Strategic Battery Behaviors and Enhanced Market Designs

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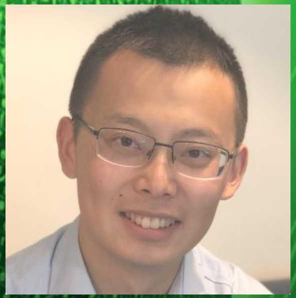
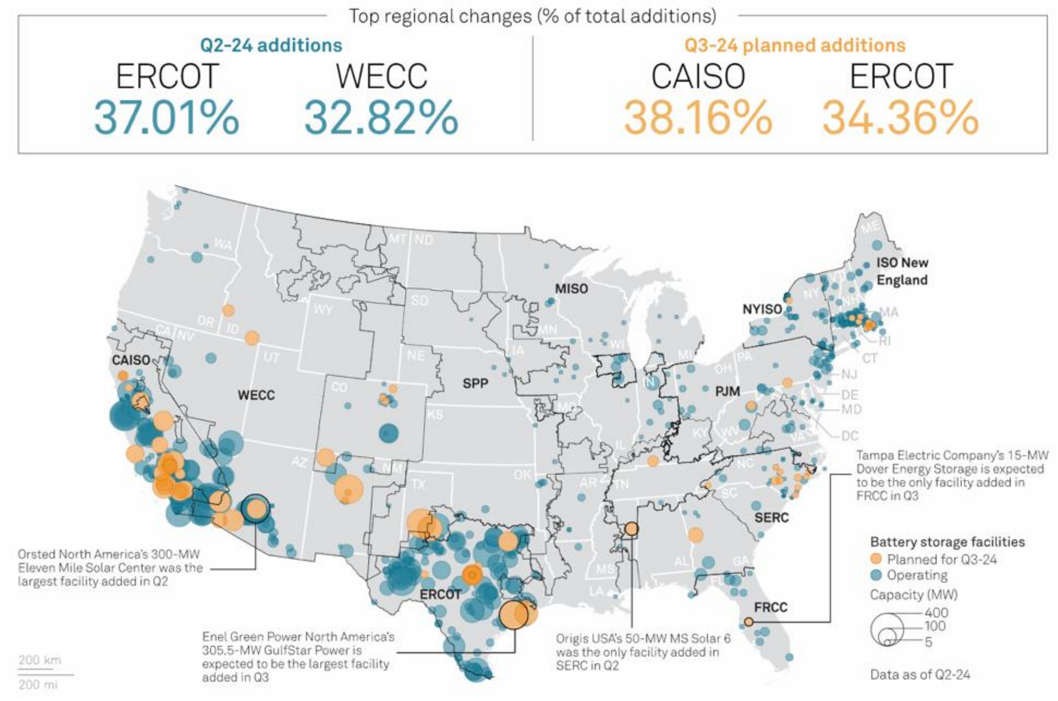
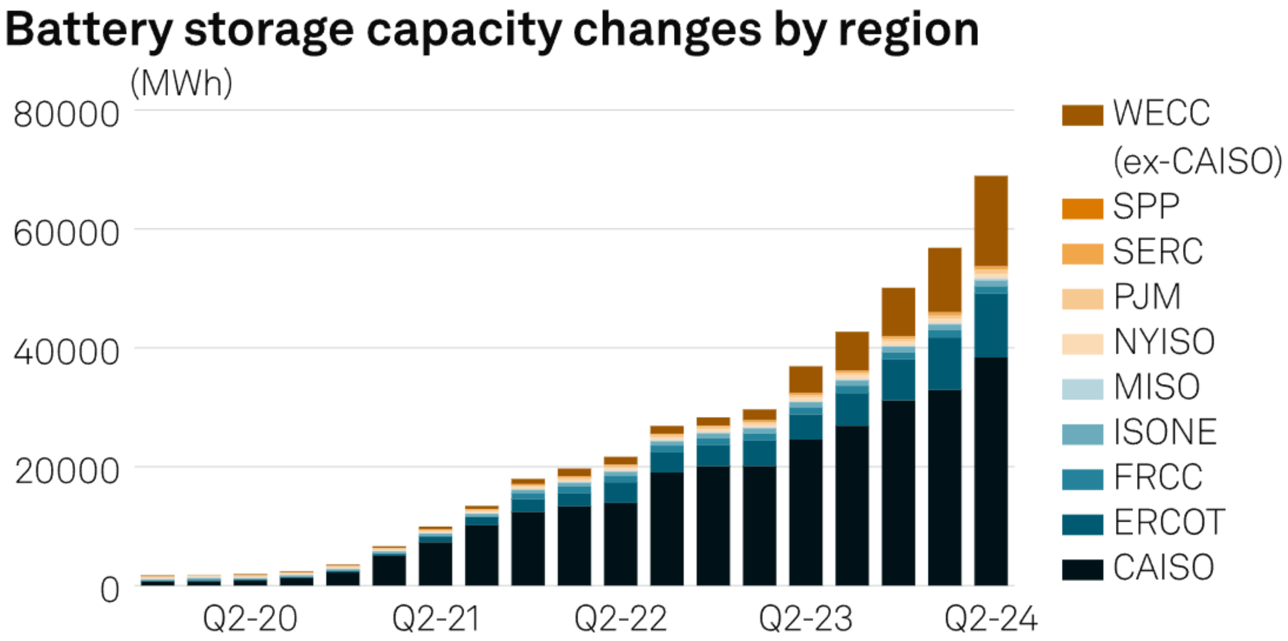


Bolun Xu

Rapid Storage Deployments in the US

- Most energy storages are developed within electricity markets regions.
- Rapid energy storage deployments since 2020, led by CAISO (**15 GW**) and ERCOT (**16 GW**).

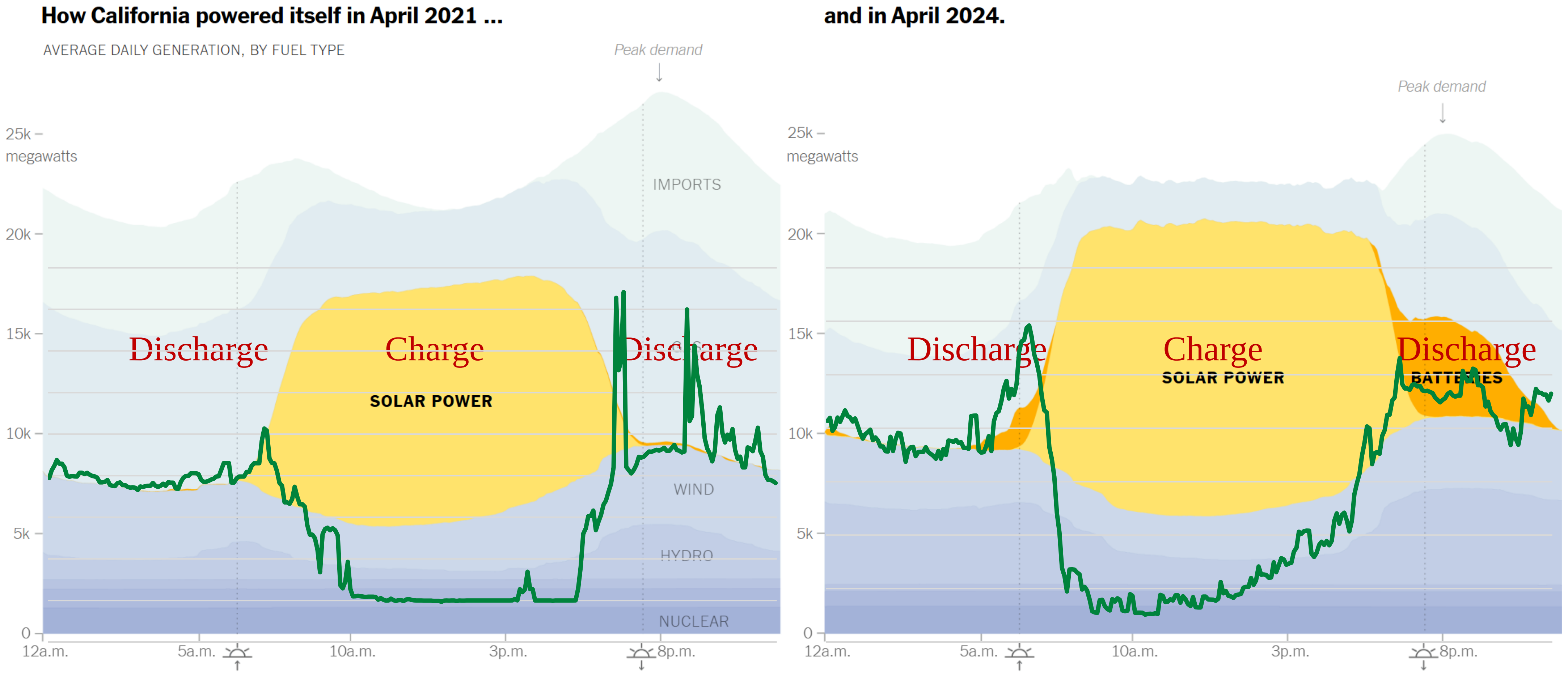




Source: US Government Filings Compiled by S&P Global Commodity Insights

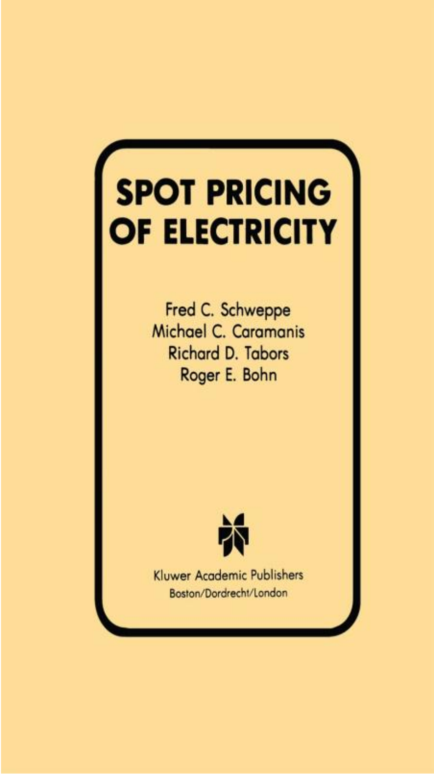
Main Storage Operation: Price Arbitrage

➢ Charge during valley periods (noon), discharge during peak periods (morning & evening).



