Multi-Resolution Stochastic Dispatch of Energy Storage Under Forecast Uncertainty

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***Abstract*—Energy storage is increasingly important for supporting resource adequacy and balancing supply and demand amid rapidly rising U.S. electricity loads driven by data center growth and broader digitalization. Determining the optimal dispatch of energy storage systems (ESSs) to maximize utilization and economic value remains challenging, particularly for long-duration applications with extended look-ahead needs. This paper proposes a multi-resolution (MR) stochastic programming (SP) framework for ESS energy arbitrage under price-forecast uncertainty. In particular, the MR construct is designed to adjust the temporal granularity of forward prices over the look-ahead horizon while preserving the essential temporal patterns needed for effective arbitrage. It applies finer resolution where forecast accuracy is higher and progressively coarser resolution where forecast precision diminishes. A two-stage SP formulation is further developed to mitigate the impact of forecast deviations on net revenue. Case studies demonstrate the effectiveness of the proposed method with realistic price forecasts across a wide range of energy storage durations and look-ahead window lengths.**

***Index Terms*—Energy storage, forecast uncertainty, multi-resolution optimization, stochastic programming, uncertainty-tolerant dispatch**

I. Introduction

Energy storage systems (ESSs) are flexible and scalable, and can respond instantaneously to unpredictable variations in demand and generation of power systems. The need for energy storage in the electrical grid has grown in recent years in response to rapidly rising U.S. electricity demand driven by hyperscale data center expansion and re-industrialization initiatives. Its capabilities of shifting energy across time to balance supply and demand, relieving peak capacity constraints, and strengthening resource adequacy are essential for reliable and cost-effective grid operation [1]. ESS can be integrated at multiple levels of the grid from small, behind-the-meter (BTM) applications up to the transmission-level with various power and energy capacities. A comprehensive review of services for energy storage valuation was conducted in [2], where five major categories were identified: bulk energy-based, ancillary-based, transmission-based, distribution-based, and customer-based services. Utility procurement targets and resource planning studies increasingly project substantial growth in grid-scale storage deployments, with higher-capacity projects now under development across the U.S. [3].

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Extensive literature addresses ESS dispatch and scheduling. Popular approaches include model predictive control (MPC), which solves a finite-horizon optimization online and explicitly enforces operational constraints, and optimization methods (linear and mixed-integer programming) that compute optimal schedules or upper bounds on net revenue under perfect information [4], [5]. These methods support both short-term dispatch and long-term valuation, where repeated scheduling and simulation estimate lifetime value for planning. Uncertainty—from load, market prices, variable generation, and model parameters—remains central: probabilistic models such as Markov decision processes, stochastic programming (SP), dynamic programming, and robust optimization have been proposed to incorporate these risks [6]. SP is among the most widely used approaches [7]; examples include bi-level stochastic scheduling for load-serving entities [8] and treatments of day-ahead (DA) and real-time price uncertainty using stochastic and robust formulations [9]. Complementary research examines practical market participation—self-scheduling, reserve products, and technology-specific nonlinear models—to address bidding strategies and market uncertainty [10].

Compared with short- and medium-duration ESSs, the extended discharge capability of long-duration storage allows it to benefit more inter-day energy shifting opportunities. Fully utilizing this capability, however, requires anticipating system and price conditions farther into the future, where forecast uncertainty increases and complicates dispatch decisions. A recently published survey [3] provides a comprehensive examination on the major components of potential value streams of longer-duration ESSs, including energy arbitrage, different ancillary services, and resource adequacy (RA) capacity, considering the existing and future development of technologies and markets. Most existing optimal scheduling/dispatch methods in the literature only consider DA optimization with a 24-hour (or shorter) look-ahead window. This is usually enough for ESS with duration up to a few hours, since the benefits gradually plateau when the length of the look-ahead window passes about 3 times the duration of the ESS. For ESSs with duration longer than 8 hours, however, looking only 24 hours ahead will probably result in sub-optimal dispatch and henceforth underestimated value. A longer look-ahead window becomes necessary to fully achieve the potential value.

