Optimal Retail Energy Procurement Under High Behind-the-Meter PV Penetration Using Multi-Year Rolling-Horizon CVaR Optimization

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***Abstract*—Electricity retailers face growing procurement risks as behind-the-meter PV adoption, volatile wholesale prices, and shifting net-load patterns reshape portfolios. Traditional one-year hedging strategies fail to capture multi-year load, PV, and price dynamics and provide limited protection against extreme losses in systems with heavy-tailed, asymmetric price distributions. This paper proposes a five-year, scenario-based portfolio optimization framework that jointly optimizes forward contracts, physical call options, day-ahead and real-time purchases, and battery operations, incorporating Conditional Value-at-Risk (CVaR) to manage tail risk. Simulations demonstrate that the approach improves profit stability and reduces extreme losses compared to standard annual hedging, highlighting the value of integrated, long-horizon risk management in renewable-rich markets.**

***Index Terms*—Behind-the-meter (BTM), conditional value-at-risk (CVaR), distributed energy resources (DER), electricity retailers, portfolio optimization, stochastic optimization.**

I. Introduction

Retail electricity markets are undergoing structural transformation due to accelerating adoption of behind-the-meter (BTM) photovoltaic (PV) systems [1], [2]. Unlike utility-scale renewables, BTM resources are installed downstream of the retailer's metering boundary and are only partially observable. As penetration increases, retailers no longer face stable gross demand; instead, they contend with stochastic net load defined as customer consumption minus distributed generation.

High BTM penetration alters retail risk in three ways. Midday net load is suppressed by PV output, reducing margins during low-price hours. Evening ramps emerge as PV declines while demand remains high, exposing retailers to scarcity-driven real-time (RT) price spikes. Forecast errors are asymmetric: PV shortfalls during peak demand generate disproportionate financial losses. These effects evolve structurally as PV adoption grows over time.

Retailers hedge procurement using layered instruments at different time scales [3], [4]: long-term forward contracts, physical call options, day-ahead (DA) purchases, RT transactions, and battery storage. The challenge is co-optimizing these instruments under uncertainty while maintaining financial resilience across multi-year net-load dynamics.

Risk management for electricity retailers has been extensively studied. Early formulations focused on forward contracting and mean–variance optimization [5], [6], but variance penalizes upside and downside symmetrically, failing to target extreme loss events. Stochastic programming has been applied to retail procurement [7], [8], yet existing studies typically suffer from: (i) single-year modeling neglecting structural growth [9], (ii) limited integration of forward contracts, options, DA/RT participation, and storage [4], (iii) absence of explicit tail-risk control [6], [10], and (iv) short-term storage focus rather than multi-year hedging [11].

Distributed PV introduces inter-temporal coupling in procurement decisions [9], [11]. Forward and option positions affect exposure to future ramp volatility and imbalance risk. Multi-stage stochastic optimization naturally captures this: first-stage commitments correspond to forward and option contracts, DA scheduling is intermediate-stage, and RT balancing with battery dispatch is recourse. Scenario-based modeling, non-anticipativity constraints, and coherent risk measures such as Conditional Value-at-Risk (CVaR) [6] are essential for tractable multi-year formulations.

A. Contributions

This paper proposes a five-year rolling-horizon stochastic optimization framework for retail energy procurement under high BTM PV penetration, with contributions:

- **Multi-Year Structural Modeling:** Captures evolving net-load distributions across five years.
- **Integrated Hedging and Operations:** Joint optimization of forward contracts, options, DA/RT purchases, and battery storage.
- **CVaR-Based Tail-Risk Control:** Mitigates extreme financial losses under heavy-tailed prices.
- **Rolling-Horizon Multi-Stage Interpretation:** Approximates full multi-stage stochastic programming while preserving tractability.
- **Robustness Evaluation:** Sensitivity analyses and out-of-sample validation.

