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Market Power and Withholding Behavior of Energy Storage Units

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***Abstract*— Electricity markets are experiencing a rapid increase in energy storage unit participation. Unlike conventional generation resources, quantifying the competitive operation and identifying if a storage unit is exercising market power is challenging, particularly in the context of multi-interval bidding strategies. We present a framework to differentiate strategic capacity withholding behaviors attributed to market power from inherent competitive bidding in storage unit strategies. Our framework evaluates the profitability of strategic storage unit participation, analyzing bidding behaviors as both price takers and price makers using a self-scheduling model, and investigates how they leverage market inefficiencies. Specifically, we propose a price sensitivity model derived from the linear supply function equilibrium model to examine the price-anticipating bidding strategy, effectively capturing the influence of market power. We introduce a sufficient *ex-post* analysis for market operators to identify potential exploitative behaviors by monitoring instances of withholding within the bidding profiles, ensuring market resilience and competitiveness. We discuss and verify applicability of the proposed framework to realistic settings. Our analysis substantiates commonly observed economic bidding behaviors of storage units. Furthermore, it demonstrates that significant price volatility offers considerable profit opportunities not only for participants possessing market power but also for typical strategic profit seekers.**

I. INTRODUCTION

Electricity markets are seeing a surging amount of battery energy storage unit participants. Jointly facilitated by the reduced cost of battery cells and removed market participation barriers [1], battery energy storage is becoming increasingly competitive. In California, the capacity of grid-scale battery energy storage increased by ten times in three years, from less than 500 MW in 2020 to 5,000 MW in mid-2023, and is projected to reach 10,000 MW in 2025 [2]. On the other hand, participation in wholesale electricity markets to arbitrage price differences is becoming the main grid service for storage units [3], surpassing frequency regulation which is a specialized service that can only accommodate very limited storage capacity [4].

Energy storage units participate in wholesale electricity markets either by self-scheduling [5] or submitting competitive economic bids [6]. In self-scheduling, storage units design their charging and discharging schedules ahead of wholesale market clearance. In economic bidding, storage units submit separate bids for charging and discharging. In both cases, storage units often perform private optimization according to their operation characteristics, degradation cost, and opportunity cost. Unlike thermal generators that directly design bid values based on their fuel costs and heat rate curves, storage units need to optimize their self-schedule bids to systematically consider factors such as future price volatility and state-of-charge constraints [7], [8], [9].

Accompanying optimized market participation is the concept of capacity withholding of storage units. Capacity withholding occurs when a resource purposefully limits its supply despite higher current price than its real marginal production cost. Capacity withholding is often a critical sign that a participant is exercising market power by limiting the supply of a given resource in order to drive up the price and obtain higher profits. Hence such conduct is strictly monitored and regulated [10]. However, such regulation does not necessarily apply to energy storage units, which, due to their limited energy capacity, must strategically target its timing to charge and discharge accounting for prices over a sequence of time rather than focusing on the price at any single specific interval. Harvey and Hogan [11] noted that *"If a unit is energy limited, its offer price will exceed the unit's incremental cost."*, and *"This economic withholding can conceptually be distinguished from the exercise of market power."*.

Nevertheless, as a regular participant in electricity markets, storage units can use the same withholding strategy to exercise market power as conventional generators. While storage units can conduct capacity withholding for justifiable motivations to seek charge and discharge arbitrage opportunities, it can further increase its withholding to exercise market power. To this end, it is extremely difficult to identify whether storage unit is exercising market power. Yet, there have not been systematic studies on the intricacies of multi-interval bidding patterns, nor have they sufficiently considered the constraints of energy-limited generation resources, including energy storage systems.

We propose a systematic framework to differentiate market manipulation from storage bids that account for legitimate withholding. The contributions of this work are two-fold.

1) We evaluate the profitability of strategic storage unit participants in the electricity market by analyzing their bidding behavior through a self-scheduling profit-maximization model. This analysis considers two sets of market roles and bidding strategies that exploit market inefficiencies: conducting competitive arbitrage as price takers or exercising market power as price makers. We design a price sensitivity model derived from the linear supply function equilibrium model to examine the price-anticipating bidding strategy, provid-

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ing a clear view of how the exercise of market power impacts prices.
2) From the perspective of the market operator, we provide insights into identifying market exploitation behavior accounting for the instances of withholding by analyzing the bidding profiles and the corresponding price series. This result proves to be a sufficient *ex-post* tool for market efficiency monitoring. By applying our framework, we resolve a conjecture made by Harvey and Hogan [11] pertaining to maximized energy utilization of energy limited units during the peak (or valley for energy storage units) price periods. Additionally, we reveal the considerable profit margin exposed to both price takers and price makers attributed to high price volatility. These findings are useful for maintaining market resilience and providing robust competitiveness.

The main results are validated using historical price data from NYISO.

II. MODEL FORMULATION

A. Competition and Market Power

Competitive arbitrage and the exercise of market power are both mechanisms that leverage market inefficiencies. Arbitrage involves market participants leveraging price difference and the ability to leverage this at no risk. In contrast, the exercise of market power involves market participants deliberately reducing their production below competitive levels in order to increase market clearing prices, thereby enhancing their profitability [11]. We aim to analyze the consequences of these bidding strategies by modeling the optimal strategy making process for multi-interval bidding from the perspective of a single storage unit. The underlying theory of market power is that the market clearing price will be influenced by the offers or bids from certain participants. We explicitly model such impact on the price at time t using a non-negative price sensitivity parameter α_t. Market participants who possess market power are characterized by a positive price sensitivity parameter, i.e., $\alpha_t > 0$, while those without market power are modeled with a zero price impact, i.e., $\alpha_t = 0$. The price at time t is modeled as

$$\lambda_t = \bar{\lambda}_t - \alpha_t q_t \tag{1}$$

where λ_t is the influenced price, $\bar{\lambda}_t$ is the nominal clearing price and q_t is the dispatch decision. It is important to clarify that $\bar{\lambda}_t$ does not necessarily represent the competitive price; rather, it signifies the price in the absence of the participation of a specific market participant.[1]

