Energy Storage Market Power Withholding Bounds in Real-time Markets

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ABSTRACT

This paper analyzes the economic withholding behavior of energy storage that exercises market power in real-time electricity markets. The arbitrage problem for storage considers a general price sensitivity model to quantify market power. We apply a stochastic dynamic programming model to calculate the marginal state of charge (SoC) value function as the opportunity cost, which can be used as the benchmark for bids. Furthermore, we derive the formulation of the market power economic withholding upper bound in a similar recursive way, which shows the maximum difference between the bids under the assumptions of exercising and not exercising market power. We prove that this bound is only based on the future peak and current price expectations, regardless of the price sensitivity model and distribution type of price uncertainty. We validate our results in simulation under both linear and nonlinear price sensitivity models, based on the real-time price data from the New York Independent System Operator.

CCS CONCEPTS

• **Hardware** → **Energy generation and storage**; **Power and energy**; • **Applied computing** → **Decision analysis**.

KEYWORDS

Energy storage, Market power, Power system economics, Dynamic programming

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1 INTRODUCTION

Sustainable energy technologies, including utility-scale renewable generation, distributed resources, and electrification solutions, offer a viable pathway to achieving Net Zero by 2050 [19]. However, these systems also introduce new challenges in maintaining the balance between electricity demand and supply, particularly at high temporal resolutions. Energy storage systems, especially battery energy storage systems, provide a robust solution to these challenges, delivering almost instantaneous response and energy provision on a temporal scale. Consequently, there has been an exponential increase in energy storage capacity in the US in the past few years, particularly in regions with substantial renewable penetration, such as CAISO and ERCOT [30]. Initially, frequency regulation was the most profitable application for energy storage. However, the regulation market is relatively shallow compared to the rapidly expanding energy storage capacity. For instance, the average requirements for regulation up and down in CAISO are less than 1GW, whereas the installed battery storage capacity exceeded 7GW as of 2023 [8, 14]. Consequently, the focus of most energy storage systems is shifting towards the energy market to capitalize on price arbitrage opportunities [29]. Given the central role of the energy market in the power sector, it's crucial to explore how energy storage influences market dynamics.

In the US, private electricity producers, who are profit-oriented strategic agents, own more than 95% of large-scale energy storage systems [30]. In CAISO, battery energy storage makes up over 7.6% of the total nameplate capacity [26]. With such a substantial share, the market power of energy storage is significant and demands attention. Energy storage systems have a distinct cost structure that differentiates them from conventional generators. The primary costs associated with energy storage include the electricity cost for charging and the degradation cost from cycling, both of which present challenges in accurate quantification [32]. Moreover, energy storage faces unique opportunity costs due to its finite capacity. Discharging at lower prices can result in lost opportunities to capitalize on higher future prices, and similarly, charging during peak prices can preclude taking advantage of lower future rates [33]. This opportunity cost is further compounded by the uncertainty of future price fluctuations. Consequently, monitoring and mitigating the market power of energy storage, typically achieved through cost-based methods for conventional generators, becomes particularly complex and challenging [28]. This complexity necessitates innovative approaches to effectively oversee and regulate the market power of energy storage, ensuring it to positively contribute to the energy market's efficiency and stability.

We propose a comprehensive analysis method of energy storage economic bids in the energy market, considering the unique cost principles and market power of energy storage systems. The main contributions of this paper are follows:

- This paper proposes a market power examination framework for energy storage based on dynamic programming. In economic bidding, wherein energy storage systems submit quantity-price pair bids to the market operator, this framework compares the optimal economic bids of energy storage when exercising market power against those not exercising market power.
- We introduce a formal theorem that defines the bounds of economic withholding by energy storage, accounting for scenarios both with and without price uncertainty. This theorem clarifies that the maximum difference between bids made with and without exercising market power depends only on the expected future peak price and the current price, unaffected by the model of price sensitivity or the uncertainty in price distribution. This theorem provides a robust theoretical foundation for monitoring energy storage's market power within the energy market.
- We validate our result using historical data from the New York Independent System Operator. The different bidding strategies and arbitrage processes are compared under different price sensitivity models and market power realization. The result also shows the revenue difference caused by gaps between actual price sensitivity and predicted price sensitivity.

We organize the remainder of the paper as follows. Section 2 provides context of our research question and reviews related literature. Section 3 describes the energy storage arbitrage formulation, market price, and storage bidding models. Section 4 and 5 present theoretical results for energy storage exercising market power and simulations with real-world price data. Section 6 concludes this paper.

2 BACKGROUND AND RELATED WORK

2.1 Energy Storage Energy Market Participation

The participation of utility-scale energy storage in the wholesale electricity market has gained significant attention, primarily due to its potential to enhance grid reliability and integrate renewable energy sources more effectively. The Federal Energy Regulatory Commission (FERC) issued Order 841 [15] to facilitate energy storage participation in wholesale electricity markets. In the US, energy storage systems can participate in energy markets primarily through two methods: self-scheduling and economic bids.

Self-scheduling enables energy storage operators to set their generation or consumption levels in advance, typically in the day-ahead market, though submissions can also occur in the real-time market. This strategy involves committing to produce or use energy irrespective of market price fluctuations, guided by predetermined operational targets or contracts. On the other hand, *economic bids* play a crucial role especially in the real-time market [5]. While operators initially place bids in the day-ahead market for preliminary scheduling, the real-time market is where they actively adjust their bids in response to actual supply and demand. This two-stage settlement process enables operators to finely tune their operations, in response to the dynamic nature of real-time pricing, to optimize their economic returns. While energy storage can submit economic bids and/or self-schedule in the real-time market, this analysis primarily focuses on economic bids due to their strategic role in managing state of charge (SoC) under price uncertainty [4]. Self-schedule bids make energy storage act as price-takers, offering their capacity irrespective of spot prices and consequently losing the advantage of their flexibility. This results in almost no or only a small amount of their capacity are bidding as self-schedule [7].

Numerous studies have explored optimal storage control and bidding strategies within the context of energy markets. Some studies focus on the self-scheduling method, with many acknowledging the influence of market prices under a price-maker setting [2, 21]. This consideration is crucial because self-scheduling lacks the flexibility to respond to real-time price fluctuations. In contrast, other research focuses on economic bidding strategies. However, many of these studies adopt a price-taker perspective [1, 10, 23, 31], often undermining the potential for energy storage operations to influence market prices actively. Addressing this gap, our paper investigates the optimal economic bidding strategies of energy storage under price uncertainty, considering the potential of market price influence.

2.2 Energy Storage Market Power

Market power is traditionally defined as the ability to profitably alter prices away from competitive levels [22]. In the context of electricity markets and the public sector, this concept has a crucial significance due to its direct impact on energy access and social welfare [3]. Unlike conventional generators, which typically exercise market power through capacity withholding or strategic bidding, energy storage systems introduce a new dimension to market power dynamics due to their operational flexibility and the associated opportunity costs of charging and discharging [13, 27]. This unique capability allows them to arbitrage market price fluctuations in a way that conventional generators cannot, requiring a comprehensive understanding of and efficient approach to monitoring their market influence.

Previous work investigating energy storage market power has primarily focused on bi-level modeling with market power considerations [4, 9, 25, 34]. Our research introduces a different perspective by examining the bidding behavior of energy storage systems when exercising market power and analyzing the specific characteristics of these bids. This approach provides insights on the strategic bidding behavior of energy storage systems and its implications for market prices and overall market health.

With the rapid increase in installed energy storage capacity and the rise of strategic behavior, mitigating market power in energy storage has become a pivotal challenge in market design [36]. Traditional research on market power monitoring, primarily focused on conventional generators, has primarily utilized fuel cost and heat rate curve parameters as the basis for monitoring [28]. However, the unique operational dynamics and cost principles of energy storage require reconsidering these traditional approaches.