II. Problem Overview

This work focuses on optimizing retailer operations in the presence of BTM resource penetration in distribution systems. In deregulated power systems, retailers exist as independent profit-making entities that supply electricity to end-use customers through retail contracts. Apart from purchasing electricity from retailers, customers are increasingly adopting BTM resources such as PV, battery energy storage and PEVs. Retailers have limited visibility of the BTM resources and their diffusion in distribution networks, hence, net-load supplied by the retailers are subjected to a higher degree of uncertainty.

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In a multi-year planning and hedging horizon, these uncertainties interact in nonlinear and compounding ways, forcing retailers to strategically optimize resources in order to sustain their operations and businesses. Accordingly, we consider a risk-averse retailer serving a portfolio of customers in a decentralized electricity market. The retailers procure electricity through different market instruments such as long-term forward contracts, options contracts and spot markets in different timescales. In the event of significant net-load uncertainty, deficiency in power is met by the retailers through spot markets at relatively higher real-time prices. Similarly, any surplus power procured may be leveraged by the retailers in real-time. A schematic representation of retailer operations is presented in Fig. 1.

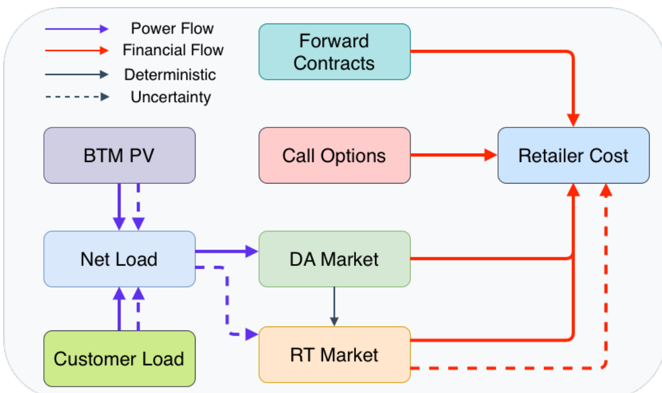

Fig. 1. Conceptual diagram of the retailer's procurement problem.

III. Methodology

This paper considers a retail electricity provider that procures energy through a combination of day-ahead (DA) contracts, forward contracts and call options, while serving uncertain net load influenced by BTM DER generation. Additionally, the retailer can leverage battery storage and participate in the real-time (spot) market to manage deviations and hedge financial risk.

A. Energy Procurement Instruments

Several market instruments compose the retailer's energy procurement portfolio. Forward base-load volume F_y^{base} (MW), constant across all hours. Forward peak-block volume F_y^{peak} (MW), applied only in specified peak hours. Call option volume $P_{y,h}^{O}$ (MW) for each representative hour, with premium $c_{y,h}$ and strike $K_{y,h}$. Day ahead (DA) purchase $P_{s,y,h}^{DA}$ (MW) chosen per scenario and hour. Real-time (RT) adjustments $P_{s,y,h}^{RT}$ (MW), positive for net purchases and negative for sales. These market instruments are bound by non-linear constraints.

$$0 \leq F_y^{\text{base}} \leq F_{\max}^{\text{base}}, \; 0 \leq \quad F_y^{\text{peak}} \leq F_{\max}^{\text{peak}}, \; 0 \leq P_{y,h}^{O} \leq P_{\max}^{O}, \tag{1}$$

Option payoffs in scenario s are given by:

$$\text{Payoff}_{s,y,h} = \max(P_{s,y,h}^{RT} - K_{y,h}, 0)\, P_{y,h}^{O}. \tag{2}$$

B. Net-load Modeling under High BTM Penetration

Gross demand and BTM-PV generation are modeled with seasonal and diurnal patterns, along with annual growth. Let $L_{s,y,h}$ denote gross load for scenario s, year y, and representative hour h.