Source: CAISO & New York Times

Electricity Market 101

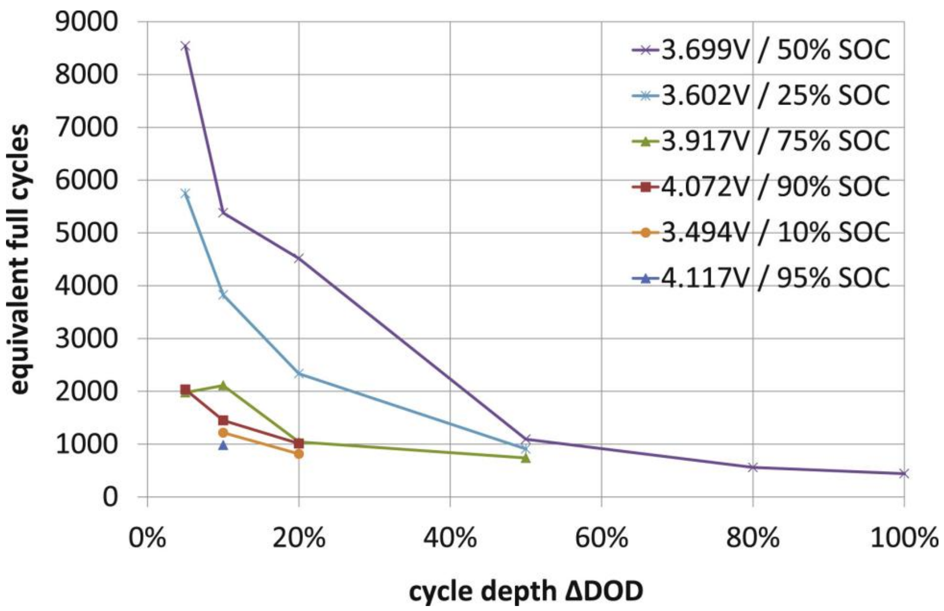


- Market participants submit bids first, then system operator clears the market.
- Bids from participants converge to **true physical marginal costs**.
- Physical capacity withholding is not allowed, **economic capacity withholding** is allowed! (a unit's offer price differ significantly from the truth cost, suggesting market power).
- For thermal generators, **fuel prices** should serve as a **baseline** for bid designs and market power monitoring.
- How about energy storage?

Storage Cost are Complex and Non-Transparent

Physical Cost

- Degradation depends on SoC
- Cannot be immediately measured



Source: Ecker et al. J of Power Sources, 2014

Opportunity Cost

- Decision depends on future prices
- Forecasts are proprietary and uncertain

Source: NYISO Real-Time Price

Real Storage Strategic Bidding Behavior

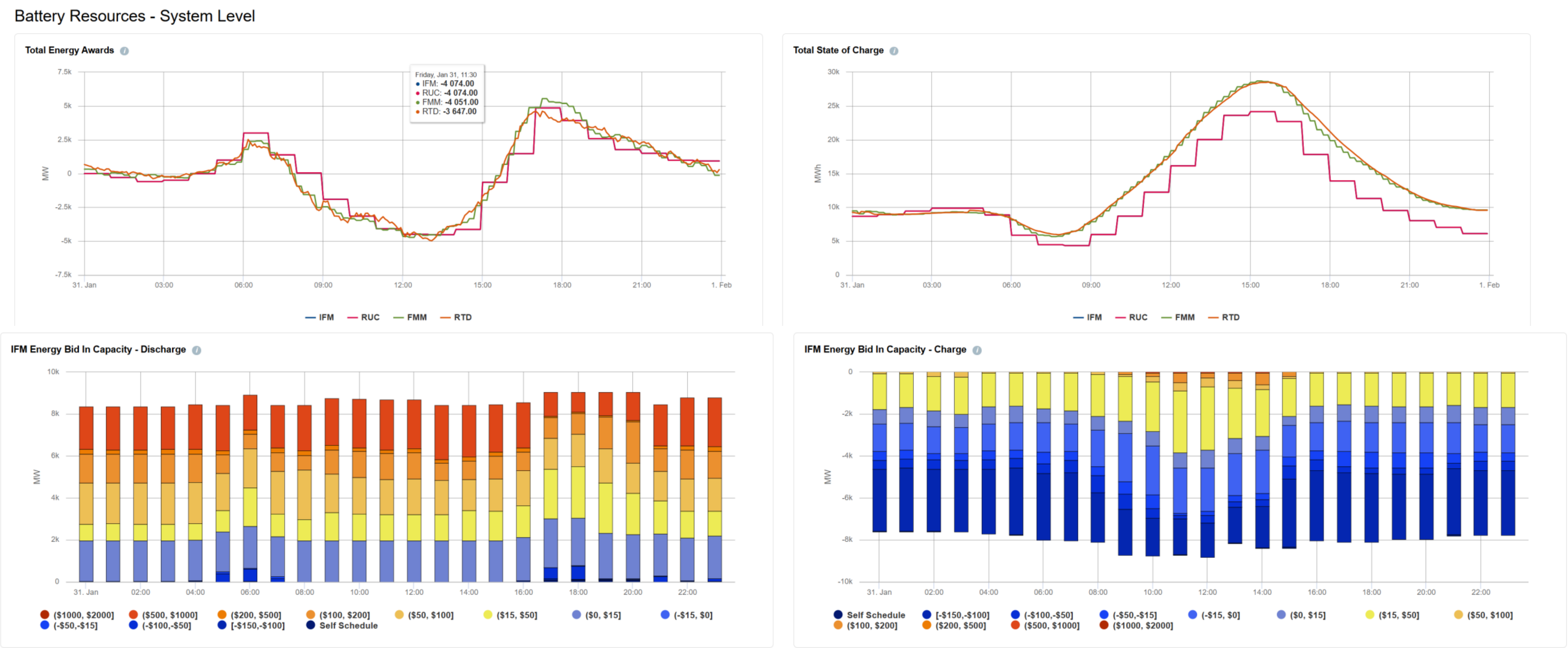
Real Storage Bid Data

California ISO | Daily Energy Storage Report

Friday, January 31, 2025 Storage Hybrid

IFM-Integrated Forward Market **RUC**-Residual Unit Commitment

FFM-Fifteen Minute Market **RTD**-Real-Time Dispatch



[1] Data resource: https://www.caiso.com/library/daily-energy-storage-reports

Methodology for Bid Analysis

- **Weighted Average of Historical Bids**

TABLE I
BID SEGMENT DEFINITIONS

Segment Label	Range ($/MW)	Segment Label	Range ($/MW)
1	[-150, -100]	7	(50, 100]
2	(-100, -50]	8	(100, 200]
3	(-50, -15]	9	(200, 500]
4	(-15, 0]	10	(500, 1000]
5	(0, 15]	11	(1000, 2000]
6	(15, 50]		

$$\overline{v} = \sum_{i=1}^{11} p_i v_i, p_i = \frac{\text{Bid segment quantity in MW}}{\text{Total bid quantity in MW}}$$

➢ Binned into discrete segments for real-time (RTPD) and day-ahead (IFM) markets

➢ Hourly data: July 1, 2023~October 1, 2024

- **Hindsight Optimal Bids**

➢ Dynamic programming—value function $Q_t\,(e_t)$

$$Q_{t-1}(e_{t-1}) = \max \lambda_t(p_t - b_t) - cp_t + Q_t(e_t)$$

➢ Analytically optimal opportunity cost $q_t(e_t)$

$$q_t(e) = \frac{\partial}{\partial e} Q_t(e)$$

Recursively

Update

$$q_{t-1}(e) = \begin{cases} q_t(e+P\eta) & \text{if } \lambda_t \le q_t(e+P\eta)\eta \\ \lambda_t/\eta & \text{if } q_t(e+P\eta)\eta < \lambda_t \le q_t(e)\eta \\ q_t(e) & \text{if } q_t(e)\eta < \lambda_t \le [q_t(e)/\eta + c]^+ \\ (\lambda_t - c)\eta & \text{if } [q_t(e)/\eta + c]^+ < \lambda_t \\ & \quad \le [q_t(e - P/\eta)/\eta + c]^+ \\ q_t(e - P/\eta) & \text{if } \lambda_t > [q_t(e - P/\eta)/\eta + c]^+ \end{cases}$$