In areas within the footprint of an ISO or RTO, the wholesale DA energy prices are determined through market

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auctions where supply- and demand-side bids settle locational marginal prices (LMPs). When bidding for Day D, these future LMPs are unknown and must be predicted based on historical data. While most existing work assumes perfect knowledge of price information—an assumption acceptable for short-duration ESSs with 24-hour horizons—it becomes invalid for systems requiring longer look-ahead windows. Extending the look-ahead window would be straightforward if future prices could be predicted with high accuracy. However, long-term predictions are inevitably more difficult due to the accumulation of errors and increasing uncertainties [11]. The forecast accuracy typically deteriorates (sometimes quite severely) as the number of steps increases.

To address these challenges, we propose a multi-resolution (MR) optimal dispatch method that combines hierarchical price representations with two-stage SP. The method represents future prices at progressively coarser resolutions as the forecast horizon extends, while preserving the information needed for profitable arbitrage. In this work, we assume the ESS participates in the DA market as a "price taker", committing to charge or discharge energy regardless of the settled LMPs. While state-of-the-art price forecasting techniques such as deep learning and statistical models continue to improve [12], our framework is agnostic to the specific forecasting method and explicitly incorporates the uncertainties inherent in any price forecast. We study how key parameters—such as storage duration, round-trip efficiency, and look-ahead horizon—affect the valuation under forecast uncertainty. The main contributions of this paper are twofold: (1) a novel MR dispatch framework that leverages price information at multiple time scales to relax long-term forecasting requirements and enable tractable optimization over long horizons; and (2) one of the first applications of SP to ESS dispatch that explicitly models long-horizon forecast uncertainty and recourse.

II. Multi-Resolution Stochastic Programming

In this section, our proposed optimal dispatch method for ESS with various durations is presented.

A. Multi-Resolution Optimization Framework

Price forecasts in lookahead window longer than 24 hours should be included when making charging/discharging decisions for the DA market. While forecasting hourly future electricity accurately is challenging and not entirely necessary, forecasting the future average prices and trend of prices is relatively easy and also informative for current charging/discharging decisions. In this paper, MR random processes are used to represent the uncertainties of prices over long look-ahead windows. The time resolution is finest (i.e., hourly) in the near term and gradually coarsens as the forecast horizon extends, reducing the number of decision variables in the optimization and the sensitivity to long-range forecast errors. An example of such MR random process model for the electric energy prices in a 21-day look-ahead window is shown in Fig. 1, where the time resolutions are designed as: hourly for the first 24 hours, 3-hour blocks for Day 2, 6-hour blocks for Day 3, and 24-hour (daily) blocks for Days 4–7, and a single 168-hour (weekly) block for each week starting at Day 8.

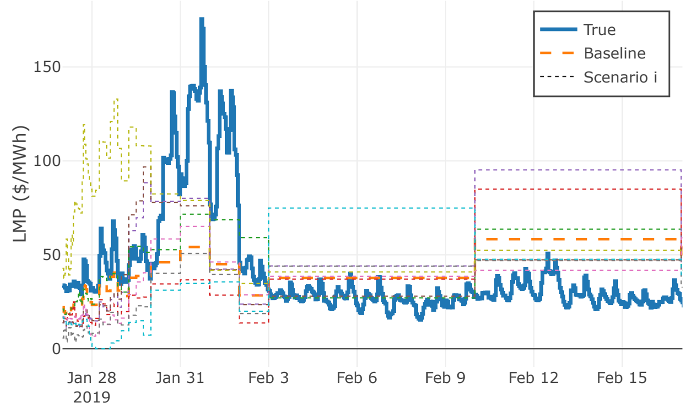

Fig. 1. Illustration of multi-resolution energy price forecast.