$$L_{s,y,h} = L_h^{\text{base}}(1 + g_L)^y + \epsilon_{s,y,h}^{L}, \tag{3}$$

where L_h^{base} is a deterministic profile capturing seasonal and diurnal variations, g_L is the annual load growth rate, and $\epsilon_{s,y,h}^{L}$ is the normally distributed stochastic uncertainty. Similarly, BTM-PV generation is modeled as follows.

$$PV_{s,y,h} = PV_h^{\text{base}}(1 + g_{PV})^y + \epsilon_{s,y,h}^{PV}, \tag{4}$$

where PV_h^{base} represents a normalized irradiance-based profile, g_{PV} is the PV growth rate, and $\epsilon_{s,y,h}^{PV}$ captures the stochastic uncertainty in PV output. Accordingly, the net load is described as follows.

$$P_{s,y,h}^{net} = L_{s,y,h} - PV_{s,y,h}. \tag{5}$$

C. Market Price Modeling

In order to precisely represent the relative load-generation imbalance and system stress, DA and RT wholesale prices are modeled as functions of residual demand. The residual demand is then normalized to depict the relative system stress. Let RD_h denote the residual demand in a base year. The price modeling is then expressed as follows.

$$RD_h = L_h^{\text{base}} - PV_h^{\text{base}}, \quad \tilde{RD}_h = \frac{RD_h}{\overline{RD}}. \tag{6}$$

1) Day-Ahead Prices: The DA price at representative hour h is modeled as a convex function of $\tilde{RD}_h$:

$$c_h^{DA} = a_0 + a_1 \tilde{RD}_h + a_2 \tilde{RD}_h^2 + \eta_h, \tag{7}$$

$$c_{y,h}^{DA} = (1 + \gamma y) P_h^{DA}. \tag{8}$$

where a_0, a_1, a_2 are coefficients chosen to yield realistic price levels, η_h is a small Gaussian perturbation, and $(1 + \gamma y)$ is a drift factor.

2) Real-Time Prices: RT prices are modeled as follows.

$$c_{s,y,h}^{RT} = c_{y,h}^{DA} + \xi_{s,y,h} + \delta_{s,y,h}, \tag{9}$$

where, $\xi_{s,y,h}$ is Gaussian noise with standard deviation dependent on RD_h and $\delta_{s,y,h}$ represents stochastic price uncertainty.

D. Retailer's Revenue

The revenue earned by the retailer is generated through supply contracts with the consumers. The revenue for a given scenario s, year y, and hour h is given as follows.

$$\text{Rev}_y = \sum_{s \in S} \sum_{h \in H} \text{C}_{s,y,h}^{ret} \cdot \text{P}_{s,y,h}^{net} \tag{10}$$

Here, $C_{s,y,h}^{ret}$ is the retail rate charged to the customer for energy and $P_{s,y,h}^{net}$ is the amount of net-energy sold to customers in scenario s, year y, and hour h.

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E. Real-Time Decomposition

In real-time, the system is subjected to uncertainty in BTM generation and load, as a result of which the net-load becomes uncertain. This is described as follows.

$$P^{RT}_{s,y,h} = P^{RT^+}_{s,y,h} - P^{RT^-}_{s,y,h}, \tag{11}$$

with $P^{RT^+}_{s,y,h} \geq 0$, $P^{RT^-}_{s,y,h} \geq 0$ for all s, y, h. Here, $P^{RT^{+/-}}$ are the positive and negative deviation in real-time net-load.

