Curtailment-Aware BESS Scheduling of Hybrid Solar Systems in Flexible Interconnection under Forecasting Uncertainties

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Abstract— **Flexible Interconnection (Flex IX) expands the hosting capacity (HC) of Distributed Energy Resources (DERs) by actively managing DER export. DERs face curtailment in Flex IX due to HC limits driven by the grid's thermal asset ratings. Without costly grid upgrades, a Battery Energy Storage System (BESS) integrated with hybrid PV farms, mitigate curtailment by storing excess PV generation. This paper develops a stochastic mixed-integer linear program (MILP) to optimize a curtailment-aware scheduling framework for a hybrid PV+BESS system. The deterministic day-ahead BESS charging/discharging schedule is optimized under probabilistic solar and load forecasting uncertainties. Two operational policies for charging/discharging are compared: (i) a fixed window and (ii) a flexible window. Results from a one-year study on an feeder in Ithaca, NY show that optimizing the dispatch of a 1 MW/4 MWh BESS in a 4.5 MW hybrid solar farm in Flex IX reduces curtailment by 61.90% and improves market revenues.**

Keywords— Battery Energy Storage System, Curtailment Mitigation, Flexible Interconnection, Hybrid PV, Mixed-Integer Linear Programming.

I. INTRODUCTION

Flexible interconnection (Flex IX) strategies are being deployed across utility networks to accommodate the rapid growth of distributed photovoltaic (PV) systems. Avangrid implemented North America's first Flex Solar IX project at two substations in Upstate New York, demonstrating over four years that dynamic grid integration of solar resources often experiences measurable curtailment caused by static thermal limits [1]. The Flex IX technology enhanced Avangrid's distribution substation hosting capacity from 7.6 MW to 15 MW while avoiding approximately $3 million in upgrade costs by managing DER output to maximize infrastructure use, support peak-load management, and maintain grid reliability, with a trade-off involving 0.06% solar curtailment since 2021. Flex IX strategies rely on active control and curtailment to safely manage variable DERs without overloading distribution assets or causing reverse power overflow [2], [3]. Data-driven methods have also been proposed for rapid grid impact assessment under increasing DER and electric vehicle (EV) penetration [4]. However, a persistent constraint remains: the thermal constraints and HC limits of distribution feeders and transformers. When DER output exceeds these limits, operators often curtail PV generation to maintain safe operation. DER curtailment can also occur due to network faults, which can be mitigated through probabilistic or MILP-based location techniques [5],[6]. To reduce this HC limitation in Flex IX, Dynamic Transformer Rating (DTR) provides additional thermal headroom under favorable ambient conditions [7]. Although DTR increases thermal capacity, it is effective primarily in colder regions. To mitigate the curtailment without upgrading the grid assets, the excess PV output during peak hours can be stored in BESS in hybrid PV+BESS farms [8]. Integrating BESS is profitable while PV output is limited by substation HC [9]. BESS is also utilized for smoothing out DER fluctuations, stabilizing grid, reducing feeder congestion, and increasing reliability [10]. Optimizing the BESS charging/ discharging schedule under Flex IX is need to be curtailment aware. Prior studies have applied Linear Programming (LP) to optimally schedule DERs with integrated BESS, focusing on cost minimization and peak load reduction while considering practical battery constraints [11]. Some studies have proposed Mixed-Integer Linear Programming (MILP)-based energy management systems with day-ahead forecasted renewable energy and load demand to reduce electricity costs and improve operational performance across seasonal variations [9], [10], [12]. By storing curtailed PV output due to HC limit during midday peaks and discharging during high Locational Based Marginal Price (LBMP) hours, hybrid PV+BESS systems not only mitigate energy losses but also create new revenue streams, making them an attractive strategy for renewable integration without costly grid reinforcements. Although optimization-based methods for PV and BESS coordination have been widely studied, many rely on deterministic forecasts of PV and load, overlooking the uncertainty inherent in renewable generation and demand [13]. Recent forecasting studies (e.g., statewide PV nowcasting and intra-day prediction frameworks) report hourly distributed PV errors broadly in the 7–20% range, with aggregated fleets commonly near 10–15% MAPE [14]. Accordingly, adopting a ±15% MAPE uncertainty band better represents practical solar variability than tighter bands, while remaining computationally manageable for MILP scheduling. Furthermore, conventional formulations often fail to incorporate Flex IX-specific operational rules, such as curtailment priority ordering, the influence of market price variability, and the use of real-time grid ratings on economic performance.