Equation (1) captures the fact that, as a market participant possessing market power, their participation in the market $(\alpha_t, q_t > 0)$ naturally brings down the market price ($\lambda_t < \bar{\lambda}_t$). This effect is particularly notable when the participant serves as a large-scale pivotal supplier, whose power capacity is essential for easing potential power shortages in the system. Hence, the nominal price $\bar{\lambda}_t$ functions as an indicator of the system's load level or supply capacity. Additionally, offering more power to the market lowers the price. Therefore, practices such as physical capacity withholding ($q_t < \bar{P}$, where $\bar{P}$ denotes the power capacity) can raise market prices, generating a profit margin for the withholding entity and possibly others but also diminishing social welfare by affecting the overall market equilibrium.

To understand the bidding behavior of participants anticipating their impact on prices and the consequent market outcomes, we consider a bid-based market that clears by relying on affine supply functions [13]:

$$q_t(\lambda_t) = a_t \lambda_t + b_t \tag{2}$$

where the parameter pair (a_t, b_t) characterizes the offer chosen by the participant for time interval t.

Generally, a rational market participant designs their bid supply function $q_t(\lambda_t)$ by solving a profit-maximization problem using price forecast $\hat{\lambda}_t$ over a future time period $t \in \mathcal{T}$:

$$q_t(\lambda_t) = \underset{a_t, b_t}{\operatorname{argmax}}\ \pi(q_t(\lambda_t); \hat{\lambda}_t) \quad \text{s.t. (2)} \tag{3}$$

where $\pi = \sum_{t \in \mathcal{T}} \hat{\lambda}_t q_t(\lambda_t) - C\left(q_t(\lambda_t)\right)$ represents the total profit and $C(\cdot)$ is a given strictly convex cost function.

Ideally, the supply function $q_t(\lambda_t)$ should reflect the actual operation costs of production in a competitive market. However, bids that incorporate price sensitivity, as determined by solving

$$q_t(\lambda_t) = \underset{a_t, b_t}{\operatorname{argmax}}\ \pi(q_t(\lambda_t), \bar{\lambda}_t - \alpha q_t(\lambda_t)) \quad \text{s.t. (2)} \tag{4}$$

may obscure the true cost information. Assuming a quadratic cost function $C(\cdot)$, we illustrate the variation in bidding behavior and the consequent market outcome in Fig. 1 (for simplicity, the subscript t in the bidding functions is neglected in the figures). $q'(\lambda)$ is the optimal solution to problem (3), and $q''(\lambda)$ is that to problem (4). As shown in Fig. 1(a), the bidding curve shifts from $q'(\lambda)$ to $q''(\lambda)$ due to the consideration of price sensitivity. This shift results in the market clearing price increasing from λ'_t to λ''_t, while maintaining the same level of power output q_t, indicating a clear reduction in economic efficiency. This alteration in the bidding curve can be seen as cost-related withholding, i.e., economic withholding. The market clearing outcome related to this behavior is shown in Fig. 1(b). Here, we use $\tilde{q}(\lambda)$ to denote the remainder of the aggregated supply function within the system. It can be seen that, as two primary approaches of conducting capacity withholding or further exercising market power [11], economic withholding through the bid supply function is equivalent to physical withholding of the amount Δq_t from the perspective of market outcomes. For simplicity, we will focus on the effects of withholding practices and refer to this as capacity withholding throughout the remainder of the paper, without loss of generality.

[1] A similar price sensitivity model is introduced in [12]. However, the model in [12] quantifies price impact via the amount of withheld production, $\lambda_t = \tilde{\lambda}_t + \alpha_t \Delta q_t$. This approach does not capture the immediate price drop following the entry of a price maker. Additionally, it calculates withheld production based on the competitive level, which complicates the analysis.

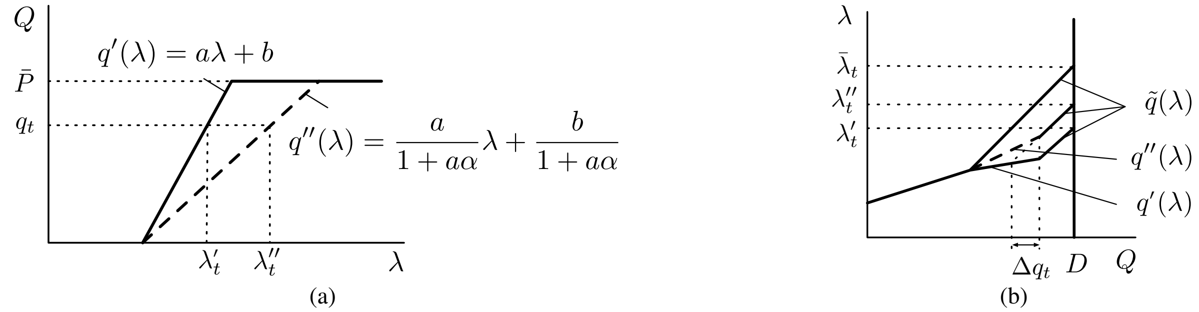


Fig. 1. Bidding behavior of participants as a price taker ($q'(\lambda)$, solid line) and a price maker ($q''(\lambda)$, dashed line) and the corresponding impacts on the market outcome: (a) bid supply curves, (b) market clearing results. The axis Q measures power output. The supply function $\tilde{q}(\lambda)$ represents the remainder of the aggregated supply within the system. Demand is considered inelastic at D, Δq_t indicates the equivalent capacity withholding. $q'(\lambda)$ is the optimal solution to problem (3), and $q''(\lambda)$ is that to problem (4).