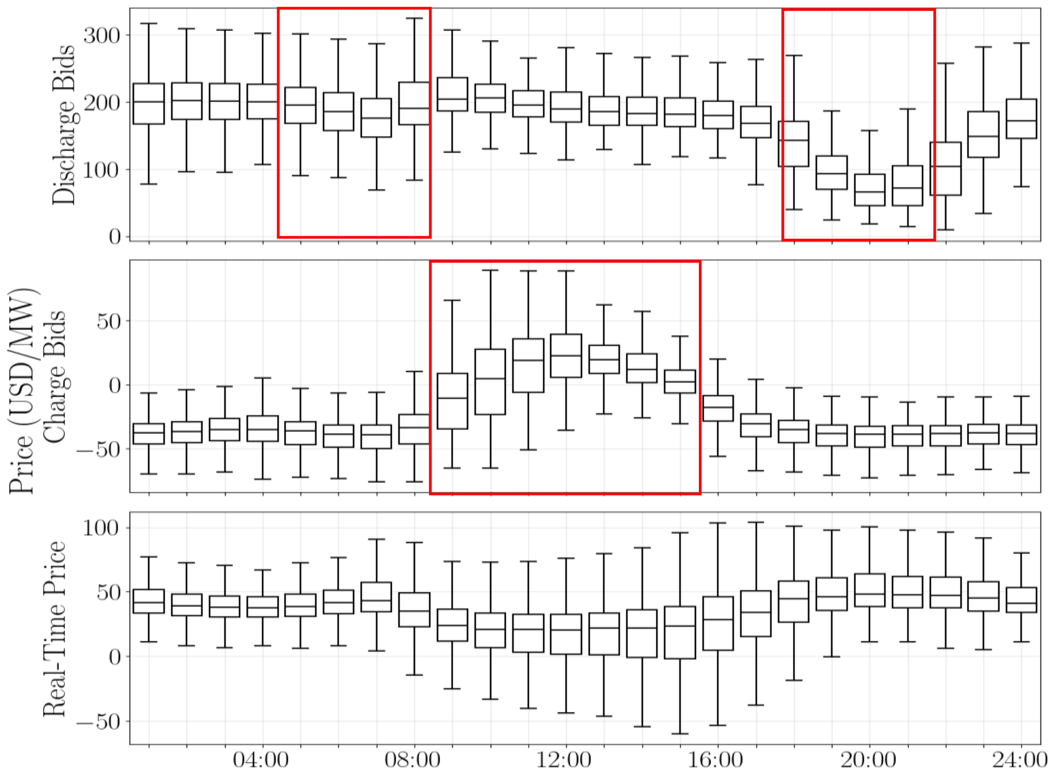
➢ Hindsight optimal bids

Discharge $\partial(cp_t - Q_t(e_t))/\partial p_t = \eta q_t(e_t)/\eta$

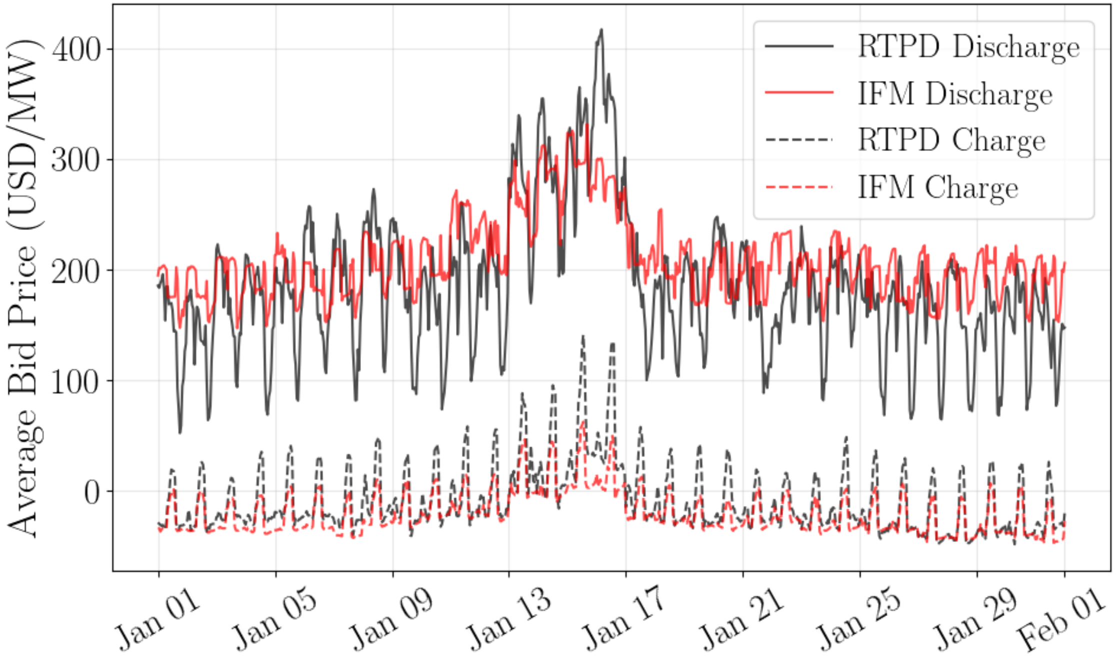
Charge $\partial(cp_t - Q_t(e_t))/\partial b_t = -\eta q_t(e_t)$

Analytical Results—General Trends

- **Strong Temporal Pattern**
  - **Decrease** discharge bids during morning and evening peak, **increase** charge bids at noon
  - Follow the "duck curve" price for arbitrage

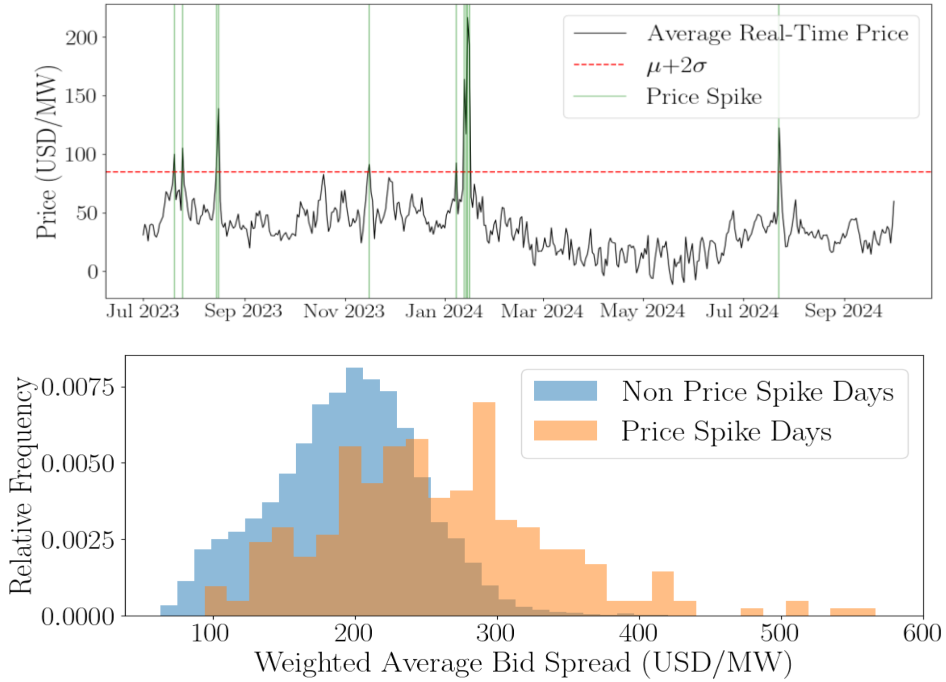


- **Strategic Withholding Behavior**
  - IFM discharge bids generally **greater** than RTPD discharge bids (**79%** of dataset)
  - IFM charge bids generally **lower** than RTPD charge bids (**87%** of dataset)

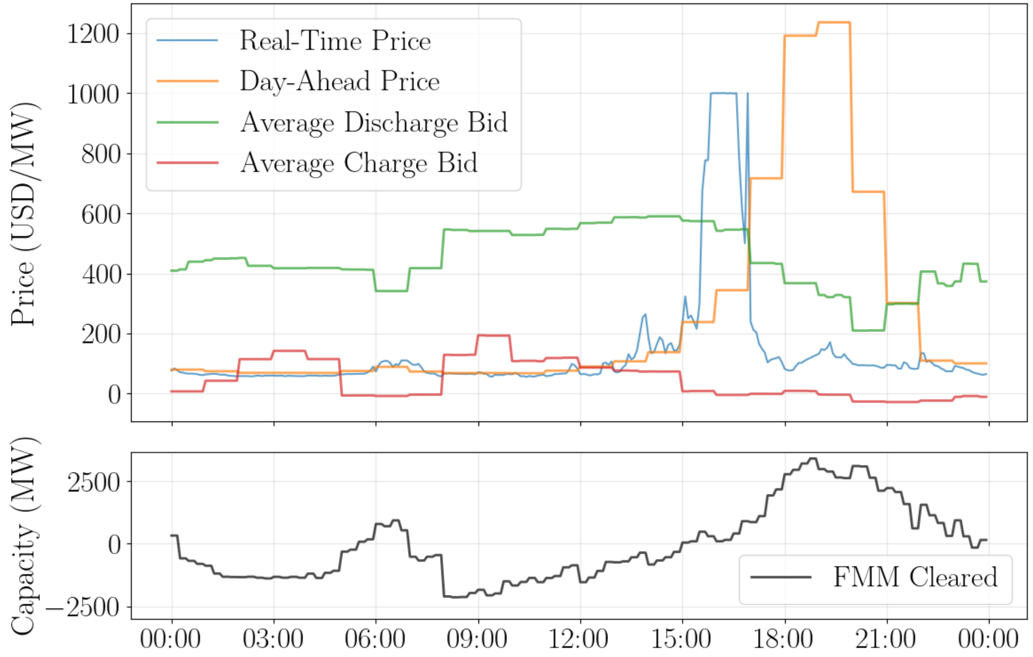


Analytical Results—Special & Extreme Scenario

- **Price Spike**
  - Price spikes identified as days where daily mean price exceeds $\mu+2\sigma$ of price
  - **Extremely high** bids (over $500/MW) during price spikes—**not true cost**



- **Bad Forecast**
  - Bids designed based on DA price (peak at **6-7pm**), differs from RT price (peak at **3-4pm**)
  - High discharge bids cause very little capacity is dispatched (**80%** SoC)—**market inefficiency**