While Avangrid's Flex IX projects have validated dynamic interconnection for non-hybrid solar farms, hybrid PV+BESS optimization requires forecasted feeder load and PV generation data to determine optimal charging and discharging schedules with day-ahead LBMPs. Currently, no stochastic MILP framework exists to optimize deterministic BESS scheduling under Flex IX curtailment rules while accounting for PV and load forecasting uncertainties. To address this gap, we develop a stochastic MILP optimization model that provides informed guidance for developers implementing hybrid PV+BESS strategies under Flex IX.

979-8-3315-8138-1

Using a synthetic Flex IX feeder case study mimicking Avangrid's pilot project, the framework demonstrates that pairing a BESS with the most curtailment-prone PV unit can substantially reduce curtailment, increase effective HC utilization through forecast-driven scheduling without costly grid upgrades, and improve revenues under uncertainty.

The main contributions of this paper are:

1) A stochastic curtailment aware MILP for hybrid PV+BESS scheduling under feeder hosting-capacity limits with day-ahead LBMP, mutually exclusive charge/discharge, and degradation costs.

2) A one-year validation on an Ithaca feeder comparing fixed vs flexible BESS scheduling where flexible control reduces annual curtailment (e.g., 0.50→0.39 GWh in 2022) and boosts economic value.

3) Sensitivity analyses on BESS energy capacity and initial state of charge (SOC) quantifying curtailment and revenue trade-offs; result shows most benefits at 4–5 MWh BESS capacity for a 4.5MW PV farm. Also different initial SOC primarily shifts dispatch timing/revenue with negligible impact on annual curtailment.

II. METHODOLOGY

This section presents the stochastic MILP formulation developed for curtailment-aware scheduling of hybrid PV–BESS systems under the Flex IX framework. The model captures the uncertainty of PV generation and feeder load through scenario sampling within a ±15% variability band [14]. It optimizes mutually exclusive charging and discharging of the BESS to balance curtailment mitigation with revenue maximization. It explicitly incorporates day-ahead LBMP signals, BESS operational dynamics, and battery degradation costs, while enforcing exclusivity of charge and discharge operations. The degradation cost model employs a segmented cycle-aging function to capture non-linear stress effects at higher depths of discharge. This stochastic formulation aligns with industry-standard day-ahead scheduling practices, with the overall objective of minimizing energy curtailment under Flex IX constraints while enhancing market revenues.

A. Optimization Model

1) PV and Load Uncertainty Modeling

Based on the forecasted solar irradiance, temperature and wind speed, PV generation is forecasted. Forecasted load is calculated based on historical load data of that specific feeder. Thousands of scenarios are generated for PV and load based on the uncertainty band.

$$P_{pv}(s,t) \sim N\left(\widehat{P_{pv}}, \sigma_{pv}^2\right), \qquad \sigma_{pv} = 0.15 * \widehat{P_{pv}} \tag{1}$$

$$P_{load}(s,t) \sim N\left(\widehat{P_{load}}, \sigma_{load}^2\right), \qquad \sigma_{load} = 0.15 * \widehat{P_{load}} \tag{2}$$

where, $\widehat{P_{pv}}$ and $\widehat{P_{load}}$ are average forecasted hourly PV generation and load value respectively. σ_{pv} and σ_{load} are standard deviation of PV and load respectively. (1) is used to generate probabilistic PV generation scenarios $P_{pv}(s,t)$ based on Gaussian Distribution.