Additionally, Fig. 1(b) suggests that the determination of the price sensitivity parameter α_t is influenced by the slopes of the system supply function ($\tilde{q}(\lambda)$ in the figure), the demand function (D in the figure), and the unit supply function. Although the specifics of this process are beyond the scope of this work, it highlights the necessity for market participants with market power to obtain the knowledge of the system demand level and the bids from other participants to accurately estimate their influence on market outcomes and making corresponding bidding decisions. Interested readers may refer to [12] for more details.

We define market participants based on their bidding strategies and their impacts on the market clearing prices as follows:

*Definition 1 (**Price Taker**):* A market participant is a price taker if they accept the existing prices as given and lack the market share to influence market prices on their own.

*Definition 2 (**Price Maker**):* A market participant is a price maker if they anticipate the influence of their bids on market prices. A price maker has sufficient knowledge of the system status, such as demand levels and the bids of other participants.

A more thorough analysis of the bidding strategies associated with these two categories of market participants will be discussed in later sections.

Remark 1: Our price sensitivity model can be generalized to scenarios where the bidding entity operates with other forms of cost functions, or participates in the market with constant cost bids or quantity bids.

B. Strategic Bidding of Energy Storage Units

We adopt a convex self-scheduling model to characterize the bidding strategies of energy storage units, utilizing a series of price point forecasts $\hat{\lambda}_t$ for all $t \in \mathcal{T}$, where $\mathcal{T} = \{1, 2, \dots, T\}$ [14]. The profit from future intervals can be regarded as the opportunity value at the current time interval. Most existing market designs require storage unit operators to make dispatch decisions based on future price estimates. This strategy reflects the allocation of limited output into a profile that maximizes total profit over the scheduling period. The solution to the profit-maximization problem forms the control policy or decision of the storage units. For ease of exposition, we assume that the storage unit accurately estimates their impact on market prices with α_t:

$$\underset{p_t, b_t, e_t}{\text{maximize}} \quad \sum_{t \in \mathcal{T}} \hat{\lambda}_t (p_t - b_t) \tag{5a}$$

$$\text{s.t.} \quad 0 \le p_t, b_t \le \bar{P}, \quad \forall t \in \mathcal{T} \tag{5b}$$

$$p_t = 0 \text{ if } \hat{\lambda}_t < 0, \quad \forall t \in \mathcal{T} \tag{5c}$$

$$e_t - e_{t-1} = -\frac{p_t}{\eta} + b_t \eta, \quad \forall t \in \mathcal{T} \tag{5d}$$

$$0 \le e_t \le E, \quad \forall t \in \mathcal{T} \tag{5e}$$

where p_t and b_t denote the amount of energy discharged and charged respectively over time interval t. We refer to intervals when $0 < p_t < \bar{P}$ or $0 < b_t < \bar{P}$ for any $t \in \mathcal{T}$ as *withholding intervals*. Objective (5a) represents the total profit π over the future period $t \in \mathcal{T}$. For price makers, it follows from (1) that the price forecast takes the form based on the price sensitivity: $\hat{\lambda}_t = \bar{\lambda}_t - \alpha_t (p_t - b_t)$, where $\alpha_t > 0$. Note that incorporating both forms of the price for profit calculation in (5a) preserves the convexity of model (5). Constraint (5b) captures the charging/discharging power lower and upper bounds. Constraint (5c) ensures that the storage unit does not discharge during periods of negative pricing, a sufficient condition to preclude simultaneous charging and discharging [14]. The inter-temporal relationship of the state of charge (SoC) e_t is defined in (5d) with charging and discharging efficiency parameter $\eta \in (0, 1]$. Inequality (5e) models energy storage capacity. We define storage units as operating in *idle scenarios* if they remain on standby according to model (5) throughout the scheduling period $\mathcal{T}$, i.e., $p_t = 0, \ b_t = 0$, for all $t \in \mathcal{T}$.

Remark 2: Although the framework for energy storage unit bidding in this paper is based on self-scheduling and neglects the operating cost $C(\cdot)$ for profit calculation, it can be easily adapted to allow economic bidding [5], accounting for the costs associated with storage discharge, such as those related to unit degradation, operation and maintenance, in its profit calculation.

III. MAIN RESULTS

We now present our framework for energy storage bidding, demonstrating the distinction between a storage unit exercising market power and competitive capacity withholding. In the sequel, we examine the bidding strategies of both *price takers* and *price makers*.

Theorem 1: Assume the energy storage unit behaves rationally and designs its bid by solving the profit-maximization problem (5) using price forecast $\hat{\lambda}_t$ over a horizon of length NT for N bidding scheduling periods, with each period of length T. Given a series of observed storage power output profiles $\{p_t,\ b_t\}$ and market clearing prices $\{\lambda_t\}$ for all $t \in \tilde{\mathcal{T}}$, where $\tilde{\mathcal{T}} = \{1, 2, \ldots, NT\}$, the storage unit is not evidently exercising market power, if the following conditions are satisfied:

1) The number of withholding intervals is no larger than the number of non-idle scheduling periods N', i.e.,
$$\sum_{t\in\tilde{\mathcal{T}}} \mathbb{1}_{\{0<p_t<\bar{P}\}} + \sum_{t\in\tilde{\mathcal{T}}} \mathbb{1}_{\{0<b_t<\bar{P}\}} \leq N' \leq N.$$
2) The price-decision relationship is consistent with Proposition 4.

Proposition 4 reveals the relationship between the control decisions of a price taker and the prevailing market prices. Details will follow in subsequent subsections.