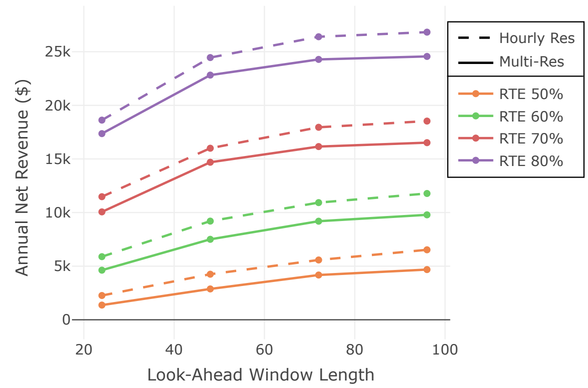

Fig. 2. Energy arbitrage net revenue: hourly resolution vs. multiple resolutions.

Using progressively coarser time blocks farther into the horizon reduces the burden of accurate long-term hourly price forecasting and attenuates accumulated uncertainty, while preserving nearly all arbitrage net revenue. Under perfect foresight, the annual arbitrage net revenue obtained with a uniform hourly resolution and with the proposed MR structure are compared in Fig. 2. Across ESSs with different round-trip efficiencies (RTEs), the MR approach yields only marginal reductions, and noticeable differences emerge only for the longest look-ahead windows, indicating that temporal aggregation imposes a negligible cost relative to its forecasting robustness benefits.

Formally, Let $\{\mathcal{T}_1, \ldots, \mathcal{T}_L\}$ be nested partitions of the look-ahead horizon, where stage ℓ uses resolution Δ_ℓ with $\Delta_1 < \cdots < \Delta_L$. Each block $k \in \mathcal{T}_\ell$ is represented by a forecasted average price Λ_k. This structure retains the essential inter-block price patterns while filtering out long-horizon high-frequency variations.

B. Optimal Dispatch Under Forecast Uncertainties

An ESS can be modeled as a scalar linear system that resembles a simplified dynamics of energy state parameterized by charging and discharging power limits, energy state limits, and efficiencies. To capture one-way efficiencies, we introduce

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two non-negative auxiliary variables, p_k^+ and p_k^-, which denote the average discharging and charging power, respectively, at the coupling point in the kth time period. The discharging and charge power ranges are

$$0 \le p_k^+ \le P_{\text{max}}, \quad 0 \le p_k^- \le P_{\text{max}}, \quad \forall k \tag{1}$$

where P_{max} is the ESS rated power and $\mathcal{K}$ is the set of indices of all time periods in the optimization window. The ESS power output can be expressed as

$$p_k = p_k^+ - p_k^-, \quad \forall k \tag{2}$$

where a positive p_k means discharging. The dynamics of energy state is modeled as

$$e_k = e_{k-1} - (p_k^+/\eta^+ - p_k^-\eta^-)T_k, \quad \forall k \tag{3}$$

where e_k is the energy state at the end of time period k, η^+ and η^- are discharging and charging efficiencies, respectively, and $T_k = \Delta_\ell, \forall k \in \mathcal{T}_\ell$ is the duration of the kth time period, which belongs to stage ℓ. The energy state range is

$$0 \le e_k \le E_{\text{max}}, \quad \forall k \tag{4}$$

where E_{max} is the energy capacity.

Let $\mathcal{K} = \mathcal{K}_{\text{DA}} \cup \mathcal{K}_{\text{F}}$, where $\mathcal{K}_{\text{DA}} = \{1, \cdots, M\}$ and $\mathcal{K}_{\text{F}} = \{M+1, \cdots, M+N\}$ denote the index sets of time periods within the DA window and forecast windows, respectively. The DA market prices λ_k, $\forall k \in \mathcal{K}_{\text{DA}}$, are deterministic and known. Let random variables Λ_k, $\forall k \in \mathcal{K}_{\text{F}}$, denote the average prices in time period k in the forecast window.