F. Retailer's Costs

The retailer's expenses consist of several components, namely, energy procurement costs, transmission and distribution costs and energy storage costs. The energy procurement cost ($C^{pr}_{s,y,h}$) is expressed as follows. Using DA price $P^{DA}_{y,h}$ and RT price $P^{RT}_{s,y,h}$, one can write:

$$\begin{aligned} C^{\text{proc}}_{s,y} = \sum_h w_h \Big(& c^f \left(F^{\text{base}}_y + \chi_h F^{\text{peak}}_y\right) + c^o_{y,h} P^O_{y,h} \\ & + c^{DA}_{y,h} P^{DA}_{s,y,h} + c^{RT}_{s,y,h} P^{RT}_{s,y,h} + c_{\text{pen}} \big(|P^{DA}_{s,y,h}| \\ & + |P^{RT}_{s,y,h}|\big) \Big) - \sum_h w_h \text{Payoff}_{s,y,h}, \end{aligned} \tag{12}$$

where, w weight of representative hour h, c_{pen} is a deviation penalty coefficient, c^f is the price for the forward contracts, c^{DA} is the day-ahead market price, c^{RT} is the real-time market price, c^o is the price for the option contracts, F_{base} is the base forward procurement, P^{RT}, P^{DA} and P^O are real-time, day-ahead and option procurement quantities, respectively.

The transmission and distribution (T&D) cost are expressed as $C^{td}_{s,y,h} = c^{td}_{y,h} P^{net}_{s,y,h}$, where, $c^{td}_{y,h}$ is the T&D cost per unit of energy for year y, hour h, and $C^{td}_{s,y,h}$ is the total T&D cost.

Battery Storage Costs: The retailer incurs costs for charging and discharging the battery. For scenario s, year y, and hour h, the battery storage cost ($C^B_{s,y,h}$) is expressed as follows.

$$C^B_{s,y,h} = c^{ch} B^{ch}_{s,h} + c^{dis} B^{dis}_{s,h} + C^{\text{deg}}_{s,y} \tag{13}$$

$C^{\text{deg}}_{s,y}$ is the battery degradation cost applied per MWh cycled, given as follows.

$$C^{\text{deg}}_{s,y} = c_{\text{deg}} \sum_h w_h \left(B^{\text{ch}}_{s,y,h} + B^{\text{dis}}_{s,y,h}\right). \tag{14}$$

Here, c^{ch} and c^{dis} represent the per unit charging and discharging costs of the battery, respectively. B^{ch} and B^{dis} represent the energy charged and discharged by the battery, and c^{deg} represents the per unit battery degradation cost.

The total procurement cost are thus, expressed as a sum of the different cost components over the scenarios.

$$\text{TC}_y = \sum_{s \in S} \sum_{h \in H} \left(C^{pr}_{s,y,h} + C^{td}_{s,y,h} + C^B_{s,y,h}\right) \tag{15}$$

G. Retailer's Profit

The retailer's profit is computed as the difference between its total revenue and costs, and is thus, expressed as follows.

$$\text{Profit}_y = \text{Rev}_y - \text{TC}_y \tag{16}$$

H. Battery Storage Modeling

A battery with energy capacity $E^{\max}$, charge/discharge limits $P^{\text{ch}}_{\max}$, $P^{\text{dis}}_{\max}$, and round-trip efficiency η is modeled through:

$$0 \leq B^{\text{ch}}_{s,y,h} \leq P^{\text{ch}}_{\max},\ 0 \leq B^{\text{dis}}_{s,y,h} \leq P^{\text{dis}}_{\max}, \tag{17}$$

$$0 \leq SOC_{s,y,h} \leq E^{\max}, \tag{18}$$

$$SOC_{s,y,h} = \begin{cases} SOC_{s,y,h-1} + \eta B^{\text{ch}}_{s,y,h} - \dfrac{1}{\eta} B^{\text{dis}}_{s,y,h}, & h > 1, \\ SOC_{s,y,1}, & h = 1, \end{cases} \tag{19}$$

with boundary conditions enforcing $SOC_{s,y,1} = SOC_{s,y,H} = 0$ for all scenarios.

I. Supply-Demand Balance

For each scenario s, year y, hour h, the retailer must satisfy net demand:

$$\begin{aligned} & F^{\text{base}}_y + \chi_h F^{\text{peak}}_y + P^{DA}_{s,y,h} + P^{RT}_{s,y,h} + B^{\text{dis}}_{s,y,h} \\ & + P^O_{y,h} \geq P^{net}_{s,y,h} + B^{\text{ch}}_{s,y,h}, \end{aligned} \tag{20}$$

where χ_h is an indicator for peak hours.