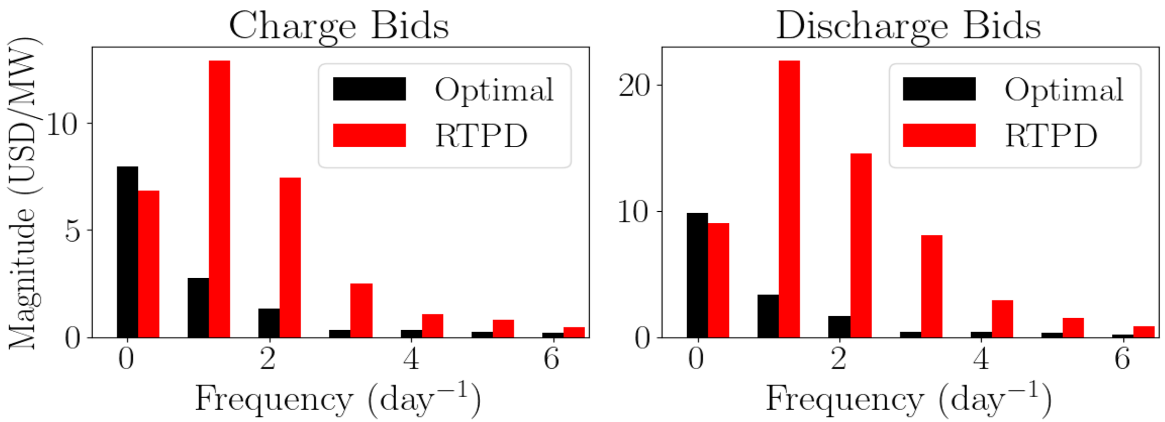


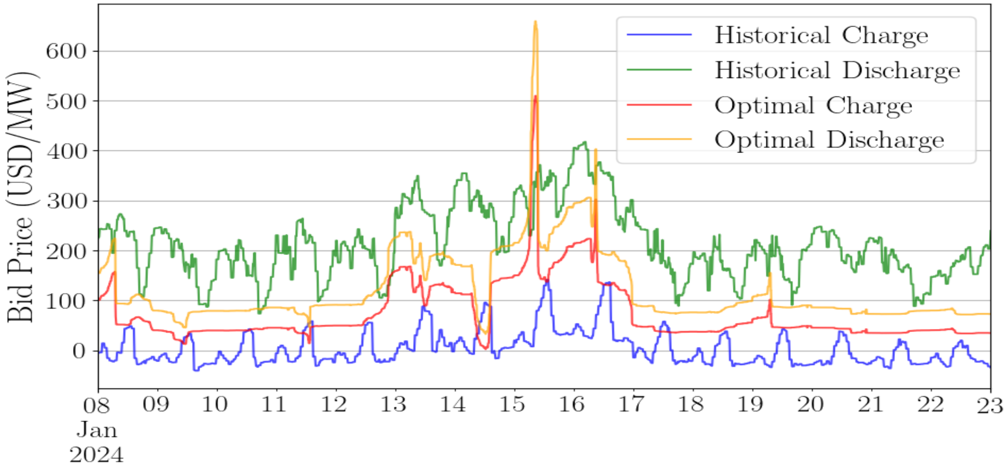
Comparative Analysis

- **Optimality Gap in Bids**

➢ Strong daily frequency of RTPD bids, optimal bids do not show **periodic behavior**

➢ Significant gap—**potential inefficiency and market power in storage operation**





What should system operator do to address this issue?

[2] N. Ma, N. Zheng, N. Qi* et al., "Comparative withholding behavior analysis of historical energy storage bids in California," *2025 IEEE Power& Energy Society General Meeting (PESGM)*. IEEE, 2025, pp. 1–5.

Locational Energy Storage Bid Bounds

Market Efficiency Enhancement

- Enhance market efficiency：(1) default bids design or (2) mitigate market power
- Default bids design: 4th highest DA-LMP with physical cost for 4-hr battery in CAISO [4], excluding future opportunity. Only be enforced when local market power is clearly identified.
- Mitigate market power: difficulty in distinguishing **legitimate** economic withholding from **exercising market power** (excessive economic withholding).
- How to set a **baseline** for identifying storage market power?

[3] CAISO, “Cost recovery and bid mitigation issues,” 2024, [Online]. Available: https://www.caiso.com/documents/presentation-battery-bid-cost-recovery-and-mitigation-data-dmm-sep-11-2024.pdf.

Oracle Dispatch and True Marginal Cost

- Derive true marginal cost of real-time dispatch from **oracle dispatch**.
- Oracle dispatch problem is not achievable due to the **non-anticipatory** netload, thus true storage marginal cost (opportunity cost) is **unknown** before real-time clearing.
- If we can generate the **baseline (cap)** of opportunity cost→**bid bounds**?

$$\min \sum_{t\in\mathcal{T}}[\sum_{i\in\mathcal{G}} C_i(g_{i,t})+\sum_{s\in\mathcal{S}} M_s(p_{s,t}+b_{s,t})]$$ Storage physical cost

$$\sum_{i\in\mathcal{G}} g_{i,t}+\sum_{s\in\mathcal{S}}(p_{s,t}-b_{s,t})=\sum_{n\in\mathcal{N}} d_{n,t}\colon \lambda_t$$ Electricity price

$$|\sum_{n\in\mathcal{N}}\pi_{l-n}(\sum_{i\in\mathcal{N}_n} g_{i,t}+\sum_{s\in\mathcal{N}_n}(p_{s,t}-b_{s,t})-d_{n,t})|\leq \overline{F}_l\colon \underline{\omega}_{l,t},\overline{\omega}_{l,t}$$ Congestion price

$$e_{s,t}-e_{s,t-1}=-p_{s,t}/\eta_s+b_{s,t}\eta_s\colon \theta_{s,t}$$ Storage opportunity cost

Charge marginal cost

$$\theta_{s,t}\eta_s-M_s$$

Discharge marginal cost

$$M_s+\theta_{s,t}/\eta_s$$

Chance-Constrained Dispatch and Bid Bounds

- Chance-constrained dispatch and adjust netload with $(1-\epsilon)$ confidence interval

$$d_{n,t} \Rightarrow d^{\epsilon}_{n,t} = \mu_{n,t} \pm F^{-1}(1-\epsilon)\sigma_{n,t}$$

- Perform chance-constrained dispatch to obtain the **opportunity cost bound** $\theta^{\epsilon}_{t,s}$
- Dynamically cap unnecessary high withholdings and monitor market power

Locational storage bid bounds

The ceiling of the hindsight optimal opportunity cost $\theta_{\tau,s}$ over the period *t* to *T* is bounded by the ceiling of $\theta^{\epsilon}_{t,s}$ over the same period with $(1-\epsilon)$ confidence

$$\mathbb{P}\left(\max_{\tau\in[t,T]}(\theta_{\tau,s}) \leq \max_{\tau\in[t,T]}\left(\theta^{\epsilon}_{\tau,s}\right)\right) \geq 1-\epsilon$$

$$\mathbb{P}(A_{s,t} \leq A^{\epsilon}_{s,t}) \geq 1-\epsilon,\ \mathbb{P}(B_{s,t} \leq B^{\epsilon}_{s,t}) \geq 1-\epsilon$$

Theoretical Analysis on Bid Bounds Dependency

SoC-dependent bid bounds

Given a monotonically increasing and quadratic or super-quadratic generation cost function, bid bounds monotonically decrease with initial SoC

$$\partial A^{\epsilon}_{s,t}/\partial e_{s,t-1} \leq 0,\ \partial B^{\epsilon}_{s,t}/\partial e_{s,t-1} \leq 0$$

Bid bounds scaling with system uncertainty

Given a monotonically increasing and quadratic or super-quadratic generation cost function, bid bounds monotonically increase with system uncertainty

$$\partial A^{\epsilon}_{s,t}/\partial \sigma_{n,t} \geq 0,\ \partial B^{\epsilon}_{s,t}/\partial \sigma_{n,t} \geq 0$$

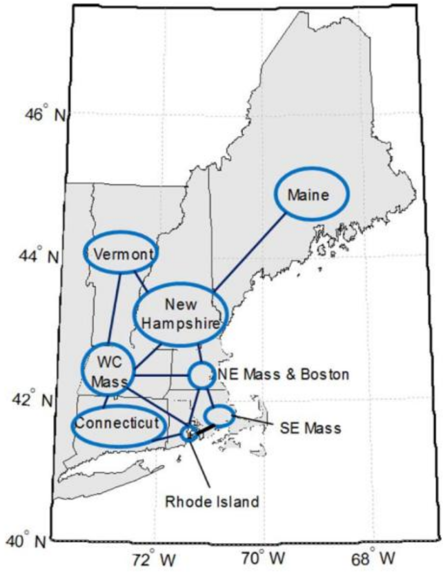
Bid bounds scaling with risk preference

Given a monotonically increasing and quadratic or super-quadratic generation cost function, bid bounds monotonically increase with risk preference

$$\partial A^{\epsilon}_{s,t}/\partial \epsilon \leq 0,\ \partial B^{\epsilon}_{s,t}/\partial \epsilon \leq 0$$

Agent-Based Market Simulation

Test System: ISO-NE 8-Zone Test System[4-5]