2) Objective Function

The model aims to minimize the expected cost from PV curtailment while maximizing the revenue from grid-exported energy, accounting for degradation costs:

$$\begin{aligned} min \sum_{s=1}^{S} \rho_s \sum_{t=1}^{T} [&LBMP(t) * P_{\mathrm{curt}}(s,t) - \sum_{j=1}^{J} c_j \,.\, d_j(s,t) \\ &- \rho_{s2} * LBMP(t) * (P_{\mathrm{pv}}(s,t) \\ &- P_{\mathrm{curt}}(s,t) - P_c(t) + P_d(t))] \end{aligned} \tag{2}$$

where, the index of scenarios $s \in \{1,2,3,\ldots.,S\}$, index of time $t \in \{0,\ldots,T-1\}$, ρ_s is probability of scenario s; $P_{\mathrm{curt}}(s,t)$ represents curtailed power, ρ_{s2} is a weighting factor for revenue. $P_c(t)$ and $P_d(t)$ denote the deterministic charging and discharging power independent of scenarios, $LBMP(t)$ is the LBMP, c_j denotes degradation cost per unit energy discharged in cycle segment j, and $d_j(s,t)$ denotes energy discharge in cycle j. c_j is calculated as follows:

$$c_j = \frac{R}{\eta_d . E_{max} . J}\left[\phi\left(\frac{j}{J}\right) - [\phi\left(\frac{j-1}{J}\right)\right] \tag{3}$$

where, $\phi(\delta) = k.\delta^n$; $\phi(\delta)$ is a cycle aging stress function with exponent n, k is stress function coefficient, R is battery replacement cost, E_{max} is rated energy capacity, and η_d *is* discharge efficiency.

3) Modelling and Constraints

To minimize curtailment and maximize revenue, mutually exclusive deterministic charging/discharging schedule is optimized. The optimized schedule charges during the peak curtailment hours and discharge during the high LBMP prices. Curtailment is calculated based on the power imbalance:

$$P_{\mathrm{im}}(s,t) \geq P_{\mathrm{pv}}(s,t) - P_{HC}(s,t) - P_c(t) + P_d(t) \tag{4}$$

where, $P_{im}(s,t)$ is the net power imbalance at scenario s at time t. $P_{HC}(s,t)$ is the dynamic hosting capacity which is determined as follows:

$$P_{HC}(s,t) = P_{xfmr}(t) + P_{load}(s,t) - P_{DER}(t) \tag{5}$$

where, $P_{xfmr}(t)$ is the transformer capacity, $P_{DER}(t)$ is summation of all other high priority DERs output in Flex IX and $P_{load}(s,t)$ is probabilistic load. The curtailment $P_{\mathrm{curt}}(s,t)$ is determined as follows:

$$P_{curt}(s,t) = \begin{cases} P_{\mathrm{im}}(s,t) & , if\ P_{\mathrm{im}}(s,t) \geq 0 \\ 0 & , if\ P_{\mathrm{im}}(s,t) < 0 \end{cases} \tag{6}$$

To represent this piecewise condition in MILP, we introduce a binary variable $U_{curt}\,(s,t) \in \{0,1\}$

$$U_{curt}(s,t) = \begin{cases} 1 & , if\ P_{\mathrm{im}}(s,t) \geq 0 \\ 0 & , if\ P_{\mathrm{im}}(s,t) < 0 \end{cases} \tag{7}$$

Using the big-M theory, (7) is linearized as

$$P_{\mathrm{im}}(s,t) \leq M * U_{curt}(s,t) \tag{8}$$

$$P_{\mathrm{im}}(s,t) \geq -M * (1 - U_{curt}(s,t)) \tag{9}$$

where, M is a large number. (6) can be further linearized by converting $P_{curt}\,(s,t)$ into a linear combination of $P_{im}\,(s,t)$ & $U_{curt}\,(s,t)$ as

$$P_{curt}(s,t) \leq P_{\mathrm{im}}(s,t) + M * (1 - U_{curt}(s,t)) \tag{10}$$

$$P_{curt}(s,t) \geq P_{\mathrm{im}}(s,t) - M * (1 - U_{curt}(s,t)) \tag{11}$$

The BESS state of charge (SOC), E(t), evolves as

$$E(t) = E(t-1) + \eta_c P_c(t)\Delta t - \frac{1}{\eta_d} P_d(t)\Delta t \tag{12}$$

979-8-3315-8138-1

$$E(t)=\begin{cases}E(0) & if\ t=0\\ E(t-1)+\eta_c P_c(t)\Delta t-\dfrac{1}{\eta_d}P_d(t)\Delta & if\ t>0\\ E(0) & when\ t=T\end{cases} \quad (13)$$

Subject to operational limits:

$$E_{min} \le E(t) \le E_{max} \quad (14)$$

$$0 \le P_c(t), P_d(t) \le P_{max} \quad (15)$$

$$P_c(t) \le P_{curt}(s,t) \quad (16)$$

where, E_{min} *and* E_{max} represent minimum and maximum SOC limits respectively, P_{max} is the maximum charging power (ramp rate) at any timestep t.