In the US, market power monitoring and mitigation are addressed through two primary approaches. The *structural approach*, which focuses on the market's design and rules, includes mechanisms like offer caps. On the other hand, the *conduct and impact approach* analyzes the behavior of market participants and the resulting market outcomes. Both approaches fundamentally rely on accurately estimating the marginal cost of generation resources [16].

However, energy storage systems present unique challenges for market power monitoring. Unlike conventional generators, energy storage must consider the aforementioned opportunity costs associated with charging and discharging, adding layers of complexity to cost estimation and bidding strategies. Previous studies have illuminated the impact of energy storage market power on both storage owner profits and broader social welfare [12, 25]. This paper introduces a theorem crucial for energy storage market power monitoring, highlighting that bid differences depend mainly on expected future and current prices. This insight offers an efficient approach to addressing energy storage challenges in market power analysis.

3 FORMULATION AND PRELIMINARIES

3.1 Energy Storage Arbitrage Model

We formulate the problem of energy storage (ES) real-time market arbitrage, assuming prices are influenced by ES activities, as a multi-period scheduling problem spanning the time horizon $\{1, 2, ..., T\}$.

$$\max_{p_t, b_t} \sum_{t=1}^{T} [(p_t - b_t)\tilde{\lambda}_t(p_t, b_t) - cp_t] + V_T(e_T) \tag{1a}$$

where the first summation term is the operation revenue, with the control decision variables p_t and b_t referring to the discharged and charged energy over period t respectively. $\tilde{\lambda}_t(p_t, b_t)$ is the electricity price in real-time market, which is formulated as a function of the storage operation. c is the marginal discharge cost which represents the ES operation and maintenance cost and degradation cost. $V_T(e_T)$ is the terminal value function of the end SoC e_T, which reflects the future value of remaining energy in storage.

Remark 1. Electricity price in real-time market. The actual electricity price in real-time markets is formulated during a sequential market clearing process, where a single-interval or multi-interval economic dispatch problem is solved. Single-interval pricing mechanism was quite prevalent in early electricity markets, where only the current period economic dispatch problem is considered in each time step. Its convenience contributes to its wide application in many electricity markets, especially in smaller or simpler market. Multi-interval pricing mechanism, such as rolling-window dispatch model, gradually became more popular as it allows for more efficient dispatch especially to meet high ramping requirements [11, 17, 18]. It has been applied in New York Independent System Operator (NYISO) and California ISO (CAISO) [6, 20]. In this paper, we use a general function to model the single-interval real-time pricing mechanism, which will be elaborated in Definition 1. Here we use price-maker energy storage (PM-ES) to refer to the storage that exercises market power during the bidding process, and use price-taker energy storage (PT-ES) to refer to the storage without considering their impacts on real-time price. We assume that both the PT-ES and the PM-ES can have access to real-time price forecasts λ_t. The difference is that PT-ES doesn't perceive itself as having the market power to influence the price. So in the arbitrage model for PT-ES, the $\tilde{\lambda}_t(p_t, b_t)$ can be simply replaced by the predicted value λ_t. In contrast, PM-ES is characterized by the clear understanding and quantification of the impact of its operation on real-time price as a function of its operation $\tilde{\lambda}_t(p_t, b_t)$.

The arbitrage problem is subject to the following constraints:

$$e_t - e_{t-1} = -p_t/\eta + b_t\eta \tag{1b}$$

$$0 \le p_t \le P, 0 \le p_t \le P \tag{1c}$$

$$p_t = 0 \text{ if } \lambda_t < 0 \tag{1d}$$

$$0 \le e_t \le E \tag{1e}$$

where Eq. (1b) represents the SoC evolution with one-way efficiency η. Eq. (1c) models the upper and lower bounds of the charging and discharging energy over period t. Eq. (1d) is the relaxed form of the non-simultaneous constraint for charging and discharging operations. Eq. (1e) models the upper and lower bounds of the SoC level.

3.2 Market Price Model

For each time period t, the system operator clears the real-time market to form the real-time price based on the current generation and load at a time and then moves the the next time period. A mapping relationship between ES operation and real-time price can be established since only the current conditions matter in the single-period sequential dispatch problem.

Definition 1. Price Sensitivity Model. For simplicity, here we use an aggregated function $h(\cdot)$ to represent the influence of ES operations on the real-time price.

$$\tilde{\lambda}_t(p_t, b_t) = \lambda_t + h(p_t - b_t) \tag{2}$$

where $h(\cdot)$ is a continuous function which satisfies the following properties:

1) *zero at origin*, i.e. $h(0) = 0$. It refers to the λ_t as the benchmark price uninfluenced by the storage operation.

2) *decreasing*, i.e. $h'(\cdot) \le 0$. This property aligns with our intuition that an increasing cost will be paid for the ES to buy each additional unit, and a decreasing revenue can be obtained for the ES to sell each additional unit.

3) $xh(x)$ *is concave*, which is to guarantee the concavity of the subsequent single-period optimization problem in Subsection 3.3. According to Eq. (1a), the revenues can be calculated through $(p_t - b_t)[\lambda_t + h(p_t - b_t)]$. So, this requirement is to ensure the revenue function is concave.

Example 1. Linear Function. To be more specific, we will further consider the following linear function. It is trivial to prove that it satisfies all three properties mentioned above.

$$h(p_t - b_t) = -\alpha_1(p_t - b_t) \tag{3a}$$

The linear price sensitivity model is utilized to illustrate the effect of a single energy storage operator's actions on market clearing prices, which is a conventional intuitive model corresponds well to the economic clearing process in the real-time market.

Remark 2. Linear Price Sensitivity Model. This price model corresponds to the traditional quadratic cost function for thermal power generation, with $\frac{1}{2}\alpha_1$ as the quadratic coefficient. It has been applied or verified in some papers studying the market power of traditional generators [24] or wind turbines [35]. Assuming that the market participants only include one PM-ES and generators, with all generators modeled as an aggregated one without upper and lower bounds (to ensure the feasibility of the clearing problem). Then, the real-time price can be derived as the function of ES operation from the power balance constraint to meet the current period's net demand.

Example 2. Nonlinear Function. The impact of storage operation on real-time pricing cannot be fully captured by linear functions, thus we introduce a cubic price sensitivity model. Higher-order sensitivity functions more accurately captures market dynamics, particularly under conditions requiring rapid ramping capabilities. The cubic model is used to represent the significant influence that flexible and rapid-response resources, like battery energy storage systems, have on price formation in real-time market:

$$h(p_t - b_t) = -\alpha_2 (p_t - b_t)^3 \tag{3b}$$

3.3 Storage Bidding Model

Motivated by the dynamic programming algorithm, the PM-ES arbitrage problem can be formulated as an iterative single-stage optimization problem:

$$V_{t-1}^{\mathrm{PM}}(e_{t-1}) = \max_{p_t, b_t} [\lambda_t + h(p_t - b_t)](p_t - b_t) - cp_t + V_t^{\mathrm{PM}}(e_t) \tag{4a}$$

subject to

$$\text{(1b) - (1e)} \tag{4b}$$

where $V_t^{\mathrm{PM}}(e_t)$ refers to the value function that reflects the opportunity value of the remaining SoC e_t at the end of the time period-t. The superscript PM indicates the perspective of the ES as a price-maker. Eq. (4a) is a generalized form, designed to incorporate varying degrees of price sensitivity knowledge, from perfect information to energy storage operators' private estimates, which accommodates the realistic scenarios of imperfect information faced by energy storage operators.