Theorem 1 suggests that the market operator can conduct *ex-post* analysis according to the observed storage power output profiles and market clearing price series to examine the exercise of market power with the aim of monitoring market efficiency. This method aligns with the *"after-the-fact standard"* approach for analysis as recommended by Harvey and Hogan in [11]. Note that from the market operator's perspective, that actual competitive bids and the resulting clearing prices are not accessible. The available information for conducting market efficiency analysis comprises solely the effective storage power output profiles and the corresponding prices. The presence of partial operation intervals during the observation period indicates instances of storage unit conducting capacity withholding. Merely counting these instances below a predefined threshold and examining the prices associated with these instances offers a practical and efficient method to differentiate the causes of capacity withholding – whether or not it results from market power exercise or competitive behavior.

The proof of Theorem 1 will compromise an examination of bidding strategies derived from simplified individual profit maximization problems discussed in subsequent subsections. Strictly speaking, we should directly deal with the bidding model (5); however, we will initially introduce a set of assumptions to facilitate preliminary discussions and propositions. These assumptions will later be revisited and removed, allowing us to generalize the conditions and validate the applicability of Theorem 1.

In the simplified profit maximization model, we focus on scenarios with short clearing periods, e.g., $T = 2, 3$. Given the short duration of storage charging and discharging, we assume the storage capacity constraint (5e) is strictly satisfied throughout the scheduling period $\mathcal{T}$ and neglect it in the model formulation:

Assumption 1 (Unsaturated SoC): During the clearing period, the energy storage SoC remains strictly feasible, i.e., $0 < e_t < E$ for all $t \in \mathcal{T}$.

In light of Assumption 1, the SoC evolution constraint (5d) reduces to:
$$\sum_{t\in\mathcal{T}} \frac{p_t}{\eta} - b_t\eta = 0. \tag{6}$$

Assumption 2 (Positive profit operation): The storage unit remains idle, i.e., $p_t = 0,\ b_t = 0$, for all $t \in \mathcal{T}$, if the induced profit is zero, i.e., $\pi = 0$.

Assumption 3 (Non-negative pricing): Prices remain non-negative, $\lambda_t \geq 0$, for all $t \in \mathcal{T}$.

Based on Assumption 3, we omit the constraint (5c) in the bidding model, however the non-simultaneous charging and discharging condition *does* still hold.

A. Withholding as Price Taker

First, we aim to analyze the withholding bidding behavior assuming that the energy storage unit participates in the market as a price taker. From Assumptions 1-3, the corresponding bidding model is:
$$\underset{p_t, b_t}{\text{maximize}} \quad \sum_{t\in\mathcal{T}} \hat{\lambda}_t(p_t - b_t) \tag{7a}$$
$$\text{s.t.} \quad \sum_{t\in\mathcal{T}} \frac{p_t}{\eta} - b_t\eta = 0 : \theta \tag{7b}$$
$$0 \leq p_t \leq \bar{P} : \delta_t^-, \delta_t^+, \forall t \in \mathcal{T} \tag{7c}$$
$$0 \leq b_t \leq \bar{P} : \beta_t^-, \beta_t^+, \forall t \in \mathcal{T} \tag{7d}$$

where the corresponding dual variable is defined after each constraint. Note that although we formulate the bidding model of price takers using $\hat{\lambda}_t$ in the objective (7a), in the presence of price makers, $\hat{\lambda}_t$ will be replaced by the influenced price based on (1) to determine the ultimate dispatch decision and profit.

The Lagrangian function of (7) is:
$$L = \sum_{t\in\mathcal{T}} \Big(\hat{\lambda}_t(p_t - b_t) + \theta \left(\frac{p_t}{\eta} - b_t\eta \right) + \delta_t^- p_t - \delta_t^+(p_t - \bar{P}) + \beta_t^- b_t - \beta_t^+(b_t - \bar{P}) \Big), \tag{8}$$

and the corresponding KKT conditions are ($\forall t \in \mathcal{T}$):
$$\frac{\partial L}{\partial p_t} = \hat{\lambda}_t + \frac{\theta}{\eta} + \delta_t^- - \delta_t^+ = 0 \tag{9a}$$
$$\frac{\partial L}{\partial b_t} = -\hat{\lambda}_t - \theta\eta + \beta_t^- - \beta_t^+ = 0 \tag{9b}$$
$$\sum_{t\in\mathcal{T}} \frac{p_t}{\eta} - b_t\eta = 0 \tag{9c}$$
$$0 \leq p_t,\ b_t \leq \bar{P} \tag{9d}$$
$$\delta_t^-,\ \delta_t^+,\ \beta_t^-,\ \beta_t^+\ \geq 0 \tag{9e}$$
$$\delta_t^- p_t = 0,\ \delta_t^+(p_t - \bar{P}) = 0 \tag{9f}$$
$$\beta_t^- b_t = 0,\ \beta_t^+(b_t - \bar{P}) = 0 \tag{9g}$$

where Eqs. (9a) and (9b) correspond to stationarity conditions, constraints (9c) and (9d) to primal feasibility, constraint (9e) to dual feasibility, Eqs. (9f) and (9g) to complementary slackness. Given that the optimization model (7) is a linear program, there is zero duality gap, yielding KKT conditions both necessary and sufficient for optimality.

Proposition 1: For a strategic price taker making bidding decisions based on model (7), the bidding decisions $\{p_t^*,\ b_t^*\}$ throughout the period $\mathcal{T}$ will include at least one interval t at capacity, i.e., $p_t^* = \bar{P}$ or $b_t^* = \bar{P}$, except for the idle scenarios.

This proof is established by considering a counterexample in which the unit does not operate at full capacity during any interval, thereby, according to the KKT conditions in (9), violating the non-idle condition as specified in Assumption 2. A detailed proof is included in the extended version [15].