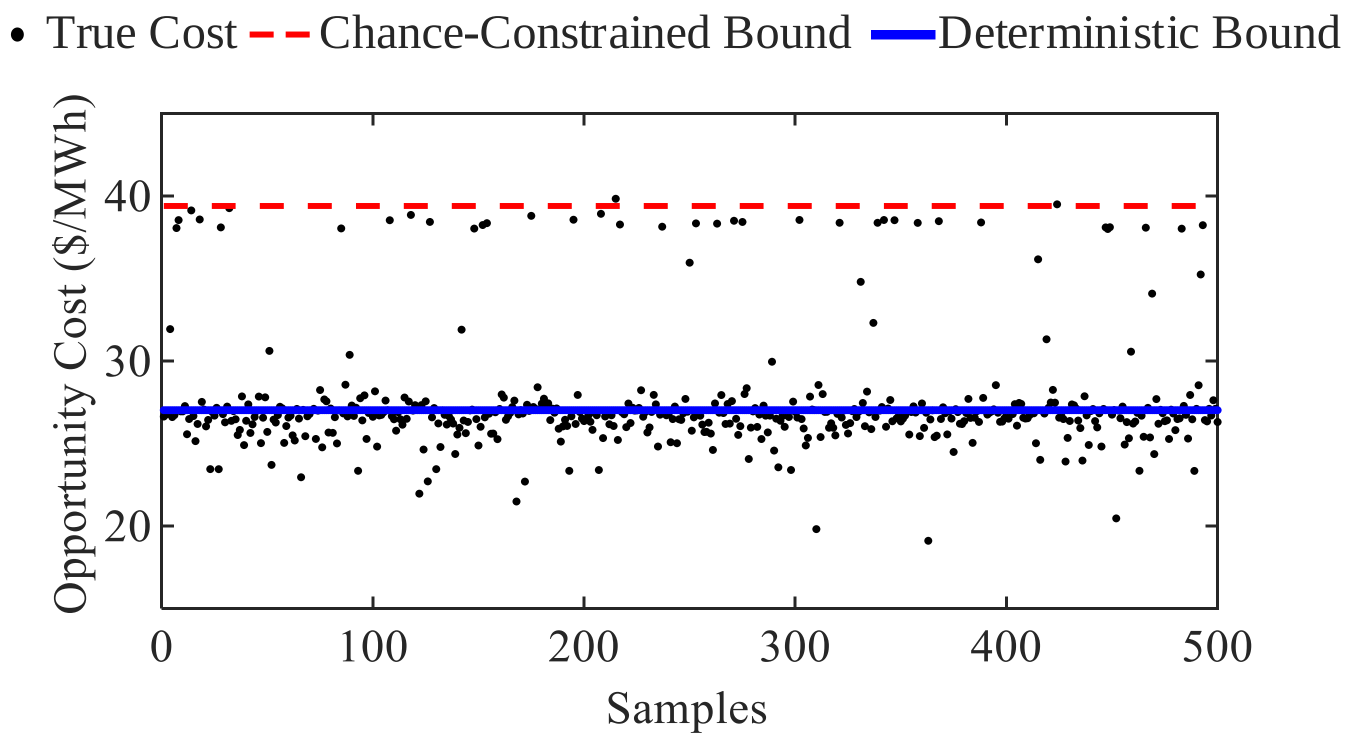
Procedure:

1. Generate 10 DA netload scenarios, each with 100 RT Montle Carlo scenarios
2. Perform DA unit commitment to derive DA price
3. For each DA scenarios, repeat the following steps for 100 RT scenarios

a) Generate **economic withholding bids**[6] with DA price and assumed price σ
b) Generated the proposed bid bounds from chance-constrained framework
c) Sequentially perform RT economic dispatch with economic withholding bids
d) Cap the bids with proposed bid bounds, and run c) again

[4] D. Krishnamurthy, W. Li, and L. Tesfatsion, "An 8-zone test system based on iso new England data: Development and application," *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 234–246, 2015
[5] Code and Data: https://github.com/thuqining/Storage_Pricing_for_Social_Welfare_Maximization
[6] X. Qin, I. Lestas, and B. Xu, "Economic capacity withholding bounds of competitive energy storage bidders," *arXiv preprint* arXiv:2403.05705,2024

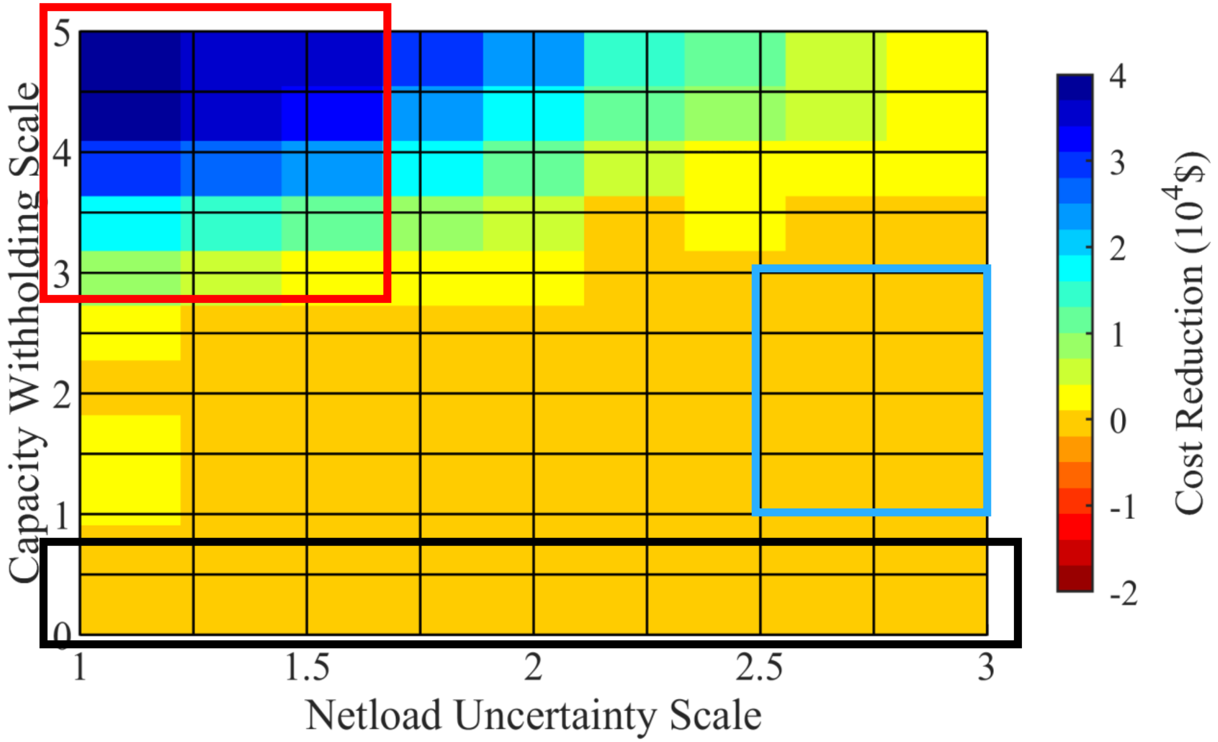
Analysis on Bid Bounds Effectiveness



- ➢ Proposed bid bounds can **reliably** cap true opportunity cost!
- ➢ CAISO deterministic bid bounds are **conservative** and may reduce storage profit.

Analysis on Bid Bounds Effectiveness

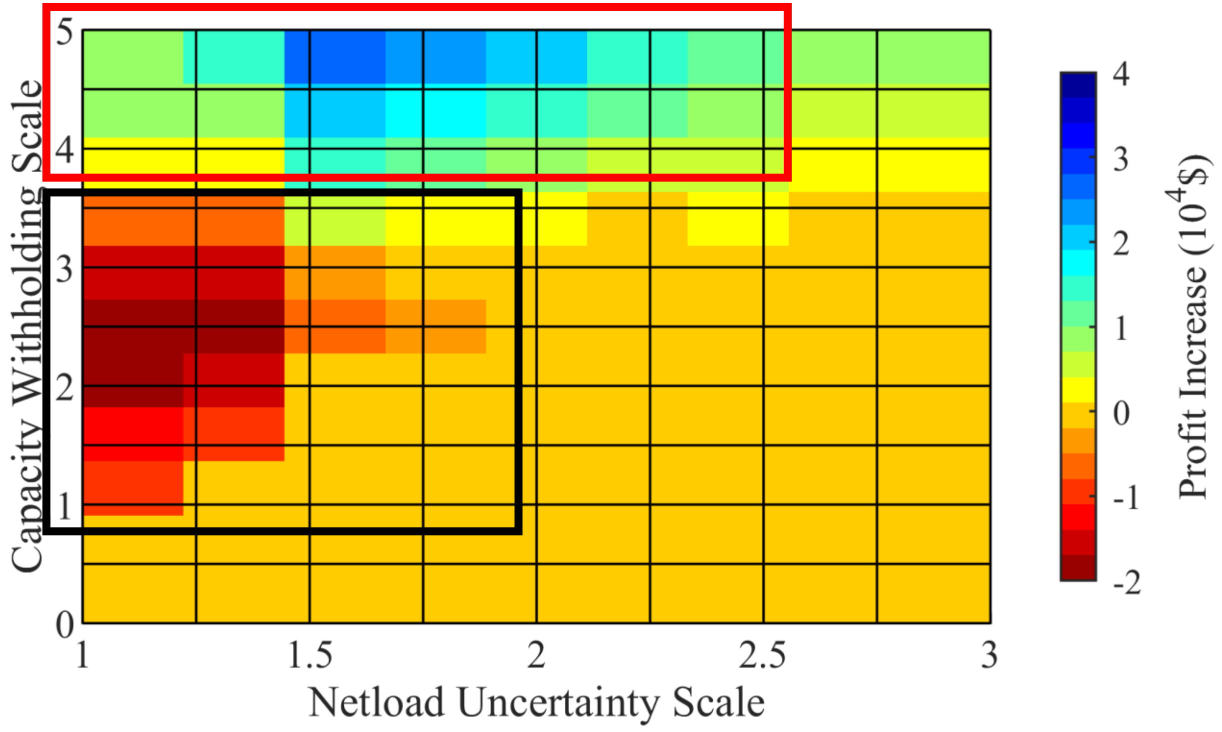
35% storage 30% renewables case



- Bid bounds ensure **reliable cost reductions**
- Bid bounds have the highest effect in **high withholding** and **low uncertainty** cases
- **No effects** on low withholding nor high uncertainty cases, suggest reasonable/ legitimate withholding
- Average system cost reduction: **0.21%**, maximum system cost reduction: **0.50%**