Proposition 1. Storage bidding model for PM-ES. We design the bids according to the marginal charging value and marginal discharging cost of the calculated opportunity value functions:

$$\hat{B}_t^{\mathrm{PM}} = -\frac{\partial}{\partial b_t}(-V_t^{\mathrm{PM}}(e_{t-1} + b_t \eta)) = \eta v_t^{\mathrm{PM}}(e_t) \tag{5a}$$

$$\hat{P}_t^{\mathrm{PM}} = \frac{\partial}{\partial p_t}(cp_t - V_t^{\mathrm{PM}}(e_{t-1} - p_t/\eta)) = c + \frac{1}{\eta} v_t^{\mathrm{PM}}(e_t) \tag{5b}$$

where $\hat{B}_t^{\mathrm{PM}}$ and $\hat{P}_t^{\mathrm{PM}}$ are the charging and discharging bid for PM-ES respectively. $v_t^{\mathrm{PM}}(e_t)$ is the derivative of the storage opportunity value function $V_t^{\mathrm{PM}}(e_t)$ in Eq. (4a).

We design the bids according to the marginal cost from both physical and opportunity perspectives. In Eq. (4a), $-cp_t$ refers to the physical cost while $V_t^{\mathrm{PM}}(e_t)$ refers to the opportunity cost. By calculating the derivative of both the two terms, we can formulate the strategic bids as Eq. (5a) and Eq. (5b) shows. The formulation of $V_t^{\mathrm{PM}}(e_t)$ will be discussed in Section 4. The detailed proof is included in Appendix A.

Corollary 1. Storage bidding model for PT-ES. The arbitrage problem for PT-ES can be formulated similarly just by specifying $h(p_t - b_t) \equiv 0$.

$$V_{t-1}^{\mathrm{PT}}(e_{t-1}) = \max_{p_t, b_t} \lambda_t (p_t - b_t) - cp_t + V_t^{\mathrm{PT}}(e_t) \tag{6a}$$

subject to

$$\text{(1b) - (1e)} \tag{6b}$$

Based on the opportunity value function $V_t^{\mathrm{PT}}(e_t)$, the bids strategy can be designed in the same way with PM-ES:

$$\hat{B}_t^{\mathrm{PT}} = \eta v_t^{\mathrm{PT}}(e_t) \tag{7a}$$

$$\hat{P}_t^{\mathrm{PT}} = c + \frac{1}{\eta} v_t^{\mathrm{PT}}(e_t) \tag{7b}$$

4 MAIN RESULTS

In this section, we define the bounds of market power economic withholding by energy storage, which clarifies the maximum difference between bids made with and without exercising market power. This definition is based only on the future peak and current price expectations, regardless of the price sensitivity model and uncertainty distribution.

Theorem 1. Market power economic withholding bound. The upper bound of ES economic withholding is determined exclusively by the expected current real-time price, $\mathbb{E}[\hat{\lambda}_t]$, and the expected peak real-time price in the future, $\mathbb{E}[\hat{\lambda}_{[t<\tau\leq T]}^{\mathrm{peak}}]$, such that:

$$v_t^{\mathrm{PM}}(e_t) - v_t^{\mathrm{PT}}(e_t) \leq (\mathbb{E}[\hat{\lambda}_{[t<\tau\leq T]}^{\mathrm{peak}}] - c)\eta - \mathbb{E}[\hat{\lambda}_t]/\eta \tag{8}$$

where the market power economic withholding upper bound is formulated as the maximum difference between the opportunity value functions when assuming the exercise of market power, $v_t^{\mathrm{PM}}(e_t)$, versus not exercising market power, $v_t^{\mathrm{PT}}(e_t)$. This bound takes into account the uncertainty in bidding processes and models the real-time price as a time-varying, stage-wise independent process, $\hat{\lambda}_t$.

To prove Theorem 1, we firstly discuss the cases under the deterministic price model, which includes Lemma 1, Lemma 2, Lemma 3, and Corollary 2. First, we give the specific update progress of marginal value function for both PT-ES and PM-ES, and economic withholding bound in a recursive way. Corollary 2 concludes the market power economic withholding upper bound under the deterministic price model. Then we will prove Theorem 1 under price uncertainty based on Lemma 4-7, which extends the deterministic cases to incorporate price uncertainty. The arbitrage problem is restated in Lemma 4 based on stochastic dynamic programming. Lemma 5 and 6 derives the analytical marginal value function update assuming the price follows a probability distribution function. Lemma 7 derives the economic withholding bound as the difference between marginal value function in Lemma 5 and Lemma 6, which will finish the proof of Theorem 1.

Remark 3. Withholding bound for bids. According to Subsection 3.3, it is trivial to prove that the actual difference in charging (discharging) bids with and without exercising market power corresponds to a linear relationship with the difference in marginal value function in Theorem 1:

$$\hat{B}_t^{\text{PM}} - \hat{B}_t^{\text{PT}} = \eta[v_t^{\text{PM}}(e_t) - v_t^{\text{PT}}(e_t)] \tag{9a}$$

$$\hat{P}_t^{\text{PM}} - \hat{P}_t^{\text{PT}} = \frac{1}{\eta}[v_t^{\text{PM}}(e_t) - v_t^{\text{PT}}(e_t)] \tag{9b}$$

Remark 4. Distribution-free withholding bound. The market power economic withholding bound in Theorem 1 depends solely on the expected current price and expected peak price in the future time period, and remains unaffected by the particular distribution type of the price uncertainty model.

Remark 4 shows that although the price uncertainty may lead to potential economic capacity withholding no matter whether storage exercises market power, it won't exacerbate the bid difference between the two scenarios. That means even when the storage hopes to exercise its market power in real-time markets, its bid must be within a specific range compared to the price-taker one. And since the expectation of real-time prices is approximately the day-ahead price, Theorem 1 makes sense in that we can use the day-ahead price as the bound for storage to exercise market power economic withholding.

Remark 5. Model-free withholding bound. Theorem 1 holds consistently, irrespective of the specific price sensitivity model, denoted as $h(\cdot)$, that is selected.

In addition to the provided analytical proof framework and the forthcoming detailed proofs including Lemma 1-7 and Corollary 2, here we give an intuitive explanation of Remark 5. Just assume the real-time price is so sensitive to the operation of storage that the derivative of $h(p_t - b_t)$ at zero is approximate infinite:

$$\lim_{\Delta x \to 0} h'(\Delta x) = -\infty \tag{10a}$$

which means no matter what the initial price is, the actual real-time price will go infinitely up or infinitely down with just minor storage operation:

$$\lim_{\Delta p_t \to 0} \tilde{\lambda}_t(p_t, 0) = -\infty \tag{10b}$$

$$\lim_{\Delta b_t \to 0} \tilde{\lambda}_t(0, b_t) = \infty \tag{10c}$$

where the storage with the price sensitivity knowledge wouldn't charge no matter how low the initial price is, and wouldn't discharge no matter how high the initial price is. Considering the discharging bid is always greater than the charging bid, here only discharging bid is considered to derive the maximum difference between price-maker and price-taker. Given that the discharging bid is a reference value, when the price falls below the discharging bid, the storage will not discharge. Therefore, to guarantee the storage will not discharge in any cases, the discharging bid can be set as the expected peak price in the future. That is why in Theorem 1, price sensitivity function $h(\cdot)$ disappears.