Proposition 2: For a strategic price taker making bidding decisions based on model (7), assuming the storage unit is not idle throughout the scheduling period $\mathcal{T}$, then

1) there must exist $\hat{\lambda}_{\min} < \hat{\lambda}_{\max}$, where $\hat{\lambda}_{\min} = \min_{t\in\mathcal{T}}\{\hat{\lambda}_t\}$ and $\hat{\lambda}_{\max} = \max_{t\in\mathcal{T}}\{\hat{\lambda}_t\}$,
2) the storage unit operates at capacity either by discharging during the highest price interval $t_{\hat{\lambda}_{\max}}$, i.e., $p^*_{t_{\hat{\lambda}\max}} = \bar{P}$, or by charging during the lowest price interval $t_{\hat{\lambda}_{\min}}$, i.e., $b^*_{t_{\hat{\lambda}\min}} = \bar{P}$.

The proof is provided in [15].

Remark 3: Propositions 1 and 2 suggest that during the scheduling period, the storage unit will operate at its capacity for at least one interval, either at the highest or the lowest price point. This insight is readily applicable to scenarios where the SoC of the storage unit is constrained throughout the period. In situations where the storage unit's maximum output is limited by its capacity, it can still be asserted, without loss of generality, that the storage unit will maximize its energy utilization during the period of highest or lowest prices. This principle aligns with the conjecture made in Section III.A of [11], which stated that *"for energy limited unit, efficient pricing would fully utilize the energy of the unit in the highest price hours over the period of the limitation"*. Our findings validate this conjecture and also extend it by exploring its implications for the bidding strategies of energy storage units.

Proposition 3: For a strategic price taker making bidding decisions based on model (7), given strictly heterogeneous prices $\hat{\lambda}_1 \neq \hat{\lambda}_2 \ldots \neq \hat{\lambda}_T$, the bidding decisions $\{p_t^*,\ b_t^*\}$ throughout the period $\mathcal{T}$ should include one and only one interval t at partial capacity, $0 < p_t^* < \bar{P}$ or $0 < b_t^* < \bar{P}$, except for the idle scenarios.

To prove the proposition above, we first prove there is at least one interval with partial capacity and then prove at most one interval with partial capacity based on the KKT conditions in (9). The full proof is included in the extended version [15].

In competitive markets, i.e., market participants bid as price takers according to model (7), we have the following price-decision relationship:

Proposition 4: Given a series of prices $\hat{\lambda}_t$ throughout the period $\mathcal{T}$, a strategic price taker makes bidding decisions $\{p_t^*,\ b_t^*\}$ based on model (7). Denote the set of discharge withholding intervals $\{u \in \mathcal{T} | \mathbb{1}_{\{0<p_u<\bar{P}\}} = 1\}$ and charge withholding intervals $\{v \in \mathcal{T} | \mathbb{1}_{\{0<b_v<\bar{P}\}} = 1\}$, then the bidding decisions take one of three outcomes:

1) If the **unit discharges at capacity** during interval x, i.e., $p_x^* = \bar{P}$, then $\hat{\lambda}_x > \hat{\lambda}_u$ and $\hat{\lambda}_x > \frac{\hat{\lambda}_v}{\eta^2}$.
2) If the **unit charges at capacity** during interval y, i.e., $b_y^* = \bar{P}$, then $\hat{\lambda}_u > \frac{\hat{\lambda}_y}{\eta^2}$ and $\hat{\lambda}_v > \hat{\lambda}_y$.
3) If the **unit keeps idle** during interval z, i.e., $p_z^* = b_z^* = 0$, then $\frac{\hat{\lambda}_z}{\eta^2} > \hat{\lambda}_u > \hat{\lambda}_z$ and $\hat{\lambda}_z > \hat{\lambda}_v > \hat{\lambda}_z\eta^2$.

The proof can be found in [15].

TABLE I. Storage Unit Control Policy as Price Taker in Two-Interval Bidding

Scenario	Interval 1		Interval 2	
	p_1^*	b_1^*	p_2^*	b_2^*
$\hat{\lambda}_1 > \frac{\hat{\lambda}_2}{\eta^2}$	$\bar{P}\eta^2$	0	0	$\bar{P}$
$\hat{\lambda}_2\eta^2 \leq \hat{\lambda}_1 \leq \frac{\hat{\lambda}_2}{\eta^2}$	0	0	0	0
$\hat{\lambda}_1 < \hat{\lambda}_2\eta^2$	0	$\bar{P}$	$\bar{P}\eta^2$	0

We illustrate the bidding strategies of price takers based on model (7) through the two-interval bidding scenario, with the control policy detailed in Table I. The decision-making process is primarily influenced by the price difference between the two intervals. Given the energy loss during the charging/discharging cycle, the storage unit operation is justified only if the profits from arbitraging the price difference offset the losses. This arbitrage strategy implies that the storage unit will utilize its full capacity for profit as long as it remains economically viable, refraining from any unjustified withholding, i.e., no partial operation below $\bar{P}\eta^2$.

B. Withholding as Price Maker

We now explore the scenario in which the storage unit operates as a price maker, anticipating the effects of its bidding behavior on the market clearing price, using the following bidding model:

$$\begin{aligned} \underset{p_t, b_t}{\text{maximize}} \quad & \sum_{t\in\mathcal{T}} (\bar{\lambda}_t - \alpha_t(p_t - b_t))(p_t - b_t) \qquad (10) \\ \text{s.t.} \quad & (7\text{b}) - (7\text{d}). \end{aligned}$$

Incorporating the impact of market power on market clearing prices into the price maker's bidding model introduces quadratic terms into the objective function (10), in contrast to the linear terms found in the price-taker's model as (7a). However, both problems are still convex.