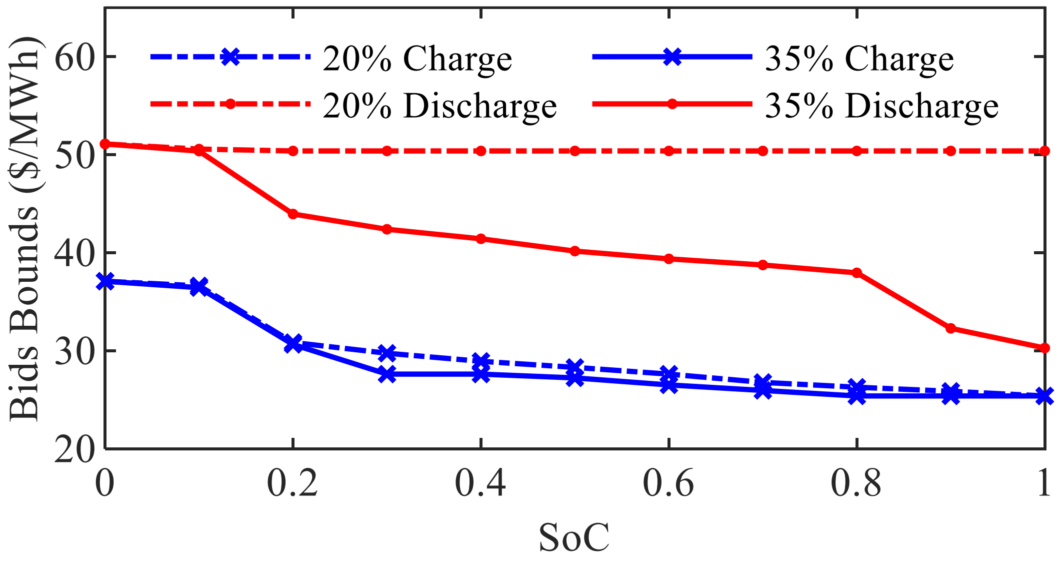
Analysis on Bid Bounds Effectiveness

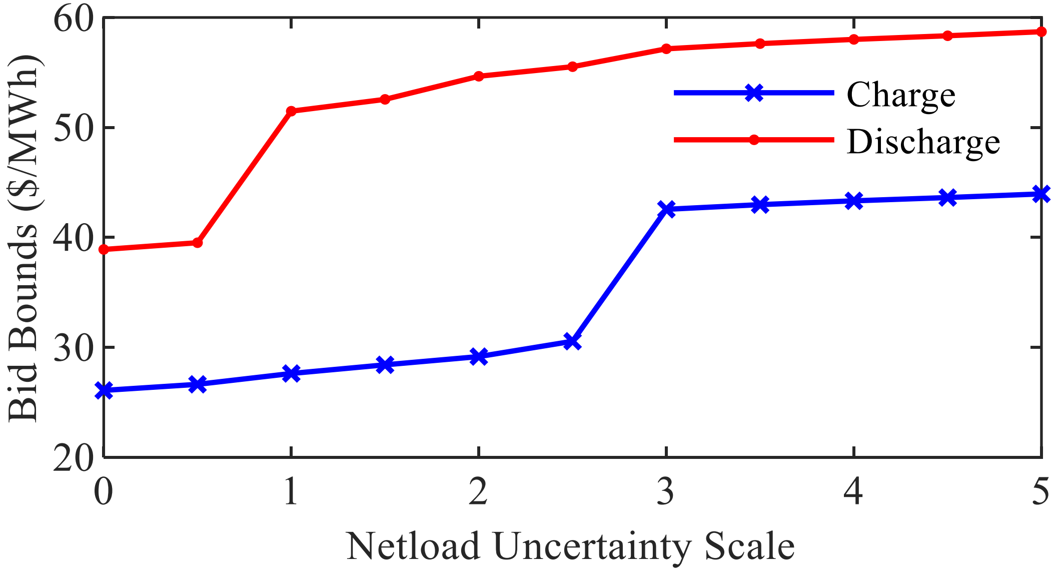
35% storage 30% renewables case



- Mixed effects over storage profits
- **Improve** profits at **high** withholding levels suggesting inefficient bids
- **Reduce** profits at **moderate** withholding and low uncertainty cases suggesting mitigated market power
- Average storage profit increase: **0.19%**, maximum storage profit increase: **19.6%**, maximum storage profit reduction: **11.6%**

Analysis on Bid Bounds Dependency





- Monotonically decrease with SoC
- Higher variation for **higher** storage capacity
- Align with price-taker SoC-dependent bid[6]

- Monotonically increase with **netload uncertainty**
- Align with price-taker withholding bids that increase with **price uncertainty**[7]

[6] X. Qin, I. Lestas, and B. Xu, "Economic capacity withholding bounds of competitive energy storage bidders," arXiv preprint arXiv:2403.05705,2024

[7] N. Zheng, X. Qin, D. Wu et al., "Energy storage state-of-charge market model," *IEEE Trans. on Energy Markets, Policy and Regulation*, vol. 1,no. 1, pp. 11–22, 2023.

Analysis on Bid Bounds Dependency

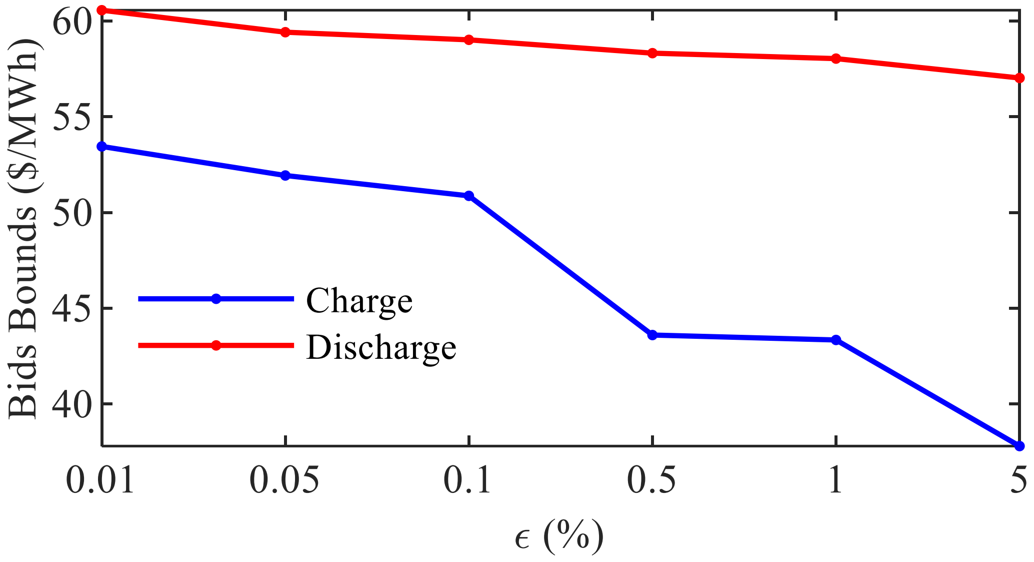


TABLE IV
COMPARISON OF ECONOMIC PERFORMANCE AND IMPROVEMENT UNDER DIFFERENT RISK PREFERENCE

Uncertainty Scale	ϵ (%)	System Cost (10^6\$)	Cost Reduction (%)	Storage Profit (10^5\$)	Profit Increase (%)
1.0	15	7.60	-0.20	1.06	-13.77
	10		-0.19		11.45
	5		-0.19		11.21
	1		-0.17		10.52
3.0	15	7.93	-0.11	0.90	8.96
	10		-0.10		8.92
	5		-0.01		3.09
	1		-0.00		1.99

- Monotonically increase with risk preference
- Large ϵ increase cost reduction effect, but may **compromise** storage profit
- Optimal setting: $\epsilon = 5\% - 10\%$
- CAISO deterministic bid bounds ($\epsilon = 50\%$): cost reduction 0.18%, profit reduction **20.5%**

Sensitivity Analysis—RES & ES Capacity

- **Better** social welfare improvement: **higher** storage capacity and economic withholding!

TABLE II
IMPACT OF STORAGE AND RENEWABLE CAPACITY ON ECONOMIC PERFORMANCE AND IMPROVEMENT UNDER LOW AND HIGH UNCERTAINTY

Renewable	Storage	Low Uncertainty				High Uncertainty			
		System Cost (10^6\$(%))		Storage Profit (10^5\$(%))		System Cost (10^6\$(%))		Storage Profit (10^5\$(%))	
		AEW	MEW	AEW	MEW	AEW	MEW	AEW	MEW
30%	20%	7.63(-0.17)	7.65(-0.23)	1.04(10.16)	0.92(14.48)	7.80(-0.06)	7.81(-0.09)	0.94(4.96)	0.92(7.72)
	35%	7.57(-0.21)	7.60(-0.48)	1.48(0.19)	1.29(12.24)	7.74(-0.09)	7.78(-0.18)	1.40(4.77)	1.37(10.69)
	50%	7.48(-0.20)	7.52(-0.40)	2.03(0.90)	1.90(6.83)	7.64(-0.07)	7.68(-0.12)	2.00(1.47)	2.00(3.89)
50%	20%	7.50(-0.11)	7.52(-0.18)	0.91(6.63)	0.78(11.68)	7.72(-0.02)	7.72(-0.04)	0.85(1.31)	0.83(2.71)
	35%	7.42(-0.10)	7.45(-0.23)	1.44(-1.10)	1.30(2.21)	7.63(-0.03)	7.66(-0.06)	1.40(1.13)	1.38(2.46)
	50%	7.37(-0.08)	7.40(-0.26)	1.77(-1.51)	1.69(2.44)	7.57(-0.05)	7.59(-0.07)	1.80(0.62)	1.85(1.89)

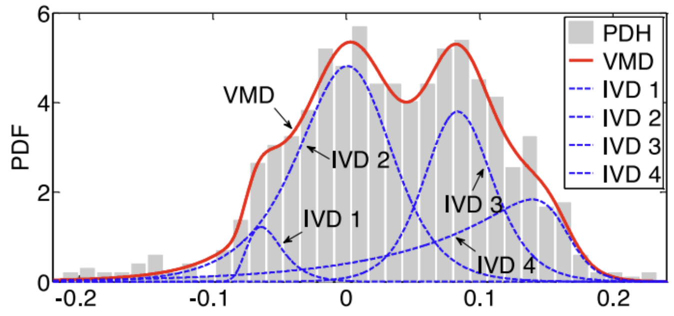
AEW: average economic withholding   **MEW: maximum economic withholding**

Sensitivity Analysis—Uncertainty Model

- Better performance with **empirical quantile** and **versatile distribution**[8]
- Worst performance with robust approximation!
- **Gaussian distribution** is not always appropriate for modeling uncertainty

TABLE III
COMPARISON OF ECONOMIC PERFORMANCE AND IMPROVEMENT UNDER DIFFERENT UNCERTAINTY MODELS

Uncertainty Scale	Model	System Cost (10^6\$)	Cost Reduction (%)	Storage Profit (10^5\$)	Profit Increase (%)
1.0	Empirical	7.60	-0.14	1.06	8.96
	Versatile		-0.15		9.71
	Gaussian		-0.19		11.21
	Robust		-0.16		10.41
3.0	Empirical	7.93	0.05	0.90	5.24
	Versatile		-0.04		4.52
	Gaussian		-0.01		3.09
	Robust		-0.00		1.75



Versatile distribution: capture skewness and multi-modal

[8] Z.-S. Zhang, Y.-Z. Sun, D. W. Gao et al., "A versatile probability distribution model for wind power forecast errors and its applicationin economic dispatch," *IEEE Transactions on Power Systems*, vol. 28,no. 3, pp. 3114–3125, 2013.