Lemma 1. Marginal value function for PT-ES. By sampling e_t among $[0, E]$, the derivative of value function for PT-ES can be calculated on a recursive computation framework stepping from the known terminal marginal value function $v_T^{\text{PT}}(e_T)$:

$$v_{t-1}^{\text{PT}}(e) = \begin{cases} v_t^{\text{PT}}(e + P\eta) & \text{if } \lambda_t \le \alpha_t^1(e) \\ \lambda_t/\eta & \text{if } \alpha_t^1(e) < \lambda_t \le \alpha_t^2(e) \\ v_t^{\text{PT}}(e) & \text{if } \alpha_t^2(e) < \lambda_t \le \alpha_t^3(e) \\ (\lambda_t - c)\eta & \text{if } \alpha_t^3(e) < \lambda_t \le \alpha_t^4(e) \\ v_t^{\text{PT}}(e - P/\eta) & \text{if } \lambda_t > \alpha_t^4(e) \end{cases} \tag{11}$$

where $\alpha_t^1(e) = v_t^{\text{PT}}(e+P\eta)\eta$, $\alpha_t^2(e) = v_t^{\text{PT}}(e)\eta$, $\alpha_t^3(e) = v_t^{\text{PT}}(e)/\eta + c$, $\alpha_t^4(e) = v_t^{\text{PT}}(e-P/\eta)/\eta + c$ are parameter functions related to storage SoC e. We omit the subscript $t-1$ in e_{t-1} for simplicity. For proofs of Lemma 1, please refer to [33].

Lemma 2. Marginal value function for PM-ES. Applying the same approach in Lemma 1, we can calculate the derivative of the value function for PM-ES on a recursive computation framework:

$$v_{t-1}^{\text{PM}}(e) = \begin{cases} v_t^{\text{PM}}(e + P\eta) & \text{if } \lambda_t \le \beta_t^1(e) \\ [\lambda_t + h(-b^*) - b^* h'(-b^*)]/\eta & \text{if } \beta_t^1(e) < \lambda_t \le \beta_t^2(e) \\ v_t^{\text{PM}}(e) & \text{if } \beta_t^2(e) < \lambda_t \le \beta_t^3(e) \\ [\lambda_t + h(p^*) + p^* h'(p^*) - c]\eta & \text{if } \beta_t^3(e) < \lambda_t \le \beta_t^4(e) \\ v_t^{\text{PM}}(e - P/\eta) & \text{if } \lambda_t > \beta_t^4(e) \end{cases} \tag{12a}$$

where $\beta_t^1(e) = v_t^{\text{PM}}(e + P\eta)\eta - h(-P) + Ph'(-P)$, $\beta_t^2(e) = v_t^{\text{PM}}(e)\eta$, $\beta_t^3(e) = v_t^{\text{PM}}(e)/\eta + c$, $\beta_t^4(e) = v_t^{\text{PM}}(e - P/\eta)/\eta - h(P) - Ph'(P) + c$ are parameter functions related to storage SoC e. The solution of $b^* \in (0, P)$ and $p^* \in (0, P)$ can be derived based on first-order conditions as following equations respectively:

$$\lambda_t + h(-b^*) - b^* h'(-b^*) = v_t^{\text{PM}}(e + b^*\eta)\eta \tag{12b}$$

$$\lambda_t + h(p^*) + p^* h'(p^*) - c = v_t^{\text{PM}}(e - p^*/\eta)\eta \tag{12c}$$

Comparing the results of Lemma 1 and Lemma 2, the formulation of marginal value function under the assumptions of whether exercising market power or not differs in the second and fourth cases. An intuitive interpretation is that assuming the PT-ES and PM-ES share the same marginal value function at period t, i.e. $v_t^{\text{PM}}(e_t) = v_t^{\text{PT}}(e_t)$ for all $e_t \in [0, E]$, when λ_t satisfies the second case in Lemma 1, the marginal value function for storage not exercising market power is only based on the current price. Since $\beta_t^1(e) < \alpha_t^1(e)$, $\beta_t^2(e) = \alpha_t^2(e)$, the storage exercising market power also lies in the second case of Eq. (12a). Considering the sensitivity price model, the real-time price will be influenced by the actual charging power b^*. As for $\beta_t^1(e) < \alpha_t^1(e)$, it can be explained that when $\lambda_t = \alpha_t^1(e)$, the storage not exercising market power decides to fully charge. While the storage exercising market power realizes that its charging behavior will increase price and finally decrease its overall revenues, so it still decides to partially charge, or in other words, to conduct economic withholding. The fourth discharging case shares a similar logic to the second one. For detailed proofs of Lemma 2, please refer to Appendix B.

Lemma 3. Economic withholding bound formulation. Assuming that for each $e \in [0, E]$ at period-t, there exist an upper bound $\theta_t(e)$ which satisfies:

$$v_t^{\text{PM}}(e) - v_t^{\text{PT}}(e) \le \theta_t(e) \tag{13}$$

then $\theta_{t-1}(e)$ can be updated in an recursive way to guarantee $v_{t-1}^{\text{PM}}(e) - v_{t-1}^{\text{PT}}(e) \le \theta_{t-1}(e)$ for each $e \in [0, E]$:

$$\theta_{t-1}(e) = \begin{cases} \theta_t(e + P\eta) & \text{if } \lambda_t \le \gamma_t^1(e) \\ v_t^{\text{PM}}(e) - \lambda_t/\eta & \text{if } \gamma_t^1(e) < \lambda_t \le \gamma_t^2(e) \\ \theta_t(e) & \text{if } \gamma_t^3(e) < \lambda_t \le \gamma_t^4(e) \\ 0 & \text{otherwise} \\ \theta_t(e - P/\eta) & \text{if } \lambda_t > \gamma_t^5(e) \end{cases} \tag{14}$$

where $\theta_{t-1}(e)$ can be formulated according to $v_t^{\text{PM}}(e)$ and $v_t^{\text{PM}}(e)$. $\gamma_t^1(e) = v_t^{\text{PM}}(e + P\eta)\eta - h(-P) + Ph'(-P)$, $\gamma_t^2(e) = \min\{v_t^{\text{PM}}(e)\eta, v_t^{\text{PT}}(e)\eta\}$, $\gamma_t^3(e) = \max\{v_t^{\text{PM}}(e+P\eta)\eta - h(-P) + Ph'(-P), v_t^{\text{PT}}(e)\eta\}$, $\gamma_t^4(e) = \min\{v_t^{\text{PM}}(e)\eta, v_t^{\text{PT}}(e)\eta\}$, $\gamma_t^5(e) = v_t^{\text{PT}}(e - P/\eta)/\eta + c$ are parameter functions related to storage SoC e.

Assuming that the arbitrage models for both PT-ES and PM-ES share the same terminal value function $V_T(e_T)$, we can get the terminal period bound $\theta_T(e) \equiv 0$. Thus we can get all the withholding upper bound at any time period using backward calculation. The detailed proof is included in Appendix C.

Corollary 2. Market power economic withholding bound under deterministic price model. When we consider the deterministic price model λ_t, the market power economic withholding bound is:

$$v_t^{\text{PM}}(e_t) - v_t^{\text{PT}}(e_t) \le (\lambda_{[t<\tau\le T]}^{\text{peak}} - c)\eta - \lambda_t/\eta \tag{15}$$

where $\lambda_{[t<\tau\le T]}^{\text{peak}}$ is the peak price in the future time period during $(t, T]$.

This corollary is trivial to show based on Lemma 3, which shows the maximum $\theta_t(e)$ must lie in the second case in Eq. (14). Then the maximum marginal value function can be formulated according to Lemma 2:

$$\begin{aligned} \max\{v_t^{\text{PM}}(e_t)\} &\le \max\{[\lambda_t + h(p^*) + p^*h'(p^*) - c]\eta\} \\ &\le (\lambda_{[t<\tau\le T]}^{\text{peak}} - c)\eta \end{aligned} \tag{16}$$

Now, we consider a more general and realistic scenario by introducing price uncertainty and extending Lemma 1, Lemma 2 and Lemma 3 in general. We apply stochastic dynamic programming in the arbitrage model and add probability terms in the formulation of the marginal value function.