The corresponding KKT conditions are ($\forall t \in \mathcal{T}$):

$$\frac{\partial L}{\partial p_t} = \bar{\lambda}_t - 2\alpha_t p_t + 2\alpha_t b_t + \frac{\theta}{\eta} + \delta_t^- - \delta_t^+ = 0 \qquad (11\text{a})$$

$$\frac{\partial L}{\partial b_t} = -\bar{\lambda}_t + 2\alpha_t p_t - 2\alpha_t b_t - \theta\eta + \beta_t^- - \beta_t^+ = 0 \qquad (11\text{b})$$

$$(9\text{c}) - (9\text{e})$$

where Eqs.(11a) and (11b) correspond to stationarity conditions, and the rest are the same as that of the optimality conditions in (9).

Proposition 5: For a strategic price maker making bidding decisions based on model (10), throughout the period $\mathcal{T}$:

TABLE II. STORAGE UNIT CONTROL POLICY AS PRICE MAKER IN TWO-INTERVAL BIDDING

Scenario		Interval 1		Interval 2	
		p_1^*	b_1^*	p_2^*	b_2^*
$\bar{\lambda}_1 > \frac{\bar{\lambda}_2}{\eta^2}$	$\bar{\lambda}_1 - 2\alpha_1\bar{P}\eta^2 \geq \frac{\bar{\lambda}_2+2\alpha_2\bar{P}}{\eta^2}$	$\bar{P}\eta^2$	0	0	$\bar{P}$
	$\bar{\lambda}_1 - 2\alpha_1\bar{P}\eta^2 < \frac{\bar{\lambda}_2+2\alpha_2\bar{P}}{\eta^2}$	$\frac{\bar{\lambda}_1-\frac{\bar{\lambda}_2}{\eta^2}}{2(\alpha_1+\frac{\alpha_2}{\eta^4})}$	0	0	$\frac{\bar{\lambda}_1-\frac{\bar{\lambda}_2}{\eta^2}}{2(\alpha_1+\frac{\alpha_2}{\eta^4})\eta^2}$
$\bar{\lambda}_2\eta^2 \leq \bar{\lambda}_1 \leq \frac{\bar{\lambda}_2}{\eta^2}$		0	0	0	0
$\bar{\lambda}_1 < \bar{\lambda}_2\eta^2$	$\frac{\bar{\lambda}_1+2\alpha_1\bar{P}}{\eta^2} > \bar{\lambda}_2 - 2\alpha_2\bar{P}\eta^2$	0	$\frac{-\bar{\lambda}_1+\bar{\lambda}_2\eta^2}{2(\alpha_1+\alpha_2\eta^4)}$	$\frac{(-\bar{\lambda}_1+\bar{\lambda}_2\eta^2)\eta^2}{2(\alpha_1+\alpha_2\eta^4)}$	0
	$\frac{\bar{\lambda}_1+2\alpha_1\bar{P}}{\eta^2} \leq \bar{\lambda}_2 - 2\alpha_2\bar{P}\eta^2$	0	$\bar{P}$	$\bar{P}\eta^2$	0

1) The bidding decisions $\{p_t^*,\ b_t^*, \forall t \in \mathcal{T}\}$ should include at least one interval t at partial capacity, $0 < p_t^* < \bar{P}$ or $0 < b_t^* < \bar{P}$, except for the idle scenarios.
2) There might exist multiple full or partial intervals.

The proof for 1) follows similar arguments to Proposition 3; 2) is apparent following the proof for Proposition 3 based on the KKT conditions (11).

The two-interval bidding scenario for price makers based on model (10) is summarized in Table II. Compared to the strategies of price takers as in Table I, the control decisions for each non-idle scenario further splits into two sub-scenarios, either $\bar{\lambda}_1 > \frac{\bar{\lambda}_2}{\eta^2}$ or $\bar{\lambda}_1 < \bar{\lambda}_2\eta^2$. Such decisions are established accounting for the economic losses associated with both charging/discharging energy loss and their potential impact on market prices, including both immediate and future contrast effects. Take the scenario where $\bar{\lambda}_1 > \frac{\bar{\lambda}_2}{\eta^2}$ for example. In addition to comparing prices based on charging and discharging efficiencies, i.e., $\bar{\lambda}_1 > \frac{\bar{\lambda}_2}{\eta^2}$, price makers also consider the marginal revenue from operational intervals. If the projected profit be substantial, i.e., with high marginal revenue as $\bar{\lambda}_1 - 2\alpha_1\bar{P}\eta^2 \geq \frac{\bar{\lambda}_2+2\alpha_2\bar{P}}{\eta^2}$, the strategy aligns with that of price takers as operating at capacity, suggesting that a larger price difference leads to greater profitability, sufficient even for arbitrage by price takers. Moreover, price makers, facing potentially lower marginal revenues, i.e., $\bar{\lambda}_1 - 2\alpha_1\bar{P}\eta^2 < \frac{\bar{\lambda}_2+2\alpha_2\bar{P}}{\eta^2}$, still possess the strategic flexibility to optimize control decisions for maximizing profit, exploiting their influence on market outcome.

C. Three-Interval Bidding Scenario

Compared to the two-interval bidding discussed earlier, the three-interval scenario demonstrates how energy storage units strategically allocate their limited resources into a portfolio that maximizes total profit based on a series of prices over the scheduling period. The three-interval bidding establishes a foundation for analyzing longer-term bidding scenarios.

Define the number of full capacity intervals throughout the scheduling period $\mathcal{T}$: $o = \sum_{t\in\mathcal{T}} \mathbb{1}_{\{p_t=\bar{P}\}} + \sum_{t\in\mathcal{T}} \mathbb{1}_{\{b_t=\bar{P}\}}$, and correspondingly for partial intervals: $s = \sum_{t\in\mathcal{T}} \mathbb{1}_{\{0<p_t<\bar{P}\}} + \sum_{t\in\mathcal{T}} \mathbb{1}_{\{0<b_t<\bar{P}\}}$.