When considering energy arbitrage as a single value stream for the ESS, we maximize the expected net revenue over the entire look-ahead window $\mathcal{K}$. Let $\boldsymbol{p}_{\text{DA}}$ denote the vector of power output, i.e., the dispatch schedule, of time periods in the DA window and $\boldsymbol{p}_{\text{F}}$ for that in the forecast window. The objective function can formulate as

$$\underset{\boldsymbol{p}_{\text{DA}}, \boldsymbol{e}_{\text{DA}}}{\text{maximize}} \quad \mathbb{E}_{\boldsymbol{\Lambda}_{\text{DA}}}\left[\sum_{k\in\mathcal{K}_{\text{DA}}} \Lambda_k p_k T_k + Q(e_M, \boldsymbol{\Lambda}_{\text{DA}})\right] \tag{5a}$$

$$= \sum_{k\in\mathcal{K}_{\text{DA}}} \mathbb{E}\left[\Lambda_k\right] p_k T_k + \mathbb{E}_{\boldsymbol{\Lambda}_{\text{DA}}}\big[Q(e_M, \boldsymbol{\Lambda}_{\text{F|DA}})\big] \tag{5b}$$

$$\text{subject to} \quad (1)(2)(3)(4),\ \forall k \in \mathcal{K}_{\text{DA}} \tag{5c}$$

where $\mathbb{E}_{\boldsymbol{\Lambda}_{\text{DA}}}[\cdot]$ denotes the expected value of a random expression with respect to random vector $\boldsymbol{\Lambda}_{\text{DA}}$ and $Q(e_M, \boldsymbol{\lambda}_{\text{DA}})$ denotes the optimal value of the second-stage optimization.

The second-stage optimization, presented in (6), attempts to find the best recourse action, i.e., the optimal schedule in the forecast window, given a realization of $\boldsymbol{\Lambda}_{\text{DA}}$ and the energy state at the end of the DA window e_M, which is one of the decision variables in the first-stage optimization.

$$Q(e_M, \boldsymbol{\lambda}_{\text{DA}}) = \max_{\boldsymbol{p}_{\text{F}}, \boldsymbol{e}_{\text{F}}} \mathbb{E}_{\boldsymbol{\Lambda}_{\text{F}}}\left[\sum_{k\in\mathcal{K}_{\text{F}}} \Lambda_k p_k T_k \,\middle|\, \boldsymbol{\Lambda}_{\text{DA}} = \boldsymbol{\lambda}_{\text{DA}}, e_M\right] \tag{6a}$$

$$\text{subject to} \quad (1)(2)(3)(4),\ \forall k \in \mathcal{K}_{\text{F}} \tag{6b}$$

$$= \max_{\boldsymbol{p}_{\text{F}}, \boldsymbol{e}_{\text{F}}} \sum_{k\in\mathcal{K}_{\text{F}}} \mathbb{E}[\Lambda_k | \boldsymbol{\Lambda}_{\text{DA}} = \boldsymbol{\lambda}_{\text{DA}}] p_k T_k \tag{6c}$$

$$\text{subject to} \quad (1)(2)(3)(4),\ \forall k \in \mathcal{K}_{\text{F}} \tag{6d}$$

The two-stage SP formulation in (5) can be approximately reformulated as a deterministic optimization problem with the *sample average approximation* (SAA) method. The problem after reformulation can then be solved by conventional optimization solvers.

III. Case Studies

To demonstrate the performance and applicability of the proposed optimal dispatch method, we test it across various scenarios with different ESS durations and look-ahead window lengths. The round-trip efficiency is set to 70%, which is typical for technologies such as flow batteries and compressed air energy storage [3]. In this section, we first introduce the price forecast methods and data employed in our case studies. This is then followed by the detailed simulation results and corresponding discussions.

A. DA Price Forecast and Scenario Generation

Our proposed optimal dispatch method takes price forecasts and their distributions as input parameters. To evaluate the method's capability of handling forecast errors of various levels under a controlled environment, we generate realistic price forecasts using a causal baseline model combined with block bootstrap scenario generation.