Lemma 4. Storage bidding model considering price uncertainty. By assuming the real-time price model as a time-varying stage-wise independent process $\hat{\lambda}_t$, the arbitrage problem for PM-ES exercising market power can be formulated as stochastic dynamic programming:

$$\begin{aligned} Q_{t-1}^{\text{PM}}(e_{t-1}|\hat{\lambda}_t) = \max_{p_t, b_t}\{[\hat{\lambda}_t + h(p_t - b_t)](p_t - b_t) \\ - cp_t + V_t^{\text{PM}}(e_t)\} \end{aligned} \tag{17a}$$

$$V_{t-1}^{\text{PM}}(e_{t-1}) = \mathbb{E}[Q_{t-1}^{\text{PM}}(e_{t-1}|\hat{\lambda}_t)] \tag{17b}$$

subject to

$$\text{(1b) - (1e)} \tag{17c}$$

the arbitrage model for PT-ES not exercising market power is:

$$Q_{t-1}^{\text{PT}}(e_{t-1}|\hat{\lambda}_t) = \max_{p_t, b_t} \hat{\lambda}_t(p_t - b_t) - cp_t + V_t^{\text{PT}}(e_t) \tag{18a}$$

$$V_{t-1}^{\text{PT}}(e_{t-1}) = \mathbb{E}[Q_{t-1}^{\text{PT}}(e_{t-1}|\hat{\lambda}_t)] \tag{18b}$$

subject to

$$\text{(1b) - (1e)} \tag{18c}$$

Note that the expectation also holds after taking the derivative:

$$v_t^{\text{PM}}(e) = \mathbb{E}[q_t^{\text{PM}}(e|\hat{\lambda}_{t+1})] \tag{19a}$$

$$v_t^{\text{PT}}(e) = \mathbb{E}[q_t^{\text{PT}}(e|\hat{\lambda}_{t+1})] \tag{19b}$$

which means we can calculate $v_t^{\text{PT}}(e)$ and $v_t^{\text{PM}}(e)$ under a similar recursive framework with Lemma 1 and Lemma 2.

Lemma 5. Marginal value function for PT-ES under price uncertainty. The marginal value function for PT-ES under price uncertainty can be calculated from the price probability density function f_t and cumulative distribution function F_t recursively:

$$\begin{aligned} v_{t-1}^{\text{PT}}(e) &= v_t^{\text{PT}}(e + P\eta)F_t(\alpha_t^1(e)) \\ &+ \frac{1}{\eta}\int_{\alpha_t^1(e)}^{\alpha_t^2(e)} uf_t(u)du \\ &+ v_t^{\text{PT}}(e)[F_t(\alpha_t^3(e)) - F_t(\alpha_t^2(e))] \\ &+ \eta\int_{\alpha_t^3(e)}^{\alpha_t^4(e)} (w - c)f_t(w)dw \\ &+ v_t^{\text{PT}}(e - P/\eta)[1 - F_t(\alpha_t^4(e))] \end{aligned} \tag{20}$$

where $\alpha_t^1(e), \alpha_t^2(e), \alpha_t^3(e), \alpha_t^4(e), \alpha_t^5(e)$ are the same parameter functions with Lemma 1. For detailed proofs of Lemma 5, please refer to [33].

Lemma 6. Marginal value function for PM-ES under price uncertainty. The marginal value function for PM-ES under price uncertainty can be calculated from the price distribution function f_t and F_t recursively:

$$\begin{aligned} v_{t-1}^{\text{PM}}(e) &= v_t^{\text{PM}}(e + P\eta)F_t(\beta_t^1(e)) \\ &+ \frac{1}{\eta}\int_{\beta_t^1(e)}^{\beta_t^2(e)} [u + h(-b^*(u)) - b^*(u)h'(-b^*(u))]f_t(u)du \\ &+ v_t^{\text{PM}}(e)[F_t(\beta_t^3(e)) - F_t(\beta_t^2(e))] \\ &+ \eta\int_{\beta_t^3(e)}^{\beta_t^4(e)} [w - c + h(p^*(w)) + p^*(w)h'(p^*(w))]f_t(w)dw \\ &+ v_t^{\text{PM}}(e - P/\eta)[1 - F_t(\beta_t^4(e))] \end{aligned} \tag{21a}$$

where $\beta_t^1(e), \beta_t^2(e), \beta_t^3(e), \beta_t^4(e), \beta_t^5(e)$ are the same parameter functions with Lemma 2. $b^*(u) \in (0, P)$ and $p^*(w) \in (0, P)$ refer to the mapping relationship between b^*, p^* and u, w, as $b^* \in (0, P)$ and $p^* \in (0, P)$ are the solutions to the following equations with u and w as parameters respectively:

$$u + h(-b^*) - b^*h'(-b^*) = v_t^{\text{PM}}(e + b^*\eta)\eta \tag{21b}$$

$$w + h(p^*) + p^*h'(p^*) - c = v_t^{\text{PM}}(e - p^*/\eta)\eta \tag{21c}$$

Lemma 7. Market power economic withholding bound formulation considering price uncertainty. When considering price uncertainty, the market power economic withholding bound θ_t can be calculated from the distribution function f_t and F_t:

$$\begin{aligned}\theta_{t-1}(e) &= \theta_t(e+P\eta)F_t(\gamma_t^1(e)) \\ &+ \int_{\gamma_t^1(e)}^{\gamma_t^2(e)} [v_t^{\mathrm{PM}}(e) - u/\eta] f_t(u)du \\ &+ \theta_t(e)[F_t(\gamma_t^4(e)) - F_t(\gamma_t^3(e))] \\ &+ \theta_t(e-P/\eta)[1-F_t(\gamma_t^5(e))]\end{aligned} \tag{22}$$

where $\gamma_t^1(e), \gamma_t^2(e), \gamma_t^3(e), \gamma_t^4(e), \gamma_t^5(e)$ are the same parameter functions with Lemma 3. It is trivial to prove that the maximum $\theta_t(e)$ corresponds with the second term:

$$\begin{aligned}\max\{\theta_t(e)\} &\leq \max\{\mathbb{E}[q_t^{\mathrm{PM}}(e) - \hat{\lambda}/\eta]\} \\ &\leq (\mathbb{E}[\hat{\lambda}^{\mathrm{peak}}_{[t<\tau\leq T]}] - c)\eta - \mathbb{E}[\hat{\lambda}_t]/\eta\end{aligned} \tag{23}$$

which concludes the proof of Theorem 1.

5 SIMULATION RESULTS

We use the historical real-time price data from the New York Independent System Operator (NYISO) as the initially uninfluenced electricity price. We set the basic storage parameters: the storage capacity $E = 0.2$ MWh, identical charging and discharging one-way efficiency $\eta = 0.9$, power rating $P = 0.1$ MW (2-hour duration). All simulations and plots are conducted in Matlab.

5.1 Storage bidding and arbitrage process

We consider three settings in this study to demonstrate the energy storage bidding strategy considering market power based on marginal value function.

- **Price taker.** Storage takes itself as a price-taker and wouldn't exercise market power. It just applies the initially uninfluenced electricity price in its arbitrage model to generate bids according to Eq. (20).
- **Linear price sensitivity model.** Storage approximates the impact of storage operation on real-time price through a linear model: $\tilde{\lambda}_t = \lambda_t - \alpha_1(p_t - b_t)$. By quantifying its market power, it strategically designs its bids according to Eq. (21a)-(21c).
- **Cubic price sensitivity model.** Storage approximates the impact of storage operation on real-time price through a cubic model which satisfies the three requirements mentioned in Definition 1: $\tilde{\lambda}_t = \lambda_t - \alpha_2(p_t - b_t)^3$. It exercises market power when designing bids according to Eq. (21a)-(21c).