J. Risk Measure and Profit-Space CVaR Reporting

The proposed optimization model follows the standard loss-based CVaR formulation. Let the annual profit in scenario s and year y be denoted by $\Pi_{s,y}$. The corresponding loss can be defined as follows. $L_{s,y} = -\Pi_{s,y}$. In order to compute the CVaR at confidence level α (typically $\alpha = 0.95$), auxiliary variables VaR_y and $z_{s,y} \geq 0$ are introduced, and impose the following constraints.

$$z_{s,y} \geq L_{s,y} - \text{VaR}_y, \quad z_{s,y} \geq 0. \tag{21}$$

Therefore, the CVaR in loss space is given as follows.

$$\text{CVaR}^{\text{loss}}_{\alpha,y} = \text{VaR}_y + \frac{1}{(1-\alpha)S} \sum_{s=1}^{S} z_{s,y}. \tag{22}$$

The risk-averse objective per year y is to maximize $\mathbb{E}[\Pi_y] - \lambda\,\text{CVaR}_{\alpha,y}$, where λ is a risk-aversion parameter.

K. Objective Function

For a given year y, the risk-averse objective is to maximize:

$$\max\ \frac{1}{S} \sum_{s \in \mathcal{S}} \Pi_{s,y} - \lambda \left(\text{VaR}_y + \frac{1}{(1-\alpha)S} \sum_s z_{s,y}\right). \tag{23}$$

The problem is formulated as a stochastic optimization model with risk management (CVaR) to address both expected costs and extreme downside risks. In the rolling-horizon implementation, (23)–(22) and all constraints (1)–(21) are solved sequentially for $y = 1, \ldots, Y$, using year-specific parameters $P^{net}_{s,y,h}$, $P^{DA}_{y,h}$, and $P^{RT}_{s,y,h}$.

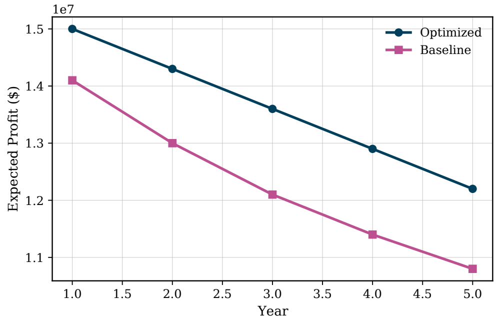

Fig. 2. Expected profit for the baseline and optimized strategies.

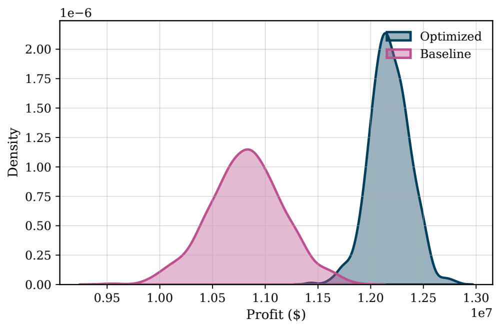

Fig. 3. Year 5 profit distribution for the optimized and baseline strategies.

IV. Results and Discussion

This section evaluates the performance of the proposed multi-year CVaR-based portfolio optimization framework to reflect typical retail energy market conditions under high PV penetration. The analysis compares the optimized strategy against a baseline in which all residual net load is procured from the real-time (RT) market without any hedging or forward/option instruments.

A. Simulation Configuration

The numerical study considers a five-year planning horizon ($Y = 5$). Uncertainty is represented using $S = 200$ Monte Carlo scenarios. Each year is modeled using $H = 24$ representative hourly blocks, with weighting factor $w_h = 365$.

