SoC-segment Bidding Model for Energy Storage

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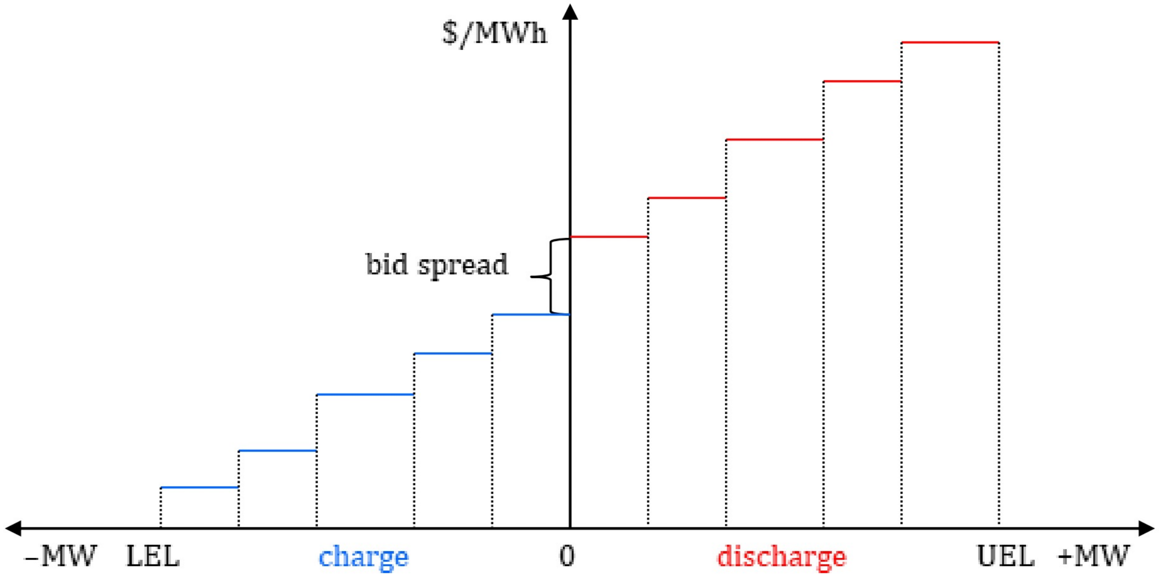
Existing LESR model

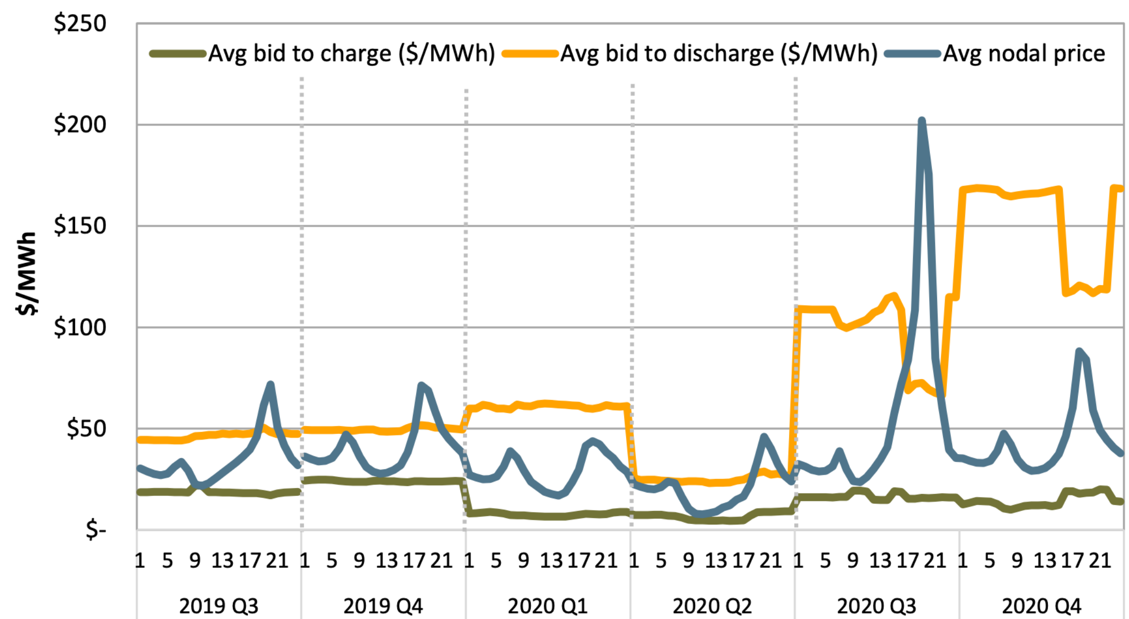
- Energy storage bids as a combination of generator and flexible demand
- Discharge bids – discharge if price is above bids
- Charge bids – charge if price is below bids
- System operator monitors SoC and efficiencies – ensure not to over discharge or charge