Corollary 1: For a strategic price maker making bidding decisions based on model (10), consider the bidding case consisting three intervals, then if there exist two intervals $j_1,\ j_2$ operating with partial capacity, $s = 2$, and one full t_0, $o = 1$ and $\bar{\lambda}_{j_2} > \bar{\lambda}_{j_1}, \bar{\lambda}_{j_2} > \bar{\lambda}_{t_0}$, a sufficient condition for this scenario is $\frac{\bar{\lambda}_{j_1}+2\alpha_{j_1}\bar{P}}{\eta^2} > \bar{\lambda}_{j_2} - 2\alpha_{j_2}\bar{P}$.

Corollary 1 also implies, in the case of three-interval bidding, when the ultimate price difference is larger between intervals j_1 and j_2, there can be no less full intervals than partial. Such analysis can be easily extended to other scenarios.

Remark 4: Higher price difference, resulting in higher profitability, complicates the distinction between withholding behavior due to strategic arbitrage versus market power exercise. Both strategies exploit market inefficiencies, however, high profit margins can mask the source of earnings, whether derived from arbitrage or price manipulation.

D. Understanding Multi-Interval Bidding

The *ex-post* analysis is established in two phases. First, the market operator counts and compares the number of full or partial intervals, For price takers, as suggested in Propositions 1 and 3, they typically participate in the market with the profiles where the number of full intervals are no more the that of partial ones, including the idle scenarios. On the other hand, for price makers, Proposition 5 and Corollary 1 indicate that most scenarios feature the number of partial intervals no less than that of full ones, suggesting the exercise of market power through capacity withholding. Exceptions occur where the number of full intervals exceed that of partial ones, notably in situations with significant price differentials, as detailed in Remark 4. Secondly, examining price-decision relationship across the intervals reveals the bidding strategy adopted by the market participant, indicating whether it involves the exercise of market power. With this analysis in place, we can now prove Theorem 1.

Proof: [**Theorem 1**] We first analyze the scenarios for price takers and price makers within the framework of Assumptions 1–3. With that analysis in place we remove the assumptions.

For price takers: From Proposition 3 we've covered that given strictly heterogeneous prices, there exists only one partial interval, which establishes a sufficient condition for Theorem 1. The statement of Theorem 1 allows for the case where prices do not change. There are three possible scenarios: i) zero withholding intervals occur, ii) there is exactly one withholding interval, and iii) more than one withholding interval occurs. Scenario i) and ii) are special cases of Proposition 3. Scenario 3 violates the framing of Theorem 1 and so we do not need to consider it.

For price makers: Proposition 5 states that the number of partial intervals is always no less than one, i.e., $s \geq 1$. When $s = 1$, assuming sufficiently small price sensitivity parameter α_t, we can conclude that the bidding profiles from price makers are indistinguishable to those observed among price takers (i.e., $\hat{\lambda}_t \approx \bar{\lambda}_t$), thus the price maker is not evidently exercising market power. However, scenarios exist where, despite the profile showing only one withholding interval, the price maker *is* exercising market power (i.e., larger α_t values). Due to space limitations, detailed scenario realizations are relegated to Table III in [15]. Here we consider one scenario (out of a possible 10) for illustrative purposes. The proof is easily adapted to all other cases.

We consider the scenario corresponding to the first row in Table III. Here if the unit was a price taker it withholds from charging, but, as a price maker, it would withhold from discharging. For the price taker, in order to derive the bidding decisions $p_b^* = \bar{P},\ b_c^* = \hat{b}$, the corresponding clearing prices need to satisfy $\hat{\lambda}_b > \frac{\hat{\lambda}_c}{\eta^2}$ as illustrated in Proposition 4. Similarly, for the price maker, following the KKT conditions (11), the bidding decisions $p_b^* = \hat{p},\ b_c^* = 0$ are derived under the condition:

$$\hat{\lambda}_c - \alpha_c < \hat{\lambda}_b + \alpha_b(\bar{P} - 2\hat{p}) < \frac{\hat{\lambda}_c - \alpha_c}{\eta^2},$$

and the resulting clearing prices are:

$$\hat{\lambda}_b' = \hat{\lambda}_b + \alpha_b(\bar{P} - \hat{p}), \quad \hat{\lambda}_c' = \hat{\lambda}_c - \alpha_c\hat{b}.$$

Given $\alpha_b(\bar{P} - \hat{p}) > 0$ and $\alpha_c\hat{b} > 0$, we have $\hat{\lambda}_b' > \frac{\hat{\lambda}_c'}{\eta^2}$. Thus, the price-decision relationship between $(\hat{\lambda}_b', \hat{\lambda}_c')$ and $(p_b^* = \hat{p}, b_c^* = 0)$ violates Proposition 4. The proof for the remaining scenarios showcased in Table III of [15] follow similar arguments.

Therefore, Theorem 1 holds for price makers under the given Assumptions 1–3. Specially, if the unit is held idle, no market power is exercised.

Next, we generalize the conditions following the relaxation of the initial assumptions. Dropping Assumption 1 generates scenarios where energy storage unit output is limited by its energy capacity, potentially leading to the occurrence of additional partial blocks. This modification does not compromise the validity of Theorem 1. Regarding Assumption 2, incorporating scenarios of active operation during zero-profit periods allows for flexible dispatch decisions $p_t^*, b_t^* \in [0, \bar{P}]$, which also does not alter the conclusions drawn in Theorem 1. Assumption 3 is initially established to simplify the analysis of KKT optimality conditions. Negative prices ensure that storage units won't discharge according to (5c), therefore $p_t^* = 0$ for certain intervals. The removal of such assumption does not impact the proof. ■