Load and PV uncertainties are generated using correlated Gaussian perturbations calibrated to preserve empirical variance and cross-correlation structure. Real-time price uncertainty is modeled as heteroskedastic noise proportional to residual demand. All scenarios are assigned equal probability.

B. Baseline Procurement Model

The baseline strategy assumes no forward contracts, no call options, and no battery storage. All net demand is procured in the real-time market:

$$F_y^{base} = F_y^{peak} = P_{y,h}^{O} = 0 \tag{24}$$

$$C_{s,y}^{baseline} = \sum_h w_h \, c_{s,y,h}^{RT} P_{s,y,h}^{net} \tag{25}$$

This benchmark reflects a purely reactive procurement strategy exposed entirely to real-time price volatility.

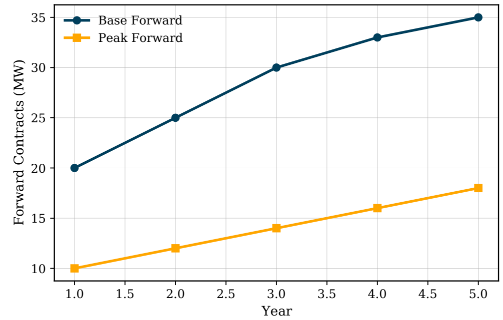

Fig. 4. Optimal base-forward and peak-forward contract quantities.

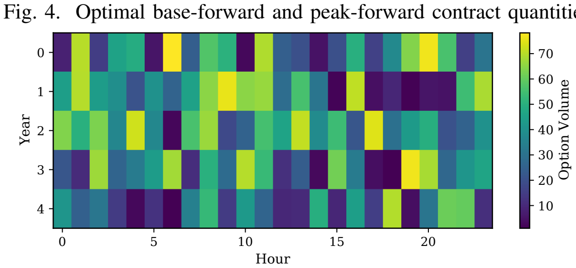

Fig. 5. Heatmap of hourly call option across all five years.

C. Expected Profit Across Years

Fig. 2 shows the expected annual profit for the optimized and baseline strategies. The baseline profit declines steadily from \$14.1M in Year 1 to \$10.8M in Year 5, driven primarily by (i) RT price volatility and (ii) increasing PV forecast uncertainty that amplifies imbalance exposure.

In contrast, the optimized strategy consistently maintains higher profitability across all years, starting at \$15.0M in Year 1 and ending at \$12.2M in Year 5. The performance gap between the two strategies widens over time, showing that multi-year rolling optimization gradually improves exposure management as uncertainty compounds with load and PV growth. The relative improvement in expected profit averages 10.5% over five years.

D. Distributional Risk Reduction

Expected profit alone does not adequately capture operational risk. Fig. 3 presents the Year 5 profit distributions for the baseline and optimized strategies. The baseline exhibits a heavier left tail, reflecting significant downside risk and occasional deep losses caused by RT price spikes coinciding with PV shortfalls. The optimized strategy shifts the entire distribution to the right while reducing variance, demonstrating the effectiveness of call options and forward contracts in truncating extreme losses. Tail metrics validate the improvement. VaR95 improves from approximately \$9.9M (baseline) to \$11.3M (optimized), CVaR95 improves from approximately \$9.4M to \$10.9M. These improvements demonstrate that the CVaR objective successfully focuses on the worst-case scenarios, enhancing both profitability and robustness.