To prevent simultaneous charging and discharging, a binary variable $u_{\text{charge}}(t) \in \{0,1\}$ is introduced.

$$P_c(t) \le P_{max} \cdot u_{\text{charge}}(t) \quad (17)$$

$$P_d(t) \le P_{max} \cdot \left(1-u_{\text{charge}}(t)\right) \quad (18)$$

For the case study with fixed charging/discharging windows, the following constraints are added by replacing (17), (18).

$$\chi_c(t)=\begin{cases}1 & , if\ t\ \epsilon\ [\tau_c^S, \tau_c^E)\\ 0 & , otherwise\end{cases} \quad (19)$$

$$\chi_d(t)=\begin{cases}1 & , if\ t\ \epsilon\ [\tau_d^S, \tau_d^E)\\ 0 & , otherwise\end{cases} \quad (20)$$

$$P_c(t) \le P_{max} \cdot \chi_c(t) \cdot u_{\text{charge}}(t) \quad (21)$$

$$P_d(t) \le P_{max} \cdot \chi_d(t) \cdot (1-u_{\text{charge}}(t)) \quad (22)$$

where χ_c and χ_d are binary variables at time t for charging and discharging window respectively; τ_c^S and τ_c^E denote start and end of charging window; τ_d^S and τ_d^E denote start and end of discharging window.

The complete MILP formulation was implemented in Pyomo for 1000 PV and load scenarios and solved using the Gurobi solver. For validation, the framework is applied to a synthetic Flex IX Ithaca feeder consisting of three solar farms connected under a Last-In, First-Out (LIFO) curtailment scheme. The lowest-priority site, which faces the highest curtailment during peak generation hours, is converted into a hybrid PV+BESS resource. The optimization uses forecasted feeder load and other DER generation profiles to compute available hosting capacity for the hybrid unit in each scenario using (5). The model then schedules deterministic BESS charging and discharging under uncertain PV and load scenarios satisfying all constraints. The subsequent results section evaluates system performance using representative daily PV and load profiles, sensitivity studies on BESS capacity, and initial state-of-charge to assess its robustness and economic trade-offs.

III. Case Study

The proposed framework is evaluated on a synthetic Flex IX feeder consisting of three solar farms connected to a 6-MVA substation, as illustrated in Fig. 1. Similar to Avangrid's Flex IX demonstration site in Spencerport, NY, three solar farms are modeled as Flex IX participants. Unlike Avangrid's pilot, which focused on non-hybrid solar farms with DER control systems, this study extends the framework by integrating a BESS to mitigate curtailment by charging during periods of high-curtailment. In this model, day-ahead forecast uncertainty in feeder load is reflected as variability in hosting capacity (HC). Then the day-ahead PV forecasts are used to optimize the model, generating a deterministic BESS charging/discharging schedule. This enables developers to evaluate BESS utilization and revenue potential under Flex IX curtailment rules and benchmark performance against Avangrid's non-hybrid Flex IX sites.

The synthetic feeder includes solar farms rated at 5 MW, 4 MW, and 4.5 MW, dispatched under a LIFO curtailment scheme, with priority order: Farm 1 > Farm 2 > Farm 3. In this configuration, the lowest-priority site, Solar Farm 3 (4.5 MW), experiences the greatest curtailment—approximately 1.26 GWh annually (20.25%). To alleviate this, Farm 3 is converted into a hybrid PV+BESS resource with a 1 MW/4 MWh storage system, enabling curtailed energy to be captured and strategically discharged during high-LBMP hours. The modeling assumptions and operating constraints are informed by Avangrid's Flex IX initiatives.