Sensitivity Analysis—Computational Efficiency

- **Over 5 minutes** for over 1000 storage units without relaxation (nonconvex with binaries)
- **Less than 2 minutes** with relaxation (linear model[9]) even for 10000 storage units

TABLE V
COMPARISON OF COMPUTATIONAL PERFORMANCE UNDER DIFFERENT STORAGE NUMBER AND RELAXATION CONDITION

Storage Number	CPU Time		Storage Number	CPU Time	
	Without Relaxation	With Relaxation		Without Relaxation	With Relaxation
5	0.58 s	0.19 s	500	3.36 s	0.89 s
10	0.96 s	0.22 s	1000	317.99 s	2.04 s
50	1.86 s	0.24 s	5000	>1h	39.92 s
100	3.26 s	0.30 s	10000	>1h	102.51 s

[9] N. Nazir and M. Almassalkhi, “Guaranteeing a physically realizable battery dispatch without charge-discharge complementarity constraints,” *IEEE Transactions on Smart Grid*, vol. 14, no. 3, pp. 2473–2476, 2021.

Conclusion and Future Work

- Storage strategic bidding can compromise market efficiency and social welfare.
- Bid bounds can reliably improve market efficiency and regulate storage market power.
- Bid bounds are unit-location specific and tuned with risk preference and uncertainty model.
- Bids bounds has strong dependency with SoC, system uncertainty and risk preference.
- Understand storage participants have valid causes for conducting economic withholding.
- Enable system operators to remain neutral, fostering competition among strategic storage participants, while capping offers to prevent excessive withholding.
- ISO can develop bid bounds based on other risk-aware approach, e.g., CVaR, DRO.

- For long-duration energy storage, the formulation should incorporate a longer horizon and seasonal uncertainty patterns[11].

[10] N. Qi and B. Xu*, "Locational Energy Storage Bid Bounds for Facilitating Social Welfare Convergence," *IEEE Transactions on Energy Markets, Policy and Regulation*, doi: 10.1109/TEMPR.2025.3579671.
[11] N. Qi*, K. Huang, Z. Fan et al., "Long-term energy management for microgrid with hybrid hydrogen-battery energy storage: A prediction-free coordinated optimization framework," *Applied Energy*, vol. 377, p.124485, 2025.

Reference

[1] Data resource: https://www.caiso.com/library/daily-energy-storage-reports
[2] N. Ma, N. Zheng, N. Qi* et al., “Comparative withholding behavior analysis of historical energy storage bids in California,” *2025 IEEE PESGM*.
[3] CAISO, “Cost recovery and bid mitigation issues,” 2024, [Online]. Available: https://www.caiso.com/documents/presentation-battery-bid-cost-recovery-and-mitigation-data-dmm-sep-11-2024.pdf.
[4] D. Krishnamurthy, W. Li, and L. Tesfatsion, “An 8-zone test system based on iso new England data: Development and application,” *IEEE TPWRS*, vol. 31, no. 1, pp. 234–246, 2015
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[8] Z.-S. Zhang, Y.-Z. Sun, D. W. Gao et al., “A versatile probability distribution model for wind power forecast errors and its application in economic dispatch,” *IEEE TPWRS*, vol. 28,no. 3, pp. 3114–3125, 2013.
[9] N. Nazir and M. Almassalkhi, “Guaranteeing a physically realizable battery dispatch without charge-discharge complementarity constraints,” *IEEE TSG*, vol. 14, no. 3, pp. 2473–2476, 2021.
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[11] N. Qi*, K. Huang, Z. Fan et al., “Long-term energy management for microgrid with hybrid hydrogen-battery energy storage: A prediction-free coordinated optimization framework,” *Applied Energy*, vol. 377, p.124485, 2025.

Thank you! Questions? Comments?

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https://bolunxu.github.io/

Comparative Withholding Behavior Analysis of Historical Energy Storage Bids in California

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***Abstract*—The rapid growth of battery energy storage in wholesale electricity markets calls for a deeper understanding of storage operators' bidding strategies and their market impacts. This study examines energy storage bidding data from the California Independent System Operator (CAISO) between July 1, 2023, and October 1, 2024, with a primary focus on economic withholding strategies. Our analysis reveals that storage bids are closely aligned with day-ahead and real-time market clearing prices, with notable bid inflation during price spikes. Statistical tests demonstrate a strong correlation between price spikes and capacity withholding, indicating that operators can anticipate price surges and use market volatility to increase profitability. Comparisons with optimal hindsight bids further reveal a clear daily periodic bidding pattern, highlighting extensive economic withholding. These results underscore potential market inefficiencies and highlight the need for refined regulatory measures to address economic withholding as storage capacity in the market continues to grow.**

***Index Terms*—Energy storage, power system economics, bidding, market power**

I. Introduction

CAISO, BESS operators are required to bid their full capacity, precluding physical withholding but allowing for economic withholding—bids crafted not on operational costs but on anticipated market opportunities.

While economic withholding by storage systems is legitimate within regulatory frameworks, it does not eliminate the risk of inefficiencies and potential market power abuse. Some BESS units may lack advanced forecasting tools or sophisticated bidding software, relying instead on ad hoc strategies. Meanwhile, others may exercise market power similarly to conventional generators, potentially inflating prices, making it challenging to differentiate between various bidding motivations. Although emerging research examines the strategic bidding and potential market power of storage systems [6]–[11], little has been done to analyze the actual bidding behavior of current market-participating energy storage systems.

In this study, we collect public BESS bid data from CAISO and analyze bidding patterns with the following key findings:

Locational Energy Storage Bid Bounds for Facilitating Social Welfare Convergence

Ning Qi, *Member, IEEE*, Bolun Xu, *Member, IEEE*

***Abstract*—This paper proposes a novel method to generate bid bounds that can serve as offer caps for energy storage in electricity markets to help reduce system costs and regulate potential market power exercises. We derive the bid bounds based on a tractable multi-period economic dispatch chance-constrained formulation that systematically incorporates the uncertainty and risk preference of the system operator. The key analytical results verify that the bounds effectively cap storage bids across all uncertainty scenarios with a guaranteed confidence level. We show that bid bounds decrease as the state of charge increases but rise with greater netload uncertainty and risk preference. We test the effectiveness of the proposed pricing mechanism based on the 8-bus ISO-NE test system, including agent-based storage bidding models. Simulation results demonstrate that the proposed bid bounds effectively align storage bids with the social welfare objective and outperform existing deterministic bid bounds. Under 30% renewable capacity and 20% storage capacity, the bid bounds contribute to an average reduction of 0.17% in system cost, while increasing storage profit by an average of 10.16% across various system uncertainty scenarios and bidding strategies. These benefits scale up with increased storage economic withholding and storage capacity.**

***Index Terms*—Energy storage, locational bid bounds, chance-constrained optimization, market power, market design**

I. Introduction

The challenge of monitoring energy storage market offers lies in calculating future opportunities caused by limited energy capacity [8]. In day-ahead markets, storage may choose to withhold capacity to arbitrage in the more volatile real-time markets [9], while in real-time markets, storage may withhold capacity in anticipation of future price spikes [10], [11]. Consequently, inaccurate prediction of future uncertainty may lead to excessively high or low bids, resulting in market inefficiency, This has also been evidenced by storage practices observed in CAISO [7]. On the other hand, storage can exercise market power by conducting economic withholding, but identifying these intentions is extremely difficult due to the inability to distinguish from economic withholding for capturing legitimate future opportunities [6]. Hence, it is essential for system operators to develop innovative regulatory approaches to mitigate storage market power and facilitate storage bidding consistent with social welfare convergence.

This paper proposes a novel approach to imposing bid bounds on storage offers, providing system operators with a preventive measure to regulate market power and enhance market efficiency. The bounds dynamically depend on future system conditions, uncertainties, risk preference, and storage physical characteristics. Our contributions are as follows:

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Long-term energy management for microgrid with hybrid hydrogen-battery energy storage: A prediction-free coordinated optimization framework

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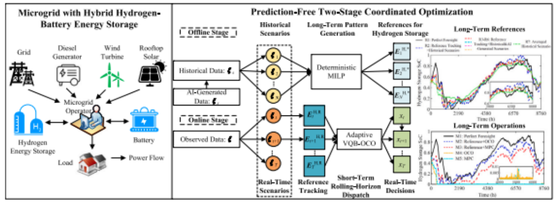
GRAPHICAL ABSTRACT



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ABSTRACT

This paper studies the long-term energy management of a microgrid coordinating hybrid hydrogen-battery energy storage. We develop an approximate semi-empirical hydrogen storage model to accurately capture the power-dependent efficiency of hydrogen storage. We introduce a prediction-free two-stage coordinated optimization framework, which generates the annual state-of-charge (SoC) reference for hydrogen storage offline. During online operation, it updates the SoC reference online using kernel regression and makes operation decisions based on the proposed adaptive virtual-queue-based online convex optimization (OCO) algorithm. We innovatively incorporate penalty terms for long-term pattern tracking and expert-tracking for step size updates. We provide theoretical proof to show that the proposed OCO algorithm achieves a sublinear bound of dynamic regret without using prediction information. Numerical studies based on the Elia and North China datasets show that the proposed framework significantly outperforms existing online optimization approaches, reducing operational costs and loss of load by approximately 60% and 90%, respectively, compared to the model predictive control method. Additionally, the introduction of long-term reference tracking contributes to over 50% of this reduction. These benefits can be further enhanced with optimized settings for the penalty coefficient and step size of OCO, as well as more historical references.