E. Evolution of Forward Hedging Decisions

Fig. 4 illustrates the optimal base-forward and peak-forward contract quantities over five years. Base-forward hedges (covering structural load) increase from 20 MW to 35 MW as load grows, while peak-forward hedges rise from 10 MW to

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TABLE I
ANNUAL PROFIT AND RISK METRICS

Year	Strategy	E[Profit] (M$)	VaR95 (M$)	CVaR95 (M$)
1	Baseline	14.1	12.8	12.3
	Optimized	15.0	13.9	13.5
2	Baseline	13.0	11.7	11.1
	Optimized	14.3	13.3	12.9
3	Baseline	12.1	10.7	10.2
	Optimized	13.6	12.5	12.0
4	Baseline	11.4	10.0	9.6
	Optimized	12.9	11.8	11.3
5	Baseline	10.8	9.9	9.4
	Optimized	12.2	11.3	10.9

18 MW, reflecting the optimizer's response to rising evening RT uncertainty caused by high PV ramp-down periods.

The systematic rise in forward volumes suggests that long-term hedging becomes more valuable as variability increases, and multi-year planning enables the optimization to adapt contract positions with minimal over-commitment.

F. Sensitivity Analysis

Option Utilization Across Hours: Fig. 5 shows the temporal distribution of option procurement. Options concentrate heavily in the evening (17:00–21:00) and around the midday PV peak (11:00–14:00), aligning with the periods of highest price and PV uncertainty. This behavior validates the model's ability to detect hours where distributional risk is high and strategically allocate flexible hedges. Options remain relatively low overnight, consistent with stable prices and low PV risk.

Quantitative Validation: Table I summarizes the performance metrics averaged over all scenarios for the five-year horizon. The metrics confirm that the optimized portfolio increases expected profit by 10–12% annually, improves VaR95 by 14–18% , improves CVaR95 by 16–20% , and significantly reduces downside exposure caused by real-time volatility. These findings demonstrate that multi-year CVaR optimization produces a more balanced and risk-aware hedging portfolio compared to myopic unhedged procurement.

Sensitivity to Risk-Aversion Parameter To evaluate portfolio shifts under different risk preferences, the optimization is solved for: $\lambda \in \{0, 0.1, 0.5, 1, 2\}$. As λ increases, forward hedge volume increases monotonically, option procurement expands in high-risk hours, and real-time exposure decreases. Expected profit decreases slightly with increasing λ, while CVaR improves significantly, confirming the trade-off between risk and return.

Sensitivity to CVaR Confidence Level The model is evaluated for confidence levels: $\alpha = \{0.90,\ 0.95,\ 0.99\}$. Higher α values increase tail protection by penalizing more extreme loss realizations. Results indicate that option procurement increases significantly at $\alpha = 0.99$, while expected profit decreases moderately. This confirms the portfolio structure is sensitive to tail-risk tolerance assumptions.

Robustness to Long-Term Forecast Error: To assess structural forecast uncertainty, load growth g_L and PV growth g_{PV} are perturbed by $\pm 25\%$ relative to assumed forecasts. Results show that although expected profit declines under misspecification, the CVaR-optimized portfolio retains approximately 75–85% of its risk-reduction advantage relative to the baseline. This demonstrates robustness of early hedging decisions to long-term forecast error.

Out-of-Sample Validation: The portfolio optimized using 200 training scenarios is evaluated on 500 independently generated out-of-sample scenarios. Expected profit declines by less than 3%, CVaR degradation remains below 4%, indicating strong generalization performance and limited overfitting to the training scenario set.

Computational Performance: For $Y = 5$, $S = 200$, and $H = 24$, the model contains approximately 70,000 continuous decision variables and 100,000 linear constraints. The problem is implemented in Pyomo and solved using HiGHS 1.12.0. Average solve time per year is 18–25 seconds on a standard desktop (16GB RAM), and the full rolling-horizon simulation completes within approximately 2 minutes. These results demonstrate tractability for practical deployment.

V. CONCLUSION

This work presents a multi-year CVaR-based portfolio optimization framework for managing uncertainty from high behind-the-meter PV penetration. Simulations indicate it increases expected profit while substantially reducing VaR_{95} and CVaR_{95} relative to an unhedged baseline. By jointly optimizing forward contracts, peak hedges, and call options, the approach mitigates tail risks and stabilizes multi-year performance. The results demonstrate that long-horizon, risk-aware hedging is essential for robust financial resilience in renewable-rich retail markets.

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