We first demonstrate the impact of market power assumption in the storage valuation and arbitrage process. Figure 1 shows the marginal value of different SoC levels under the above three settings. Although these value curves exhibit the same monotonically decreasing trend, the storage that exercises market power tends to smooth its value curve, which means there exist less sharp drop than the price-taker. It can be explained by the marginal value function formulations for price-maker and price-taker in Lemma 1 and Lemma 2. We first assume that at time t-period, price-maker and price-taker share the same marginal value function, ie. $v_t^{\mathrm{PM}}(e) = v_t^{\mathrm{PT}}(e)$ for all $e \in [0, E]$, as is shown in Figure 2. The black line refers to the same marginal value function at time t-period. The red line and

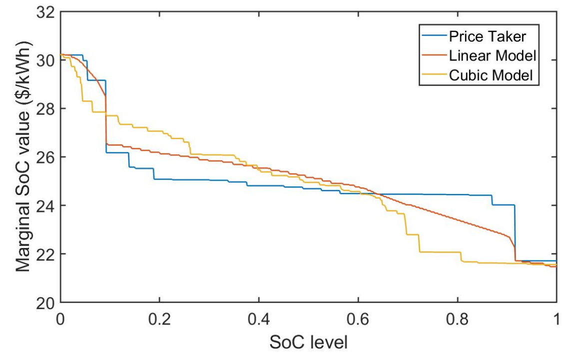

Figure 1: Marginal value for different SoCs at hour 7

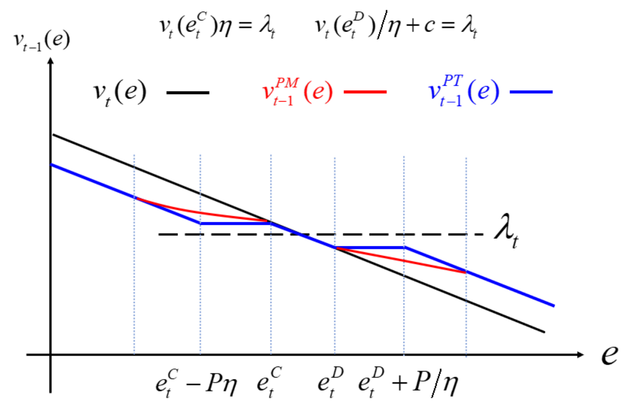

Figure 2: Schematic diagram of the marginal value function for price-maker and price-taker under same initial conditions

the blue line refer to the marginal value functions for PM-ES and PT-ES at time $t-1$ respectively. e_t^C and e_t^D are two crucial spots satisfying $v_t(e_t^C)\eta = \lambda_t$ and $v_t(e_t^D)/\eta + c = \lambda_t$ respectively. It can be seen that when $e < e_t^C$, the blue line consist two parts: the part with the same slope as the initial $v_t(e)$, and the part with 0 slope. The red line also consist two parts: the part with the same slope as the initial $v_t(e)$, and the part with gentle slope compared with $v_t(e)$. From a global perspective, there exist more 0-slope parts in blue line, leading to more sharp drops compared with the red line. Such theoretical discussion corresponds with the simulation results in Figure 1.

Considering storage can design its charging and discharging bids by multiplying a constant on the opportunity value function as shwon in Eq. (5a),(5b) and Eq. (7a),(7b), we only compare opportunity value functions in the following discussion. The arbitrage process based on the above bidding strategy is shown in Figure 3 and Figure 4, with the corresponding electricity price. The results align with our intuition that storage that exercises market power tends to conduct additional withholding when other price-taker storage decides to charge or discharge fully. When the price is high, the storage discharging behavior will cause the price to drop, leading to a preference for less discharge. Similarly, when the price is low, the storage charging behavior will increase the price, in turn leading to less charging operation.

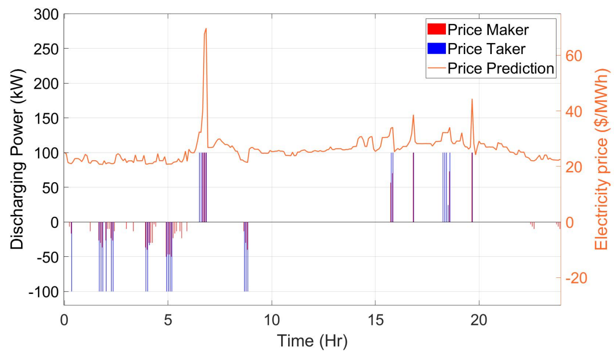

Figure 3: Storage arbitrage operation under linear price sensitivity model

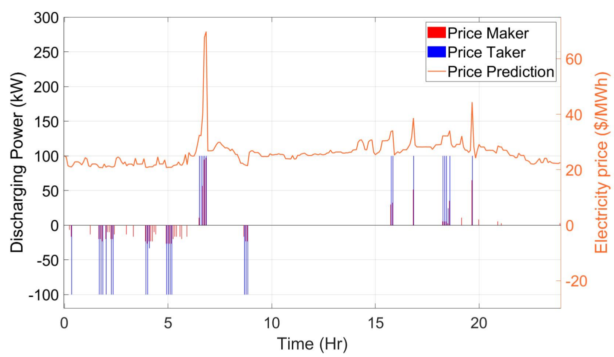

Figure 4: Storage arbitrage operation under cubic price sensitivity model

We calculate the market power economic withholding bound $\theta_t(e_t)$ according to Eq. (22) and compare it with the actual difference of bids made with and without exercising market power, as is shown in Figure 5. The results validate our formulation of $\theta_t(e_t)$. Note that $\theta_t(e_t)$ is always non-negative even if the bid made without market power does exceed the bid made with market power. That is because we only care about the excess portion when defining the upper bound.

5.2 Sensitivity Analysis

The effects of different coefficients in the linear price sensitivity model on storage arbitrage behavior are shown in Figure 6. The parameters of each price sensitivity model are 0, 0.001, 0.005, 0.01 and 0.02. As the parameter α_1 increases, the impact of storage operations on real-time electricity prices becomes more significant, and it is also more likely to lead to additional withholding for energy storage.

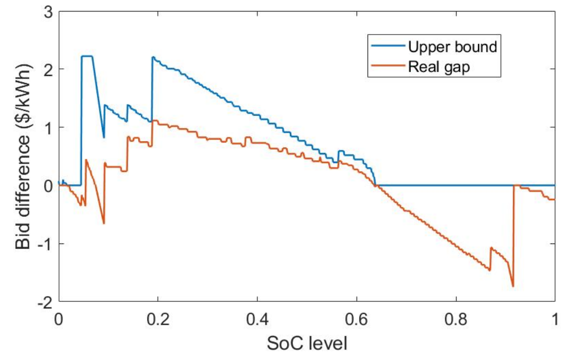

Figure 5: Market power economic withholding bound

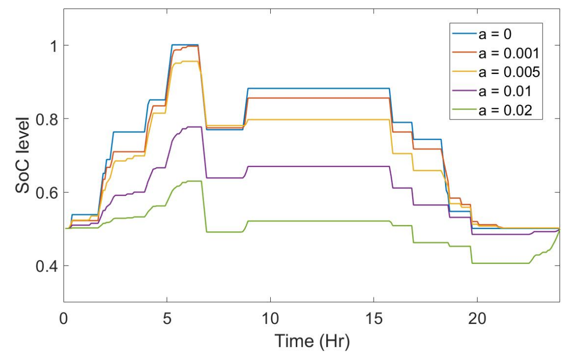

Figure 6: SoC level changes under different linear price sensitivity parameters

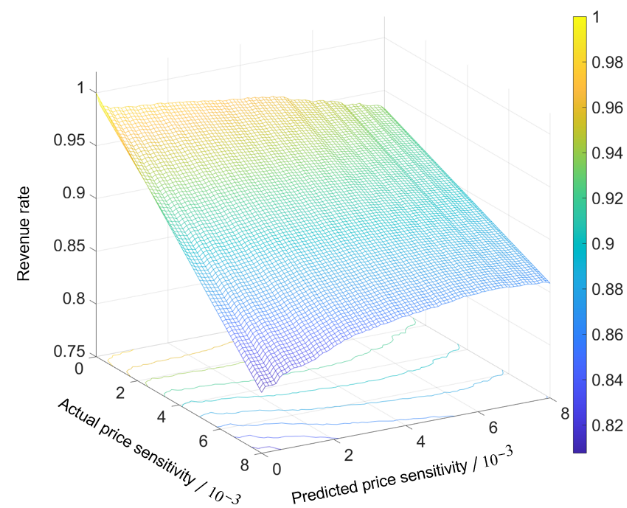

Figure 7: Revenue under gaps between actual price sensitivity and predicted price sensitivity