The baseline forecast is constructed using only historical data available prior to the forecast period, ensuring causality. For each forecast starting at time t, we extract three key patterns from a training window of preceding weeks: (1) a weekly seasonal pattern obtained via a 168-hour moving average, (2) a slow trend estimated from a longer 720-hour moving average, and (3) hour-of-week statistics (mean μ_h and standard deviation σ_h for each hour-of-week h). The baseline forecast at each future hour combines the hour-of-week mean adjusted by the ratio of trend to seasonal pattern. This approach captures both diurnal and weekly price cycles while adapting to recent market conditions.

To generate scenario forecasts that reflect realistic uncertainty, we employ a two-step process. First, residuals are computed and standardized by $\tilde{\epsilon}_k = (\lambda_k - \mu_{h(k)})/\sigma_{h(k)}$. Second, error paths for each scenario are constructed via block bootstrap: randomly selected blocks of consecutive standardized residuals (e.g., 168-hour blocks) are sampled with replacement and concatenated to form a forecast-length error sequence. This block resampling preserves the temporal autocorrelation structure inherent in price forecasts. Each scenario is then obtained by adding these scaled errors back to the baseline:

$$\Lambda_k^{(i)} = \text{baseline}_k + \tilde{\epsilon}_k^{(i)} \cdot \sigma_{h(k)}, \quad \forall k, i \tag{7}$$

where $\Lambda_k^{(i)}$ is the price for Scenario i at time step k and $\tilde{\epsilon}_k^{(i)}$ is the block-bootstrapped standardized residual. This methodology generates price scenarios that maintain hour-specific heteroscedasticity, temporal correlation, and realistic deviations from the baseline, providing a robust testbed for evaluating storage dispatch under forecast uncertainty. An example of the forecast baseline and 8 generated scenarios is shown in Fig. 1.

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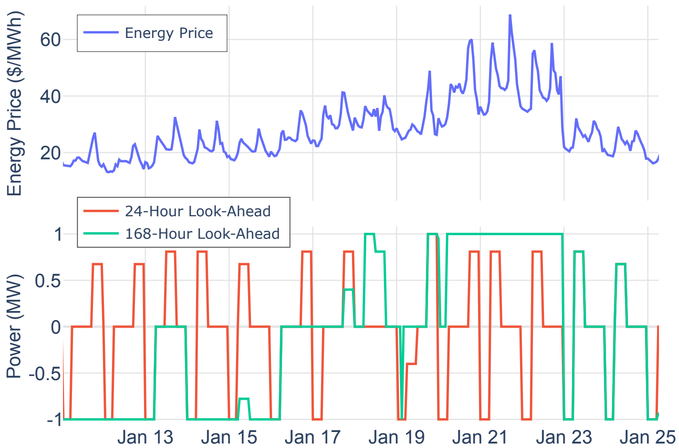

Fig. 3. Optimal dispatch with different look-ahead windows.

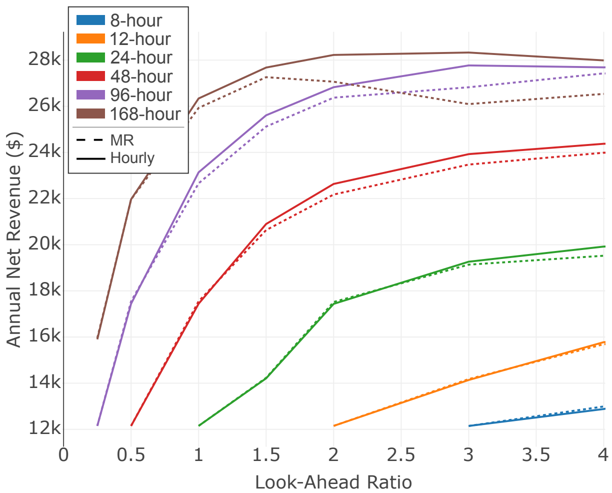

Fig. 4. Comparison of annual energy arbitrage net revenue for ESSs with different durations: multiple resolutions vs. hourly Resolution with perfect foresight.