Bidding and dispatch model

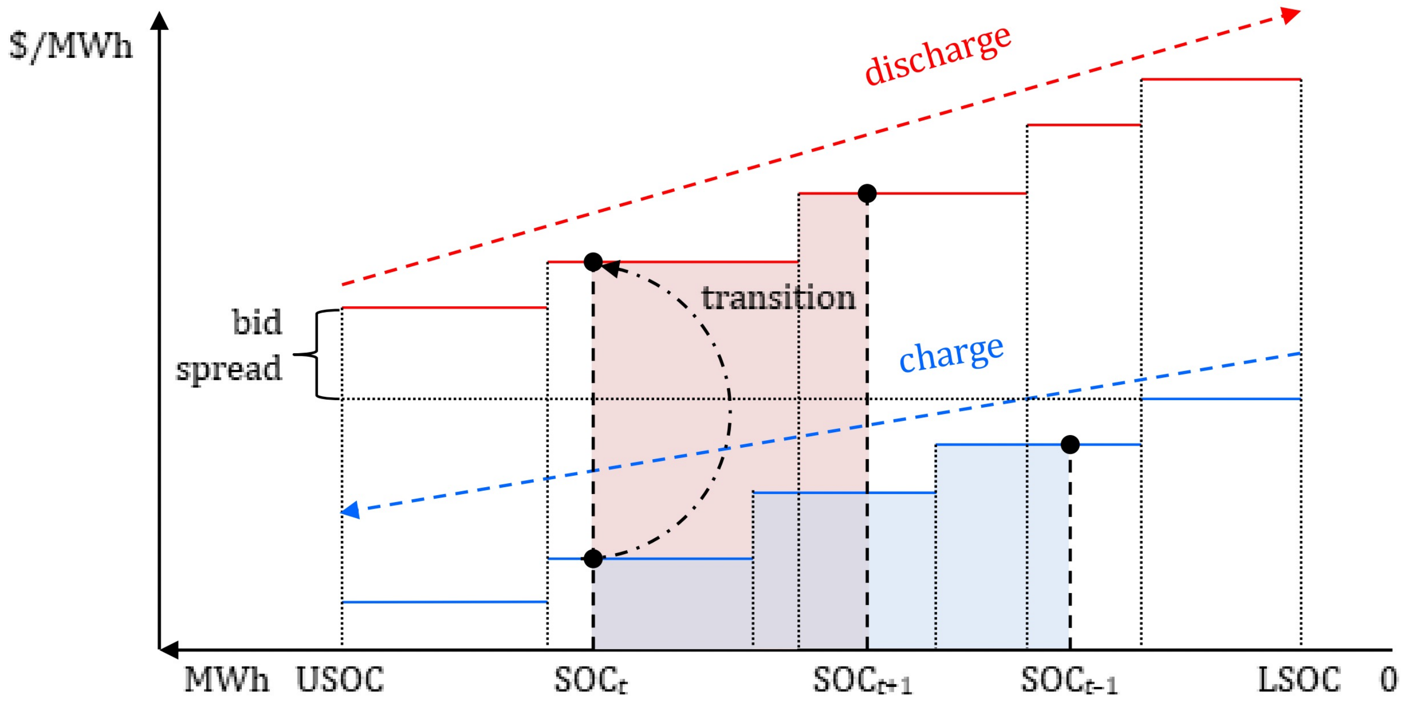
- FERC Order 841
- Storage bid as a generator + flexible demand

CAISO bid data:



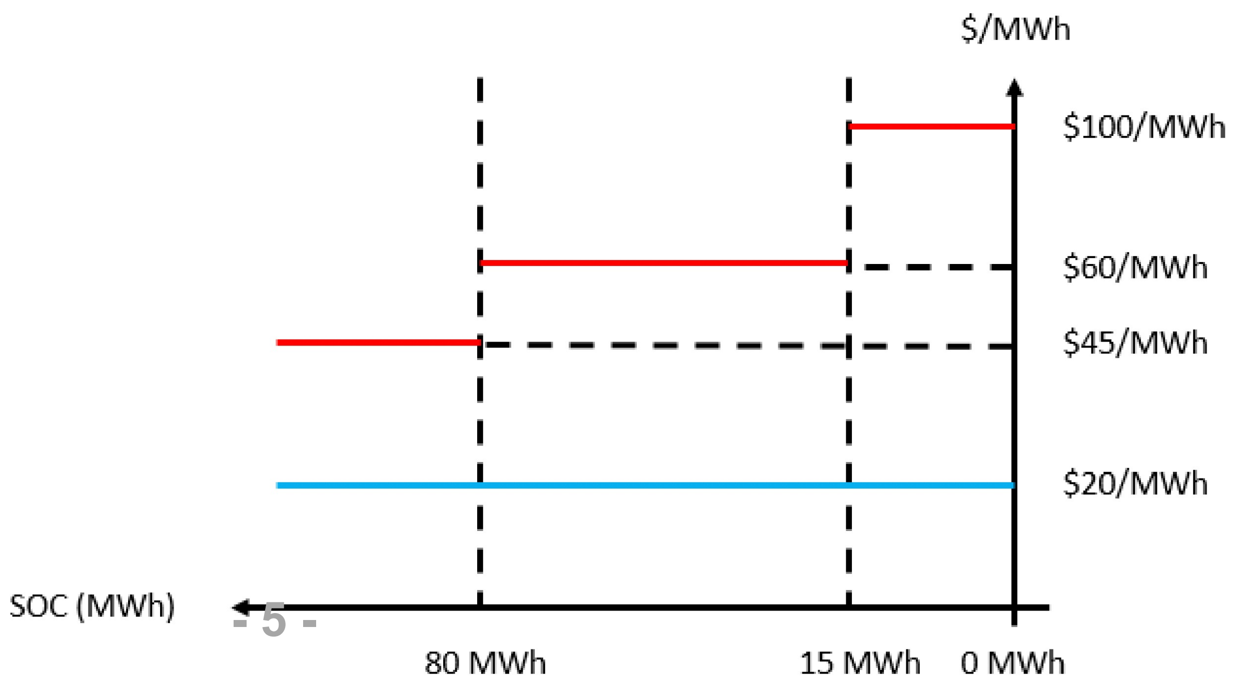
Newly proposed energy bids

- Segment bids with respect to storage state-of-charge
- Lower SoC – higher bid value



Example

- Example: 25MW/100MWh storage
- Charge bid – 1 segment at $20/MWh
  - Storage will charge whenever price is below $/20MWh
- Discharge bids – 3 segments
  - $45/MWh (100-80), $60/MWh (80-15), $100/MWh (15-0)
  - Storage will discharge to 80% SoC if price above 45, 15% if price is above 60, 0% if price is above 100.



Connection to dynamic programming

- Objective: generate optimal energy-segment bids to maximize arbitrage profit

- Method: dynamic programming – energy segment bids based on value-to-go function

- Advantages:
  - in-house algorithm that solves the bidding dynamic programming within ms.

Formulation – deterministic arbitrage

Stored energy

Discharge

Value-to-go function

Maximized profit

Price

Charge

Cost

$$Q_{t-1}(e_{t-1}) = \max_{b_t, p_t} \lambda_t (p_t - b_t) - c p_t + Q_t(e_t)$$

Power rating:	$0 \leq b_t \leq P, \; 0 \leq p_t \leq P$
No discharge when negative price:	$p_t = 0 \text{ if } \lambda_t < 0$
SoC efficiency:	$e_t - e_{t-1} = -p_t/\eta + b_t \eta$
Energy ratings:	$0 \leq e_t \leq E$