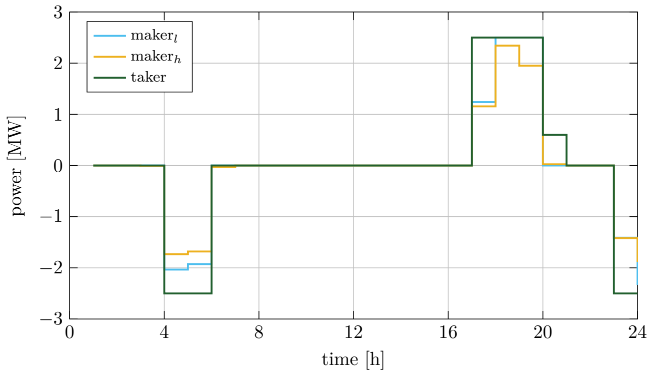
IV. NUMERICAL EXPERIMENTS

We validate the proposed framework for energy storage unit bidding by simulating a 24-interval dispatch in the day-ahead market. Our simulation features a 2.5MW/10MWh storage unit that starts and ends at 50% SoC, with charging and discharging efficiencies set at 0.9. Note that the energy capacity constraint (5e) is taken into account in the simulation. We compare the bidding profiles and resulting profits between price takers and price makers, using price data from a winter day in New York City in 2018, as reported by NYISO [16]. This price series serves as the benchmark for competitive market clearing prices. Nominal clearing prices $\bar{\lambda}_t$ are calculated by assuming that non-withholding power supply from the price taker is contributed to the market, thereby leading to competitive prices. The price sensitivity parameter α_t is modeled to be linearly proportional to the competitive price level, reflecting the load level and the slope of the remaining supply function, with an average value of \$1.00/MWh/MWh for low market power price makers and \$2.00/MWh/MWh for high market power cases. Note that this parameter is amplified for the purposes of validating our framework in the simulation and would be expected to be significantly lower in practical scenarios [12].

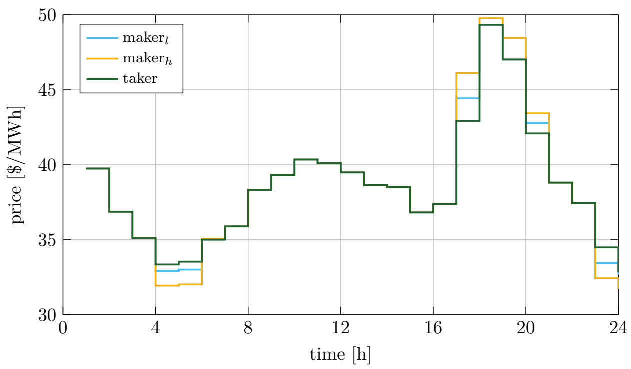
The market clearing results are presented in Fig. 2. Figure 2(a) illustrates the capacity withholding behavior of price makers with both low and high market power in comparison to price takers. Figure 2(b) displays the resulting shifts in market clearing prices from the competitive benchmark, highlighting the exercise of market power.

Figure 2(a) illustrates that, as a price maker, capacity withholding occurs mainly during periods of peak or valley prices to arbitrage price differences. For example, during peak hours, price makers may withhold storage discharging to raise prices, e.g., 5-9pm, as reflected by the corresponding market clearing prices in Fig. 2(b). Conversely, during off-peak hours, they might withhold charging to lower prices. Furthermore, a price maker with a higher degree of market power can exert a more significant influence on the market. This is demonstrated by the more aggressive withholding behavior and the subsequent alterations in clearing prices during both peak and off-peak periods. Notably, even when applying the price maker's bidding model (10), there are instances where the price maker bids similarly to the price taker, leading to identical power outputs and market clearing prices, e.g., 8am-5pm. This indicates that they are not actively exercising market power during these times. For the price taker, there is only one interval of withholding, i.e., 8-9pm, consistent with Theorem 1. This theorem provides a criterion for identifying evident instances of market power exercise. Specially, in some cases, such as from 6-7pm, the power production from the price maker might exceed that of the price taker, which could seem counterintuitive at first glance but could be interpreted as strategic practices aimed at maximizing profit. The profits generated under these scenarios are summarized in Table III.

Table III indicates that the price maker exercises market power to gain additional profit. When possessing a higher level of market power, the price maker's earnings are 76% greater than in scenarios where they act as a price taker (\$49.11 vs \$37.95), and 25% greater with a lower level of



(a) Storage power output



(b) Market clearing price

Fig. 2. Storage unit control policy and the resulting market clearing price considering different market participants as price maker with low market power (maker$_l$), high market power (maker$_h$), and price taker: (a) storage power output (positive values mean that unit is discharging), (b) market clearing price.

TABLE III. PROFIT OF MARKET PARTICIPANTS UNDER DIFFERENT LEVEL OF MARKET POWER

Scenario	Price Taker ($)	Price Maker ($)
No market power	37.95	–
Low market power	47.50	42.02
High market power	66.66	49.11

market power ($42.02 vs $37.95). Interestingly, in markets where a price maker is present, price takers may achieve higher profits than the price maker ($42.02 vs $47.50 and $49.11 vs $66.66), aligning with findings discussed in [17]. This observation highlights the vulnerability of market inefficiencies to strategic exploitation.

V. CONCLUSIONS

We examine the multi-interval strategic bidding withholding of energy storage units adopting a self-scheduling model, considering both price takers and price makers. For price makers, we introduce a bidding strategy that anticipates market prices through a price sensitivity analysis. The proposed framework serves as an *ex-post* market monitoring tool, allowing market operators to distinguish market power exercise from competitive withholding by observing the withholding instances within the bidding profiles and the corresponding clearing prices. Our findings support the economic bidding behaviors commonly seen among storage units and reveal that significant price fluctuations present substantial profit opportunities for both market power holders and strategic profit-seekers. In future work, we aim to enhance our model by incorporating uncertainty in price forecasts into the framework and develop corresponding criteria for market power assessment.

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