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Formulation of Oracle Economic Dispatch

- Oracle economic dispatch

$$\min \sum_{t\in\mathcal{T}}\Big[\sum_{i\in\mathcal{G}} C_i(g_{i,t}) + \sum_{s\in\mathcal{S}} M_s(p_{s,t}+b_{s,t})\Big] \quad (1a)$$

s.t. $\forall i\in\mathcal{G}, \forall s\in\mathcal{S}, \forall l\in\mathcal{L}, \forall t\in\mathcal{T}$

$$\sum_{i\in\mathcal{G}} g_{i,t} + \sum_{s\in\mathcal{S}} (p_{s,t}-b_{s,t}) = \sum_{n\in\mathcal{N}} d_{n,t}:\ \lambda_t \quad (1b)$$

$$\Big|\sum_{n\in\mathcal{N}} \Phi_{l-n}\Big(\sum_{i\in\mathcal{N}_n} g_{i,t} + \sum_{s\in\mathcal{N}_n} (p_{s,t}-b_{s,t}) - d_{n,t}\Big)\Big| \le \overline{F}_l:\ \underline{\omega}_{l,t}, \overline{\omega}_{l,t} \quad (1c)$$

$$\underline{G}_i \le g_{i,t} \le \overline{G}_i - r_{i,t} \quad (1d)$$

$$\sum_{i\in\mathcal{G}} r_{i,t} \ge \rho \sum_{n\in\mathcal{N}} d_{n,t} \quad (1e)$$

$$-RD_i \le g_{i,t} - g_{i,t-1} \le RU_i \quad (1f)$$

$$0 \le b_{s,t} \le \overline{P}_s \quad (1g)$$

$$0 \le p_{s,t} \le \overline{P}_s \quad (1h)$$

$$b_{s,t} \perp p_{s,t} \quad (1i)$$

$$\underline{E}_s \le e_{s,t} \le \overline{E}_s \quad (1j)$$

$$e_{s,t} - e_{s,t-1} = -p_{s,t}/\eta_s + b_{s,t}\eta_s:\ \theta_{s,t} \quad (1k)$$

- Single-period economic dispatch

$$\min \sum_{i\in\mathcal{G}} C_i(g_{i,t}) + \sum_{s\in\mathcal{S}} (A_{s,t}p_{s,t} - B_{s,t}b_{s,t}) \quad (2a)$$

s.t. (1b)–(1f)

$$0 \le b_{s,t} \le \min\{\overline{P}_s, (\overline{E}_s - e_{s,t-1})/\eta_s\} \quad (2b)$$

$$0 \le p_{s,t} \le \min\{\overline{P}_s, (e_{s,t-1} - \underline{E}_s)\eta_s\} \quad (2c)$$

Lagrangian relaxation

$$A_{s,t} = \partial(M_s p_{s,t} + \theta_{s,t}p_{s,t}/\eta_s)/\partial p_{s,t} = M_s + \theta_{s,t}/\eta_s \quad (3a)$$

$$B_{s,t} = -\partial(M_s b_{s,t} - \theta_{s,t}b_{s,t}\eta_s)/\partial b_{s,t} = \theta_{s,t}\eta_s - M_s \quad (3b)$$

$A_{s,t}$, $B_{s,t}$: True marginal costs of discharge and charge

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Chance-Constrained Economic Dispatch

- Chance-constrained economic dispatch

$$\min \sum_{t\in\mathcal{T}}[\sum_{i\in\mathcal{G}} C_i(g_{i,t})+\sum_{s\in\mathcal{S}} M_s(p_{s,t}+b_{s,t})] \quad (4a)$$

$$\text{s.t. } \forall i\in\mathcal{G},\ \forall s\in\mathcal{S},\ \forall l\in\mathcal{L},\ \forall t\in\mathcal{T}$$

$$\mathbb{P}(\sum_{i\in\mathcal{G}} g_{i,t}+\sum_{s\in\mathcal{S}}(p_{s,t}-b_{s,t})\geq\sum_{n\in\mathcal{N}} d_{n,t})\geq 1-\epsilon:\ \hat{\lambda}_{s,t} \quad (4b)$$

$$\mathbb{P}(|\sum_{n\in\mathcal{N}}\Phi_{l-n}(\sum_{i\in\mathcal{N}_n} g_{i,t}+\sum_{s\in\mathcal{N}_n}(p_{s,t}-b_{s,t})-d_{n,t})|\leq\overline{F}_l)$$

$$\geq 1-\epsilon:\ \underline{\hat{\omega}}_{l,t},\hat{\overline{\omega}}_{l,t} \quad (4c)$$

$$\underline{G}_i\leq g_{i,t}\leq\overline{G}_i-r_{i,t}:\ \underline{\hat{\nu}}_{i,t},\hat{\overline{\nu}}_{i,t} \quad (4d)$$

$$\mathbb{P}(\sum_{i\in\mathcal{G}} r_{i,t}\geq\rho\sum_{n\in\mathcal{N}} d_{n,t})\geq 1-\epsilon \quad (4e)$$

$$-RD_i\leq g_{i,t}-g_{i,t-1}\leq RU_i:\ \underline{\hat{\kappa}}_{i,t},\hat{\overline{\kappa}}_{i,t} \quad (4f)$$

$$0\leq b_{s,t}\leq\overline{P}_s:\ \underline{\hat{\alpha}}_{s,t},\hat{\overline{\alpha}}_{s,t} \quad (4g)$$

$$0\leq p_{s,t}\leq\overline{P}_s:\ \underline{\hat{\beta}}_{s,t},\hat{\overline{\beta}}_{s,t} \quad (4h)$$

$$b_{s,t}\perp p_{s,t} \quad (4i)$$

$$\underline{E}_s\leq e_{s,t}\leq\overline{E}_s:\ \underline{\hat{\iota}}_{s,t},\hat{\overline{\iota}}_{s,t} \quad (4j)$$

$$e_{s,t}-e_{s,t-1}=-p_{s,t}/\eta_s+b_{s,t}\eta_s:\ \hat{\theta}_{s,t} \quad (4k)$$

- Deterministic reformulation

$$\sum_{i\in\mathcal{G}} g_{i,t}+\sum_{s\in\mathcal{S}}(p_{s,t}-b_{s,t})\geq\sum_{n\in\mathcal{N}}(\mu_{n,t}+F^{-1}(1-\epsilon)\sigma_{n,t}) \quad (5a)$$

$$\sum_{n\in\mathcal{N}}\Phi_{l-n}(\sum_{i\in\mathcal{N}_n} g_{i,t}+\sum_{s\in\mathcal{N}_n}(p_{s,t}-b_{s,t})-\mu_{n,t}- \quad (5b)$$

$$F^{-1}(1-\epsilon)\sigma_{n,t}\geq-\overline{F}_l,\ \sum_{n\in\mathcal{N}}\Phi_{l-n}(\sum_{i\in\mathcal{N}_n} g_{i,t}+\sum_{s\in\mathcal{N}_n}(p_{s,t}-b_{s,t})$$

$$-\mu_{n,t}+F^{-1}(1-\epsilon)\sigma_{n,t})\leq\overline{F}_l$$

$$\sum_{i\in\mathcal{G}} r_{i,t}\geq\rho\sum_{n\in\mathcal{N}}(\mu_{n,t}+F^{-1}(1-\epsilon)\sigma_{n,t}) \quad (5c)$$

- ✓ Normal distribution $F^{-1}(1-\epsilon)=\Phi^{-1}(1-\epsilon)$
- ✓ Versatile distribution $F^{-1}(1-\epsilon\,|\,a,b,c)=c-\ln\big((1-\epsilon)^{-1/b}-1\big)/a$
- ✓ Robust approximation

Type & Shape	$F^{-1}(1-\epsilon)$	ϵ
No Assumption (NA)	$\sqrt{(1-\epsilon)/\epsilon}$	$0<\epsilon\leq 1$
Symmetric Distribution (S)	$\sqrt{1/2\epsilon}$	$0<\epsilon\leq 1/2$
	0	$1/2<\epsilon\leq 1$
Unimodal Distribution (U)	$\sqrt{(4-9\epsilon)/9\epsilon}$	$0<\epsilon\leq 1/6$
	$\sqrt{(3-3\epsilon)/(1+3\epsilon)}$	$1/6<\epsilon\leq 1$
Symmetric & Unimodal Distribution (SU)	$\sqrt{2/9\epsilon}$	$0<\epsilon\leq 1/6$
	$\sqrt{3}(1-2\epsilon)$	$1/6<\epsilon\leq 1/2$
	0	$1/2<\epsilon\leq 1$

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Sensitivity Analysis—Scarcity Scenario

- Bid bounds are effective with extremely high prices and economic withholding.
- **Better** performance with **higher** price and withholding level

TABLE V
COMPARISON OF ECONOMIC PERFORMANCE AND IMPROVEMENT UNDER SCARCITY SCENARIOS

Generation Curtailment Ratio	Max Real-Time Price ($)	Withholding Scale	System Cost (10^6\$)	Storage Profit (10^5\$)
0	52.02	5	7.43 (-0.03)	0.32 (2.59)
	57.58	10	7.51 (-0.04)	0.24 (14.86)
20%	78.31	5	9.74 (-0.07)	1.73 (8.15)
	90.32	10	9.75 (-0.23)	1.26 (23.36)
40%	218.63	5	15.28 (-0.21)	7.48 (4.02)
	234.92	10	15.36 (-1.27)	7.11 (25.41)