Solution algorithm

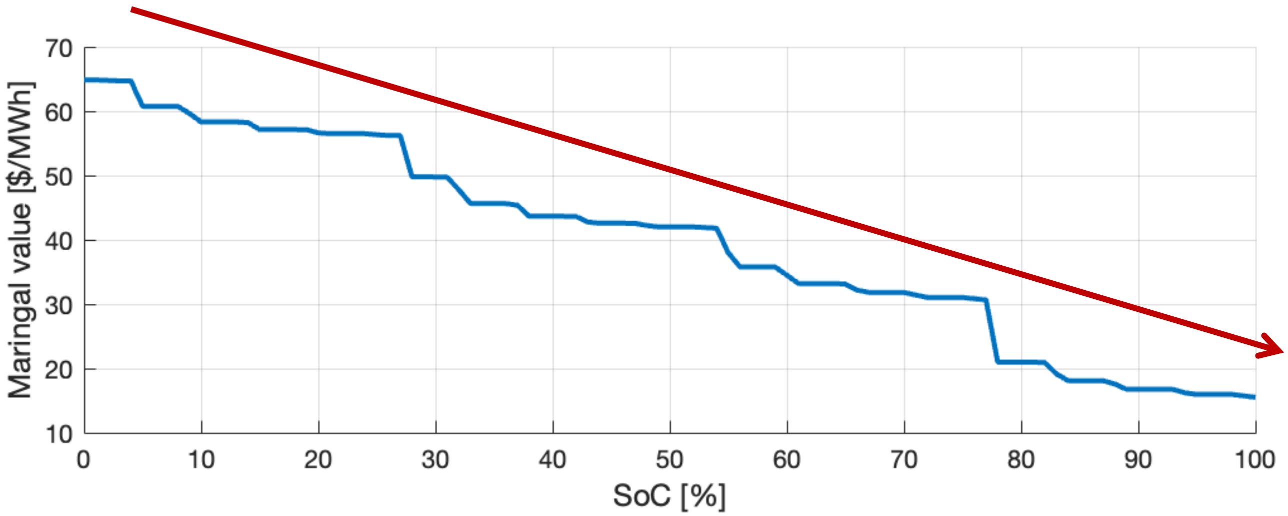
$$Q_{t-1}(e_{t-1}) = \max_{b_t, p_t} \lambda_t(p_t - b_t) - cp_t + Q_t(e_t)$$

Update the derivative of value function analytically ($q_t(e) = \partial Q_t(e)/\partial e$):

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

Marginal SoC opportunity value

- $q_t(e)$



Marginal opportunity value diminishes with higher SoC

From value function to SoC bids

Profit maximization:

$$Q_{t-1}(e_{t-1}) \quad = \max_{b_t, p_t} \underbrace{\boxed{\lambda_t(p_t - b_t)}}_{\text{Revenue}} \underbrace{\boxed{- cp_t + Q_t(e_t)}}_{\text{Cost – to be engineered into bids}}$$

SoC constraints:

$$e_t - e_{t-1} = -p_t/\eta + b_t\eta \quad \Rightarrow \quad \frac{\partial e_t}{\partial p_t} = -\frac{1}{\eta}, \qquad \frac{\partial e_t}{\partial b_t} = \eta$$

Storage cost curve:

$$C = cp_t - Q(e_t) \quad \Rightarrow$$

Discharge curve

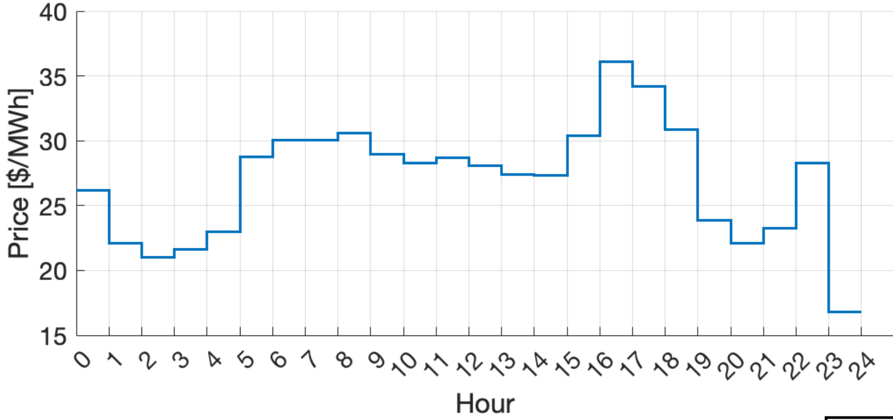
$$\frac{\partial C}{\partial p_t} = c + \frac{1}{\eta} q_t(e_t)$$

Charge curve

$$\frac{\partial C}{\partial b_t} = \eta q_t(e_t)$$

Example

Price profile:



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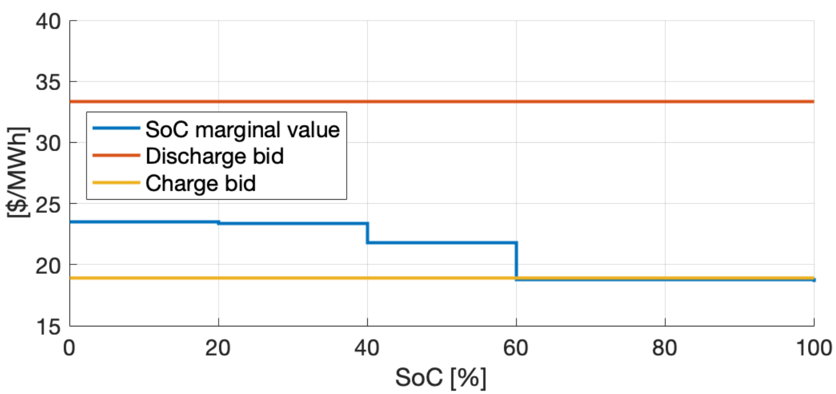
Storage parameters:

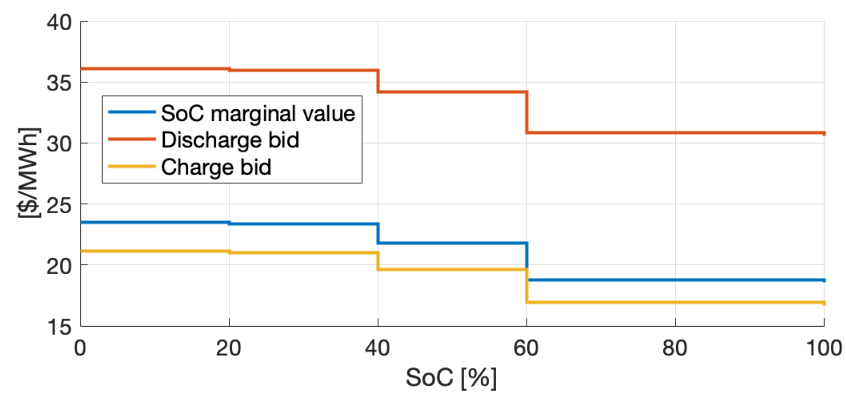
- 4 Hour duration
- 85% round-trip eff.
- 10$/MWh discharge cost

Solve dynamic programming (<1ms computation time)

1-seg bid (power bids)



5-seg bid (SoC bids)



Dispatch model – Single-period

Power bid model:

$$\min_{p_{m,t}, b_{m,t}, g_{k,t}} \sum_k C_k(g_{k,t}) + \sum_m c^{\mathrm{p}}_{m,t} p_{m,t} - c^{\mathrm{b}}_{m,t} b_{m,t}$$

subjects to

$$0 \le p_{m,t} \le \boxed{P^{\mathrm{p}}_m(e_{m,t-1})}$$

$$0 \le b_{m,t} \le \boxed{P^{\mathrm{b}}_m(e_{m,t-1})}$$

other generator, network, nodal balance constraints

Update power rating to reflect SoC limits

SoC-seg bid model:

$$\min_{p_{m,t}, b_{m,t}, g_{k,t}, e_{m,t}} \sum_k C_k(g_{k,t}) + \sum_m c_m p_{m,t} - v_{m,t}$$