Meanwhile, we also provide a comparative analysis showing the storage arbitrage profit probing different actual market price sensitivities and the sensitivity assumed by the storage participant, which means a gap exists between the self-predicted price sensitivity parameter and the actual parameter. Under such circumstances, the storage cannot earn as much revenue as expected when designing bids. The whole simulation is conducted under the linear price sensitivity assumption with different α_1, ranging from 0 to 0.008. Figure 7 shows the revenue ratio under different predicted and actual parameters. The x-axis represents the actual price sensitivity parameter, while the y-axis represents the sensitivity parameter predicted by the price-maker. The z-axis represents the normalized revenues under different pairs of actual and predicted parameters. The storage gains the most revenue when both parameters are zero, which means storage operation will not influence the real-time price, and storage is aware of this fact. In general, the entire graph exhibits the shape of a ridge formed by the points when the predicted parameter equals the actual parameter. That means with a fixed actual price sensitivity, When the predicted parameter deviates from the actual one, the revenue will decrease, regardless of whether the deviation is positive or negative. With a perfect price sensitivity quantification, our price-maker algorithm can indeed obtain higher market profits.

6 CONCLUSION

In this study, we proposed an analytical energy storage market power examination framework through dynamic programming. By comparing the different strategic bids made with and without exercising market power, we introduce the upper bound of economic withholding caused by market power based on the price expectation. This bound stands regardless of the model of price sensitivity and uncertainty in price distribution. We validate our proposed algorithm on numerical experiments based on data from NYISO. Both linear and nonlinear price sensitivity models are tested. Furthermore, we analyze the impact of the accuracy of price sensitivity parameter prediction by calculating the overall revenues under different settings.

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A PROOF OF PROPOSITION 1

First, we consider the charging bids, where $b_t > 0$, $p_t = 0$. By factoring the marginal charging revenues in Eq. (4a)

$$\frac{\partial V_{t-1}^{\mathrm{PM}}(e_{t-1})}{\partial b_t} = -\lambda_t - h(-b_t) + b_t h'(-b_t) + \eta v_t^{\mathrm{PM}}(e_t) \tag{24}$$

The bids can be derived by assuming $b_t \to 0$. Then according to the first and second assumptions of function $h(\cdot)$ in Definition 1, $h(-b_t) \to 0$. Then we can get

$$\lim_{b_t \to 0} \frac{\partial V_{t-1}^{\mathrm{PM}}(e_{t-1})}{\partial b_t} = -\lambda_t + \eta v_t^{\mathrm{PM}}(e_t) \tag{25}$$

Then we can define the charging bid as

$$\hat{B}_t^{\mathrm{PM}} = \eta v_t^{\mathrm{PM}}(e_t) \tag{26}$$

The discharging bid can be calculated in a similar way, by factoring the marginal discharging cost in Eq. (4a)

$$\frac{\partial V_{t-1}^{\mathrm{PM}}(e_{t-1})}{\partial p_t} = \lambda_t + h(p_t) + p_t h'(p_t) - c - \frac{1}{\eta} v_t^{\mathrm{PM}}(e_t) \tag{27}$$

Assuming $p_t \to 0$, then we can get

$$\lim_{b_t \to 0} \frac{\partial V_{t-1}^{\mathrm{PM}}(e_{t-1})}{\partial p_t} = \lambda_t - c - \frac{1}{\eta} v_t^{\mathrm{PM}}(e_t) \tag{28}$$

We can define the discharging bid as

$$\hat{P}_t^{\mathrm{PM}} = c + \frac{1}{\eta} v_t^{\mathrm{PM}}(e_t) \tag{29}$$

B PROOF OF LEMMA 2

We restate the single-period economic scheduling problem for storage arbitrage based on dynamic programming as follows:

$$V_{t-1}^{\mathrm{PM}}(e_{t-1}) = \max_{p_t, b_t} [\lambda_t + h(p_t - b_t)](p_t - b_t) - c p_t + V_t^{\mathrm{PM}}(e_t) \tag{30a}$$

subjects to:

$$e_t - e_{t-1} = -p_t/\eta + b_t \eta : (\mu_t) \tag{30b}$$

$$0 \le p_t \le P : (\sigma_{t1}, \sigma_{t2}) \tag{30c}$$

$$0 \le b_t \le P : (\sigma_{t3}, \sigma_{t4}) \tag{30d}$$

$$p_t = 0 \text{ if } \lambda_t < 0 \tag{30e}$$

$$0 \le e_t \le E \tag{30f}$$

where μ_t is the dual variable associated with the SoC evolution constraint Eq. (30b). $\sigma_{t1}, \sigma_{t2}, \sigma_{t3}, \sigma_{t4}$ are the complementary slackness variables associated with the upper bound constraints of charging or discharging power rate. We use the first-order optimal condition to calculate the derivative of $V_{t-1}^{\mathrm{PM}}(e_{t-1})$ as:

$$\begin{aligned} v_{t-1}^{\mathrm{PM}}(e_{t-1}) = {} & [\lambda_t + h(p_t - b_t)]\left(\frac{\partial p_t}{\partial e_{t-1}} - \frac{\partial b_t}{\partial e_{t-1}}\right) \\ & + p_t h'(p_t - b_t)\frac{\partial p_t}{\partial e_{t-1}} + b_t h'(p_t - b_t)\frac{\partial b_t}{\partial e_{t-1}} \\ & - c\frac{\partial p_t}{\partial e_{t-1}} + v_{t-1}^{\mathrm{PM}}(e_t)\frac{\partial e_t}{\partial e_{t-1}} = 0 \end{aligned} \tag{31}$$

According to Karush-Kuhn-Tucker (KKT) conditions and non-simultaneous charging and discharging constraint Eq. (30e), the solutions have to satisfy the following equations:

$$\mu_t = v_t^{\mathrm{RM}}(e_t) \tag{32a}$$

$$\lambda_t + p_t h'(p_t) + h(p_t) - c - \mu_t/\eta + \sigma_{t1} - \sigma_{t2} = 0 \tag{32b}$$

$$-\lambda_t + b_t h'(-b_t) - h(-b_t) + \mu_t \eta + \sigma_{t3} - \sigma_{t4} = 0 \tag{32c}$$

Then we can conclude the following results:

$$p_t = \begin{cases} P & \text{if } \lambda_t \le v_t^{\mathrm{PM}}(e + P\eta)\eta \\ p^* & \text{else} \\ 0 & \text{if } \lambda_t > v_t^{\mathrm{PM}}(e)\eta \end{cases} \tag{33a}$$

$$b_t = \begin{cases} P & \text{if } \lambda_t > v_t^{\mathrm{PM}}(e - P/\eta)/\eta + c \\ b^* & \text{else} \\ 0 & \text{if } \lambda_t \le v_t^{\mathrm{PM}}(e)/\eta + c \end{cases} \tag{33b}$$

where $b^* \in (0, P)$ and $p^* \in (0, P)$ are the solutions to the following equations respectively:

$$\lambda_t + h(-b^*) - b^* h'(-b^*) = v_t^{\mathrm{PM}}(e + b^*\eta)\eta \tag{33c}$$

$$\lambda_t + h(p^*) + p^* h'(p^*) - c = v_t^{\mathrm{PM}}(e - p^*/\eta)\eta \tag{33d}$$