B. Effectiveness of Multi-Resolution Optimal Dispatch

An example of the optimal dispatch with different look-ahead window lengths are presented in Fig. 3. With the 24-hour look-ahead window, the optimal dispatch only captures the arbitrage opportunities within a day. On the other hand, with the 168-hour (one-week) look-ahead window, the optimization is able to consider arbitrage opportunities over longer periods. Hence, the ESS is charged more from Jan 12 to 17 and discharged more from Jan 18 to 22, favoring the larger inter-day price differences over the smaller intra-day ones.

Fig. 4 presents the annual energy arbitrage net revenue achieved by our proposed MR optimization framework compared to conventional hourly resolution optimization under perfect foresight, evaluated across ESSs with different durations. As expected, increasing the look-ahead window generally raises arbitrage net revenue, yet the marginal benefit diminishes and net revenue saturate beyond a certain look-ahead ratio — the look-ahead window length divided by the ESS duration. Solid curves show results with hourly resolution, while dashed curves report performance of our proposed MR optimization. The vertical gap between each solid curve and its corresponding dashed curve quantifies the net revenue loss caused by the MR approximation; this loss tends to grow with look-ahead window length as the resolution gets coarser. Overall, the net revenue loss relative to hourly resolution is small, confirming the effectiveness of the proposed MR framework. The only notable degradation occurs for the 168-hour ESS when the look-ahead ratio exceeds one, where the weekly-resolution reduces net revenue and even causes it to decline with further horizon extension from 1.5 to 3 weeks.

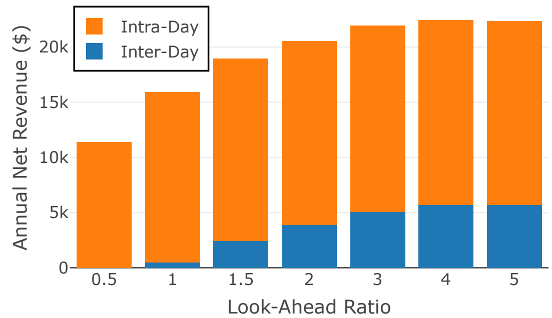

Fig. 5. Annual net revenue from intra-day and inter-day energy arbitrage.

The asymptotic (plateau) arbitrage net revenue depends on storage duration: longer-duration systems attain higher plateau values because they can capture longer-term price spreads, whereas shorter-duration systems exhaust available opportunities at shorter look-ahead windows. To clarify the effects of look-ahead horizon and storage duration on arbitrage, we plot the annual net revenue from intra-day and inter-day arbitrage for a 48-hour ESS in Fig. 5 as a function of the look-ahead ratio. When the ratio is small (≤ 1), nearly all net revenue originates from intra-day opportunities. As the look-ahead window increases, inter-day arbitrage net revenue grows substantially and becomes a larger share of total net revenue; this increase levels off once the look-ahead ratio exceeds about 3, indicating diminishing marginal returns from further extending the horizon.

However, once duration is sufficient to capture the dominant inter-day price spreads, additional capacity yields smaller gains because it can only exploit remaining, smaller price differentials while increasing opportunity costs from longer charge-discharge cycles. This phenomenon highlights the diminishing returns associated with extending the duration of ESSs beyond a certain threshold. Consequently, one must carefully evaluate the trade-offs between annual net revenue and the capital and operational costs associated with larger energy capacities, ensuring that investments in longer-duration systems are justified by the expected returns.