subjects to

$$0 \le p_{m,t} \le P^{\mathrm{p}}_m(e_{m,t-1})$$

$$0 \le b_{m,t} \le P^{\mathrm{b}}_m(e_{m,t-1})$$

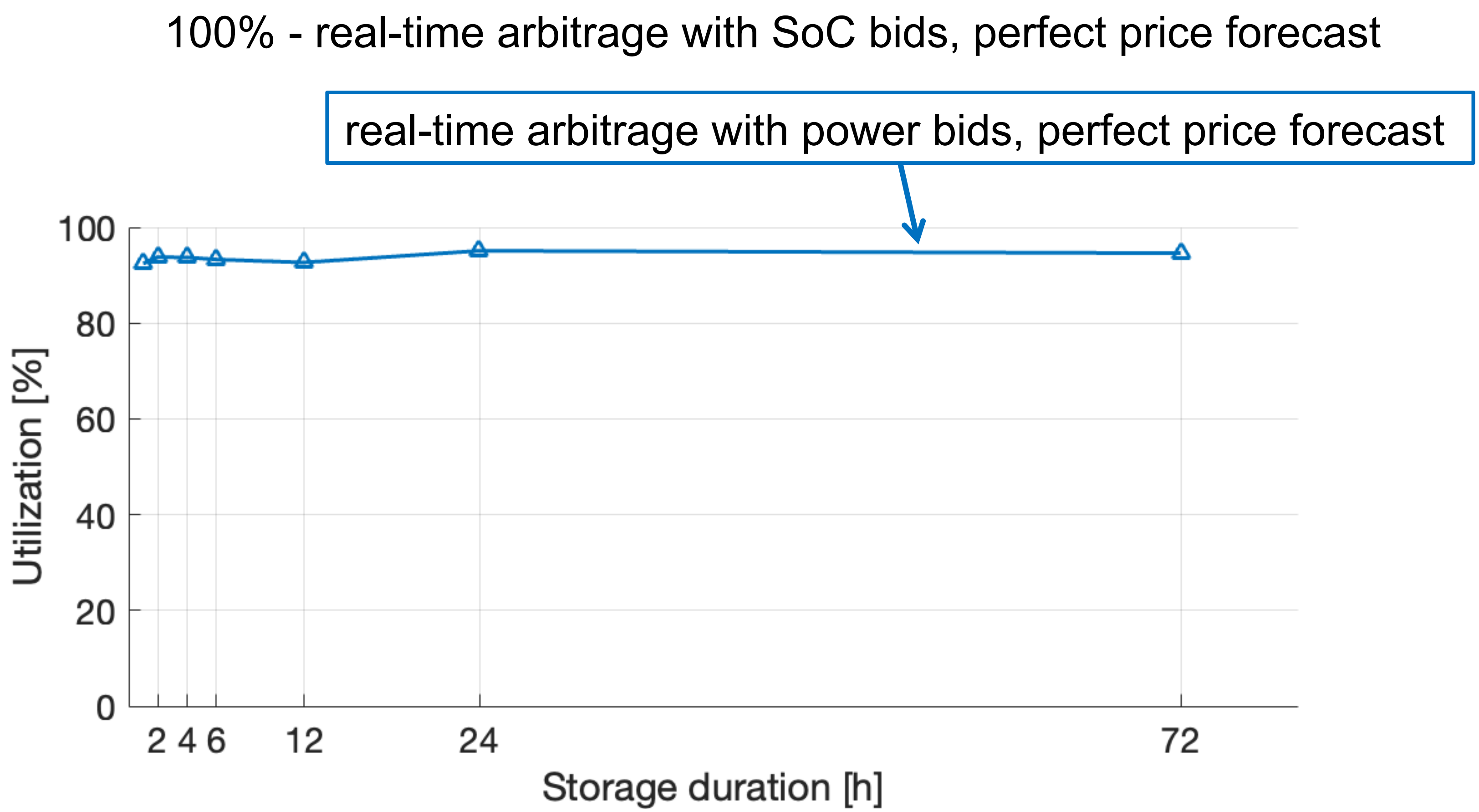
$$e_{m,t} = e_{m,t-1} - p_{m,t}/\eta_m + b_{m,t}\eta_m$$