Accordingly, we can get the partial derivative expressions:

$$\frac{\partial p_t}{\partial e} = \begin{cases} 0 & \text{if (30c) binding} \\ \eta - \eta\frac{\partial e_t}{\partial e} & \text{if (30c) not binding} \end{cases} \tag{34a}$$

$$\frac{\partial b_t}{\partial e} = \begin{cases} 0 & \text{if (30d) binding} \\ \frac{1}{\eta}\frac{\partial e_t}{\partial e} - \frac{1}{\eta} & \text{if (30d) not binding} \end{cases} \tag{34b}$$

$$\frac{\partial e_t}{\partial e} = \begin{cases} 1 & \text{if (30c) and (30d) binding} \\ 1 + \eta\frac{\partial b_t}{\partial e} - \frac{1}{\eta}\frac{\partial p_t}{\partial e} & \text{if (30c) or (30d) not binding} \end{cases} \tag{34c}$$

By replacing the decision variables and partial derivative expressions given by Eq. (33a) and Eq. (34a) in Eq. (31), we obtain the formulation of $v_t^{\mathrm{PM}}(e)$ in five cases:

Case 1: $b_t = P, p_t = 0$. Storage charges at full power rate P so that the constraints Eq. (30c) and Eq. (30d) are binding. This case happens when the price is quite low which satisfies $\lambda_t \le v_t^{\mathrm{PM}}(e + P\eta)\eta - h(-P) + Ph'(-P)$. Hence $\frac{\partial p_t}{\partial e} = \frac{\partial b_t}{\partial e} = 0$, $\frac{\partial e_t}{\partial e} = 1$. Then we can get the marginal value function:

$$v_{t-1}^{\mathrm{PM}}(e) = v_t^{\mathrm{PM}}(e + P\eta) \tag{35a}$$

Case 2: $0 < b_t < P, p_t = 0$. Storage charges partially when the price is moderately low that $v_t^{\mathrm{PM}}(e + P\eta)\eta - h(-P) + Ph'(-P) < \lambda_t \le v_t^{\mathrm{PM}}(e)\eta$. Then the constraints Eq. (30c) is not binding. Hence

$\frac{\partial e_t}{\partial e} = 1 + \eta \frac{\partial b_t}{\partial e}$, $\frac{\partial p_t}{\partial e} = 0$. Then we can get the marginal value function:

$$v_{t-1}^{\text{PM}}(e) = [\lambda_t + h(-b^*) - b^* h'(-b^*)]/\eta \tag{35b}$$

Case 3: $p_t = b_t = 0$. Storage doesn't charge or discharge so the constraints Eq. (30c) and Eq. (30d) are binding. This case happens when the price is similar to the current marginal value function $v_t^{\text{PM}}(e)\eta < \lambda_t \le v_t^{\text{PM}}(e)/\eta + c$. Hence $\frac{\partial p_t}{\partial e} = \frac{\partial b_t}{\partial e} = 0$, $\frac{\partial e_t}{\partial e} = 1$. Then we can get the marginal value function:

$$v_{t-1}^{\text{PM}}(e) = v_t^{\text{PM}}(e) \tag{35c}$$

Case 4: $p_t = 0, 0 < b_t < P$. Storage discharges partially when the price is moderately high that $v_t^{\text{PM}}(e)/\eta + c < \lambda_t \le v_t^{\text{PM}}(e - P/\eta)/\eta - h(P) - Ph'(P) + c$. Then the constraints Eq. (30c) is not binding. Hence $\frac{\partial e_t}{\partial e} = 1 - \frac{1}{\eta}\frac{\partial p_t}{\partial e}$, $\frac{\partial b_t}{\partial e} = 0$. Then we can get the marginal value function:

$$v_{t-1}^{\text{PM}}(e) = [\lambda_t + h(p^*) + p^* h'(p^*) - c]\eta \tag{35d}$$

Case 5: $b_t = 0, p_t = P$. Storage discharges at full power rate P so that the constraints Eq. (30c) and Eq. (30d) are binding. This case happens when the price is quite high which satisfies $\lambda_t > v_t^{\text{PM}}(e - P/\eta)/\eta - h(P) - Ph'(P) + c$. Hence $\frac{\partial p_t}{\partial e} = \frac{\partial b_t}{\partial e} = 0$, $\frac{\partial e_t}{\partial e} = 1$. Then we can get the marginal value function:

$$v_{t-1}^{\text{PM}}(e) = v_t^{\text{PM}}(e - P/\eta) \tag{35e}$$

Then we finish the proofs of Lemma 2.

C PROOF OF LEMMA 3

To calculate the maximum difference between Eq. (11) and Eq. (12a), the most intuitive way is to list all the 25 situations and calculate the difference, respectively. For simplicity, we only analyze the cases where the δ_t is greater than 0 here since the upper bound only cares about the maximum term.

Case 1: PM-ES lies in the first case, where $\lambda_t \le v_t^{\text{PM}}(e + P\eta)\eta - 2\alpha_1 P$. Then we can calculate the difference as follows:

$$\begin{aligned} v_{t-1}^{\text{PM}}(e) - v_{t-1}^{\text{PT}}(e) &= v_t^{\text{PM}}(e + P\eta) - v_{t-1}^{\text{PT}}(e) \\ &\le v_t^{\text{PM}}(e + P\eta) - v_t^{\text{PT}}(e + P\eta) \\ &\le \theta_t(e + P\eta) \end{aligned} \tag{36}$$

Case 2: PM-ES lies in the second case, while PT-ES lies in the first or second case, where $v_t^{\text{PM}}(e + P\eta)\eta - 2\alpha_1 P < \lambda_t \le \min\{v_t^{\text{PM}}(e)\eta, v_t^{\text{PT}}(e)\eta\}$. Then we can calculate the difference as follows:

$$\begin{aligned} v_{t-1}^{\text{PM}}(e) - v_{t-1}^{\text{PT}}(e) &\le [\lambda_t + h(-b^*) - b^* h'(-b^*)]/\eta - \lambda_t/\eta \\ &= [h(-b^*) - b^* h'(-b^*)]/\eta \\ &= [v_t^{\text{PM}}(e + b^*\eta)\eta - \lambda_t]/\eta \\ &\le v_t^{\text{PM}}(e) - \lambda_t/\eta \end{aligned} \tag{37}$$

Case 3: PT-ES lies in the fifth case, where $\lambda_t > v_t^{\text{PT}}(e - P/\eta)/\eta + c$. Then we can calculate the difference as follows:

$$\begin{aligned} v_{t-1}^{\text{PM}}(e) - v_{t-1}^{\text{PT}}(e) &= v_{t-1}^{\text{PM}}(e) - v_t^{\text{PT}}(e - P/\eta) \\ &\le v_t^{\text{PM}}(e - P/\eta) - v_t^{\text{PT}}(e - P/\eta) \\ &\le \theta_t(e - P/\eta) \end{aligned} \tag{38}$$

Case 4: PM-ES lies in the second or third case, while PT-ES lies in the third or fourth case, where $\max\{v_t^{\text{PM}}(e + P\eta)\eta - h(-P) + Ph'(-P), v_t^{\text{PT}}(e)\eta\} < \lambda_t \le \min\{v_t^{\text{PM}}(e)\eta, v_t^{\text{PT}}\eta\}$. Then, we can calculate the difference as follows:

$$\begin{aligned} v_{t-1}^{\text{PM}}(e) - v_{t-1}^{\text{PT}}(e) &\le v_{t-1}^{\text{PM}}(e) - v_{t-1}^{\text{PT}}(e) \\ &\le \theta_t(e) \end{aligned} \tag{39}$$

Then we finish the proofs of Lemma 3.