C. Mitigation of Uncertainties with SP

SP is employed in our proposed approach to mitigate the impact of forecast uncertainties for energy arbitrage with ESSs. By considering the ensemble of random forecast errors and optimize accordingly with recourse actions, the energy

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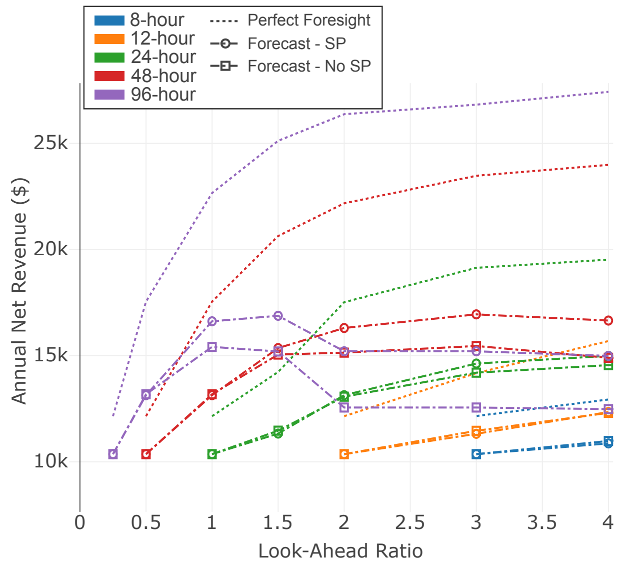

Fig. 6. Annual energy arbitrage net revenue with multi-resolution stochastic programming for different storage durations and look-ahead ratios.

arbitrage net revenue can be maximized. Fig. 6 compares the annual energy arbitrage net revenue obtained with and without SP for ESSs with various durations. While forecast errors inevitably reduce the arbitrage net revenue compared with the perfect foresight case, our proposed MR-SP consistently outperforms the method without SP, indicating the effectiveness of the proposed method in mitigating the impact of forecast uncertainties.

The improvement from SP is more pronounced for ESSs with longer durations using longer look-ahead windows. This is because longer look-ahead windows are more susceptible to forecast errors, and longer-duration ESSs rely more on long-term price forecasts for optimal dispatch. Nevertheless, as the look-ahead window extends further, the arbitrage net revenue could stagnate or even decrease due to the increased vulnerability to forecast errors. These results highlight the practical trade-off between extending the look-ahead window to capture more inter-day arbitrage and the increased vulnerability to forecast error—an effect that motivated the MR-SP approach developed in this work to recover value while mitigating risks due to long-term price forecast errors. Another observation is that arbitrage net revenue generally increases with ESS duration, but with diminishing marginal returns per unit of added energy capacity.

Practically, these observations imply a saturation horizon for arbitrage net revenue: beyond a certain duration, incremental capacity produces negligible additional annual net revenue and may not justify the capital cost. The MR-SP framework introduced here can be used to estimate the marginal net revenue curve and to identify the economically optimal duration by comparing the expected incremental arbitrage net revenue (under forecast uncertainty) against marginal capital and operational costs.

IV. Conclusions and Future Work

This paper presented an MR-SP framework for optimally dispatching ESSs under price-forecast uncertainty over extended look-ahead horizons. The proposed MR structure enables long-horizon optimization by adaptively reducing temporal granularity where forecast precision deteriorates, preserving the key temporal patterns that drive profitable arbitrage while limiting problem size. The two-stage SP formulation further improves robustness by explicitly modeling forecast uncertainty and recourse actions. Case studies demonstrated three key findings: (1) extended look-ahead windows significantly increase arbitrage net revenue for medium- and long-duration ESSs; (2) the MR approach captures most of the value of full-resolution optimization with only marginal net revenue loss; and (3) the SP formulation consistently outperforms deterministic dispatch under forecast errors, especially for long durations that rely more heavily on forecasts over extended horizon. These results suggest that the proposed method provides a practical and computationally efficient pathway for uncertainty-tolerant dispatch of ESSs. Future work will extend this framework to stacked services and broader operational contexts, including applications in microgrids, resilience analysis, and uncertainties beyond price forecasts.

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