$$E_{m,0} \le e_{m,t} \le E_{m,J}$$

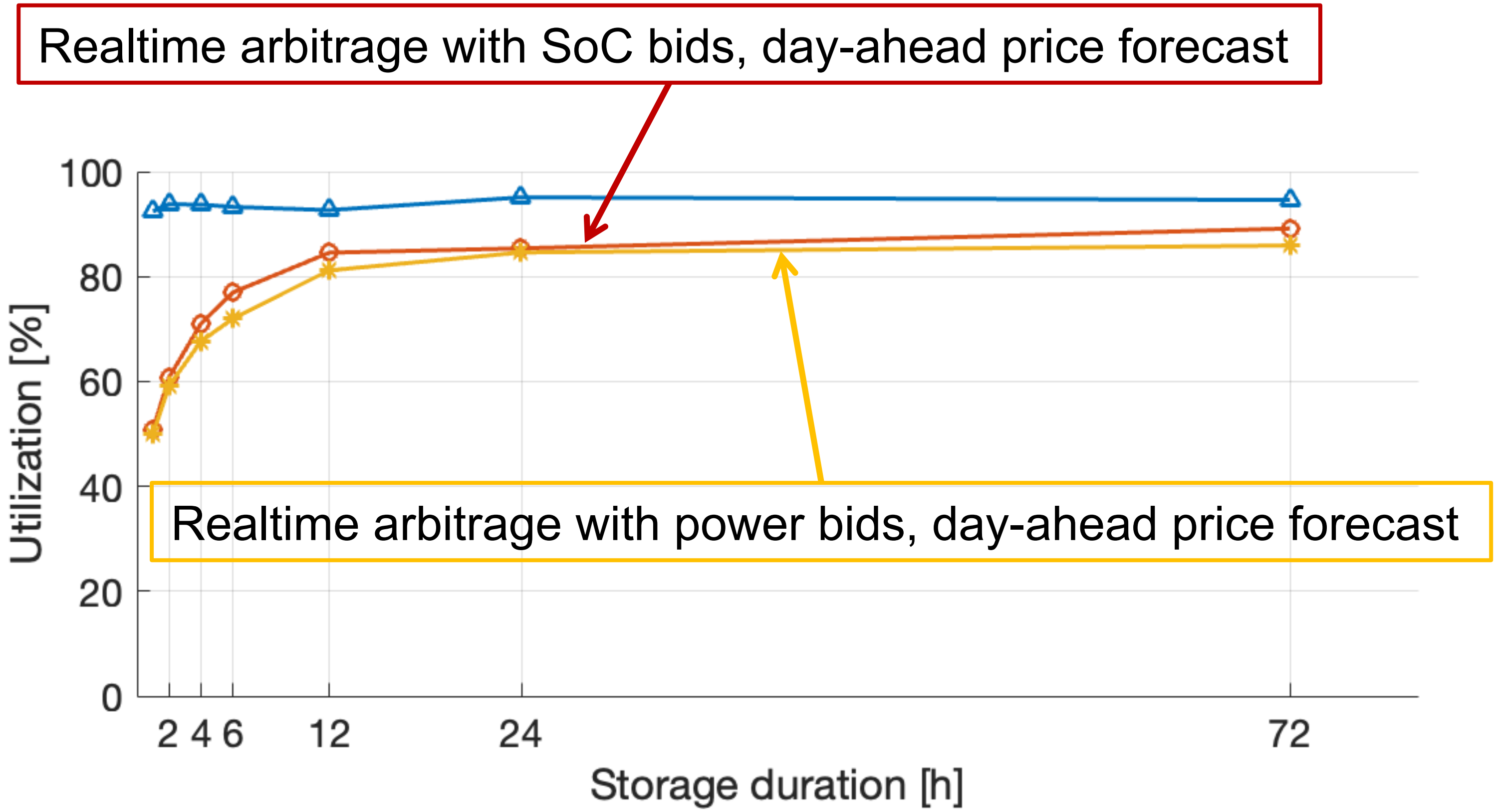
Piece-wise linear value function bids

$$\boxed{v_{m,t} \le c^{\mathrm{e}}_{m,j,t}(e_t - E_j) + \sum_{\tau=1}^{j-1} c^{\mathrm{e}}_{m,\tau,t}(E_{m,\tau} - E_{m,\tau-1})}$$

