, linking investment and operation decisions through a linearized daily-peak representation of demand charges. A CVaR extension is incorporated to quantify tail-risk exposure.

Results show that increasing the risk-aversion weight $\lambda$ shifts the optimal design from low-investment/high-risk to higher-investment/lower-risk configurations. Compared to the no-storage baseline, the optimized BESS configuration reduces the total annual cost to €84.8k (–5.0%), corresponding to savings of about €4.6k per year. This improvement is achieved with a 16.6 kW / 33.1 kWh BESS under $\alpha = 0.95$ and $\lambda = 0.05$.

Future work will focus on out-of-sample simulation-based validation and an extended multi-objective formulation that explicitly accounts for battery aging effects.

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