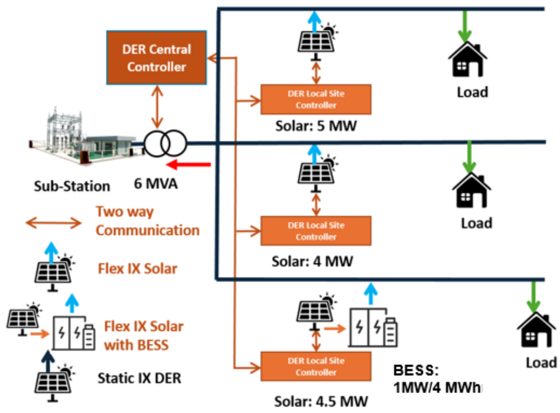

Fig. 1. Flex IX feeder with three solar farms connected to a 6 MVA substation; Farm 3 is converted to hybrid PV with a 1 MW/4 MWh BESS.

TABLE I Parameter for Simulation

P_{max}	E_{max}	E_{min}	η_c	η_d
1000	4000	0	0.95	0.95
τ_c^S	τ_c^E	τ_d^S	τ_d^E	J
10	14	16	20	4
n	k	R	ρ_s	ρ_{s2}
2	0.01	4e6	5000	0.5

A. Data Sampling and Scenario Generation

Historical feeder load data from the Ithaca, NY substation (Oct 2021 – Oct 2022) are used as the median values of the day-ahead forecasted load. The PV generation profile is derived from forecasted meteorological data obtained through NASA POWER [15]. For each hour t, 1000 probabilistic scenarios are generated within a ±15% variability band around the hourly median of the observed PV and load values, with equal probability ($\rho_s = 0.001$) assigned to each scenario. Day-ahead LBMP data are collected from the NYISO market archive [16]. This approach captures realistic variability in PV and load for the stochastic MILP optimization framework. The sampled load values and transformer capacity are summed to estimate the total hosting capacity (HC). After subtracting the estimated outputs of Farm 1 and Farm 2 based on meteorological conditions, the available HC for Farm 3 in each scenario is calculated using (5). The resulting PV and load scenarios serve as probabilistic inputs for hybrid PV+BESS scheduling under Flex IX, and the simulation parameters are summarized in Table I.

979-8-3315-8138-1

B. Simulation Result for Fixed Window Scheduling

The capacity of the BESS is 1MW/4MWh with 95% round trip efficiency. This fixed charging/discharging scheduling window is considered as a conservative case study. We considered 10 AM – 2 PM as charging window to capture the peak solar power during this period. And we considered 4 PM - 8 PM as fixed discharging window as this time solar power decreases and LBMP price is higher. The operation of the hybrid PV+BESS under fixed window scheduling for one representative day (May 29, 2022) is shown in Fig. 2. The HC drops during day time due to power injection from Farm 1 and Farm 2. The battery charges primarily between 10:00 and 13:00, coinciding with peak PV generation and periods of curtailment risk. The state of charge (SOC) reaches to maximum capacity of 3157.89 kWh around 13:00. Discharging is then initiated in the late afternoon (16:00–19:00) when PV output declines and day ahead LBMP increases, allowing the hybrid solar farm developer to maximize revenue. The exclusivity of charging and discharging is enforced by the MILP constraints, ensuring realistic operation.

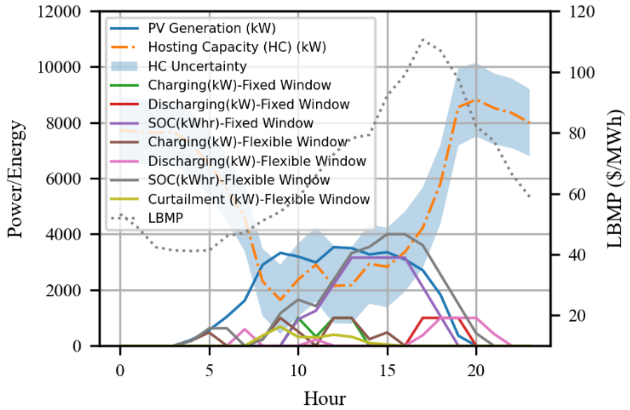

Fig. 2. Optimized BESS operation with fixed and flexible charging, discharging window (May 29, 2022).

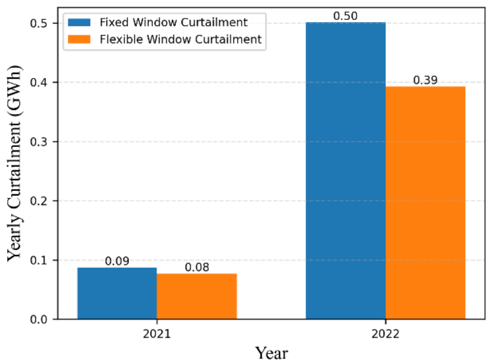

Fig. 3. Fixed window vs flexible window scheduling yearly curtailment. Timeline: 2021 (Oct – Dec), 2022 (Jan -Oct).

C. Simulation Result for Flexible Window Scheduling

Flexible scheduling window allows the BESS to optimize charging and discharging to both minimize curtailment and maximize energy revenue. With mutually exclusive charge/discharge enforced, Fig. 2 shows the battery begins charging at 8:00 when HC falls below Farm 3's output and the SOC reaches its 4 MWh capacity at 15:00. Solar curtailment decreases from 3.86 MWh (fixed window) to 2.53 MWh (flexible window), a 34.45% reduction for that day, which aggregates to a substantial annual benefit. As show in Fig. 2, flexible scheduling consistently lowers annual curtailment relative to a fixed window: in 2021 it drops from 0.09→0.08 GWh (-11.1%), and in 2022 from 0.50→0.39 GWh (-22.0%). Farm 3 without BESS is faced with ~1.26 GWh curtailment; with BESS this falls to 0.48 GWh under flexible scheduling. Thus, flexible control provides the larger curtailment relief while preserving the ability to target higher-price discharge periods. For a solar farm with 4.5MW capacity facing frequent curtailment, a 1MW/4 MWh BESS could nearly eliminate 61.90% energy curtailment, deferring costly grid upgrades. These results confirm that the proposed framework effectively coordinates BESS operation to achieve both curtailment reduction and market-driven economic discharging.

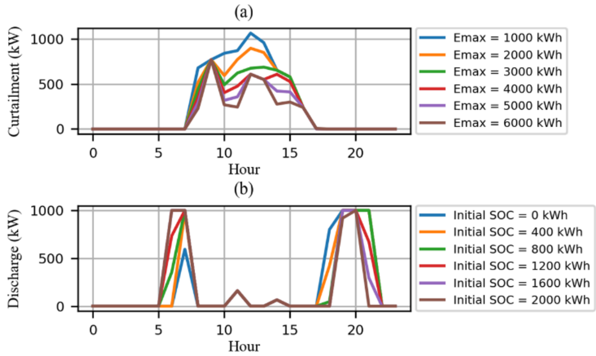

Fig. 4. (a) Hourly curtailment profiles for different maximum BESS SOC levels (E_{max}). (b) Hourly discharging profiles for different initial BESS SOC levels (E_0) (May 29, 2022).

TABLE II RESULT FOR DIFFERENT BATTERY CAPACITIES

Emax (kWh)	Total Curtailment (MWh)	Total Charging (MWh)	Total Discharging (MWh)	Total Revenue ($)
1000	694.74	491.15	443.26	380491.37
2000	604.82	832.32	751.17	384480.01
3000	530.80	1098.29	991.21	387020.14
4000	469.58	1322.77	1193.80	388340.71
5000	424.97	1492.28	1346.79	388804.04
6000	391.78	1604.33	1447.91	388611.77

IV. SENSITIVITY ANALYSIS

A. Impact of Battery Capacity (E_{max})

To assess storage sizing impacts, the BESS energy capacity $E_{max} \in \{1,2,3,4,5,6\}\ MWh$ was evaluated using the full-year Ithaca dataset with day-ahead LBMP. As shown in Fig. 4(a) and Table II, when E_{max} increases, annual curtailment drops from 694.74 to 391.78 MWh (≈ 44% reduction), while battery utilization rises. Revenue improves from \$380.49k at 1 MWh to a maximum of \$388.80k at 5 MWh (+2.2% over the baseline), then slightly decreases to \$388.61k at 6 MWh, indicating diminishing economic returns beyond 4–5 MWh. Thus, sizing around 4–5 MWh captures most of the curtailment relief and revenue benefit, whereas further upsizing yields modest additional curtailment reduction with negligible revenue gain. This suggests developers should size storage primarily for curtailment absorption, not for complete elimination, as market signals do not reward oversizing.

B. Impact of Initial State of Charge (E_0)

As shown in Fig. 4(b) and Table III, the effect of the initial SOC is evaluated by sweeping $E_0 \in \{0,400,800,1200,1600,2000\}$ kWh with $E_{max} = 4\ MWh$ over the full year for this Ithaca feeder. Annual curtailment is essentially

979-8-3315-8138-1

invariant to E_0, it changes only from 469.58 to 469.74 MWh (<0.04% swing), indicating that curtailment is primarily driven by feeder limits and PV/load coincidence rather than SOC initialization. In contrast, dispatch shifts markedly with E_0. As E_0 increases, total charging falls while total discharging rises from 1193.8 MWh to 1655.52 MWh (+38.6%). Revenue increases monotonically from $388,340.71 to $432,933.01 (+11.5%). The mechanism is: a higher initial SOC enables immediate discharge into early high-price hours, and the value of that early arbitrage outweighs the lost midday headroom for PV absorption. Operationally, E_0 is an effective control knob for price-responsive scheduling with day-ahead LBMP forecasts.

TABLE III RESULT FOR INITIAL BATTERY SOC

E0 (kWh)	Total Curtailment (MWh)	Total Charging (MWh)	Total Discharging (MWh)	Total Revenue ($)
0	469.58	1322.77	1193.8	388340.71
400	469.58	1272.8	1286.65	397603.18
800	469.65	1222.45	1379.14	406760.86
1200	469.74	1173.38	1472.79	415707.53
1600	469.74	1122.68	1564.98	424378.10
2000	469.74	1070.16	1655.52	432933.01

These results highlight that the initial SOC primarily affects the timing of energy dispatch rather than the magnitude of curtailment, with an operational trade-off between capturing early price spikes and maximizing PV absorption.

V. CONCLUSION

This work presents the first stochastic MILP-based scheduling framework for hybrid PV+BESS systems designed specifically for Flex IX applications. Building on operational insights from Avangrid's Flex IX projects, the proposed curtailment-aware framework explicitly incorporates PV and load forecast uncertainties to derive a deterministic day-ahead BESS schedule. Forecasted feeder load is used to estimate available hosting capacity, while forecasted PV generation enables optimal charge/discharge decisions that account for degradation costs and day-ahead LBMP signals across a ±15% uncertainty band. Using a full year of data from an Ithaca feeder, results show that adding a 1-MW/4-MWh BESS to the most curtailment-prone PV site significantly reduces Flex IX curtailment relative to a no-BESS case (≈1.2 GWh for Farm 3). The choice of scheduling policy is also important: a flexible window consistently outperforms a fixed window, reducing annual curtailment from 0.50→0.39 GWh in 2022 and 0.09→0.08 GWh in late 2021, while still enabling profitable market-driven discharging. Overall, the hybrid configuration eliminates up to 61.90% of the energy that would otherwise be curtailed, enabling substantial utilization gains without requiring grid reinforcements. Sensitivity analyses further provide actionable design guidance. Increasing BESS energy capacity beyond 4–5 MWh yields diminishing economic returns, as most curtailment relief and arbitrage value are captured within this range. The initial state of charge primarily affects the timing of discharge—shifting energy toward high-price hours—while having negligible impact on total curtailment. Overall, these findings demonstrate that hybrid PV+BESS resources offer a practical and economically attractive pathway for utilities and developers to expand DER hosting under Flex IX. The results provide clear guidance for storage sizing, operational set-points, and scheduling strategies. Future work will explore multi-asset coordination across feeders, tighter coupling to probabilistic forecasts, and real-time control implementations to validate performance under communication constraints..

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