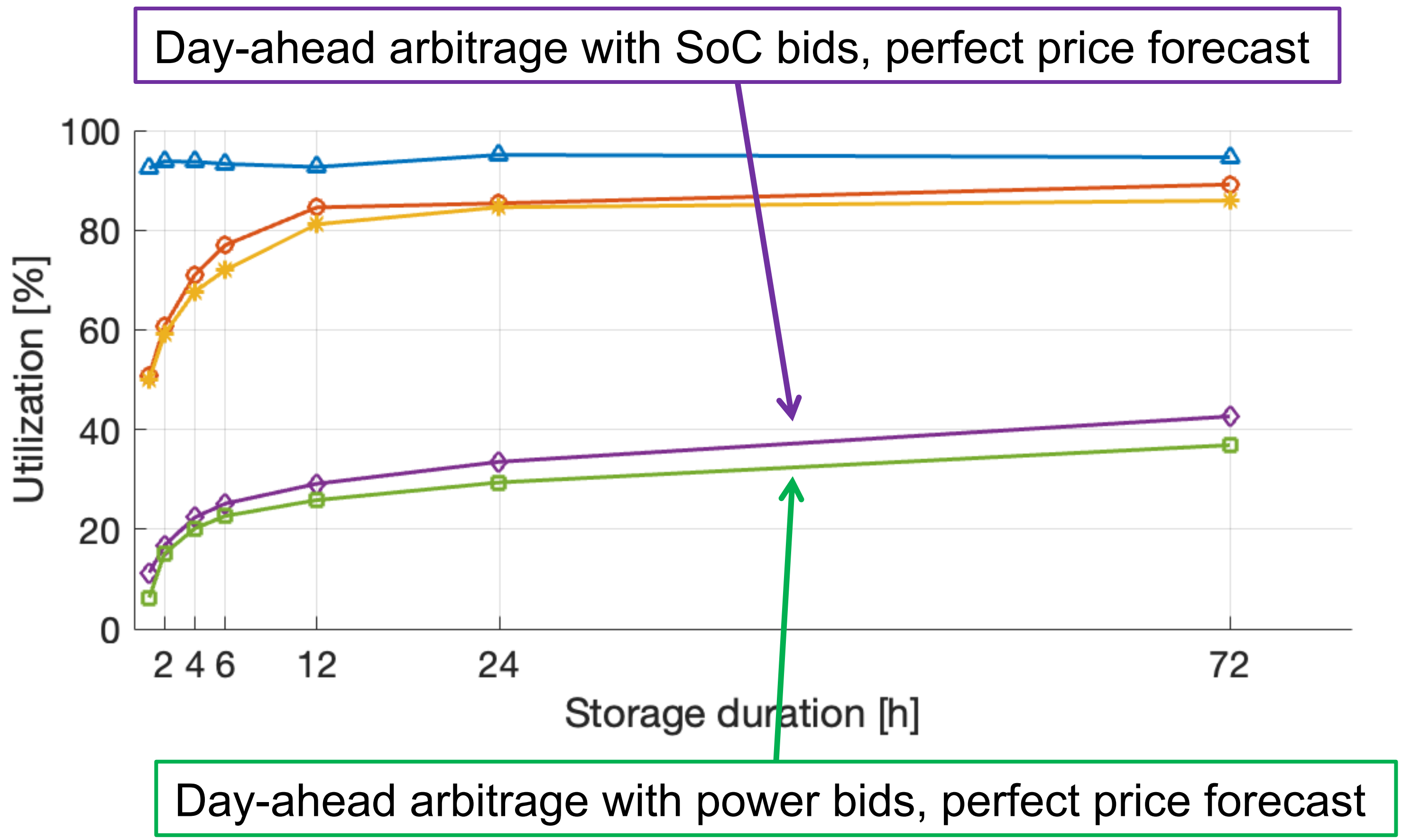
Arbitrage profit in NYC 2019



Arbitrage profit in NYC 2019



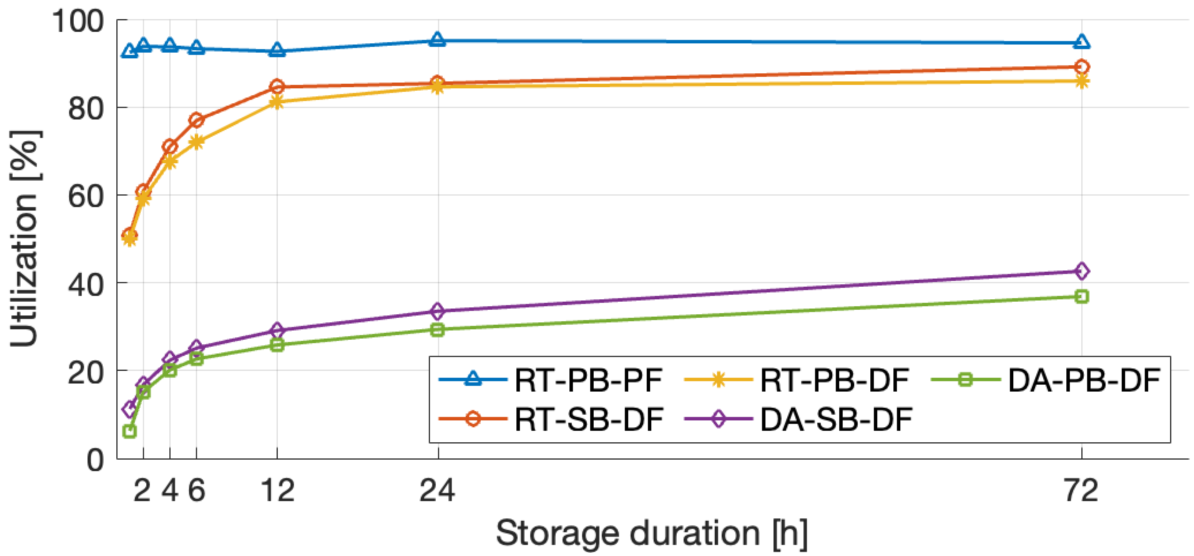
Arbitrage profit in NYC 2019



Arbitrage profit in NYC 2019

- SoC-seg bids provide 5% to 10% improvement compared to power bids

100%: SoC bids with perfect price prediction (perfect arbitrage)
RT-PB-PF: power bids with perfect price prediction
RT-SB-DF: SoC bids with day-ahead price predictions
RT-PB-DF: power bids with day-ahead price predictions
DA-SB-DF: SoC bids in day-ahead markets
DA-PB-DF: power bids in day-ahead markets



Advanced bidding design

Solve a dynamic programming arbitrage problem with:

- Uncertainties $\Longrightarrow$ Stochastic dynamic programming

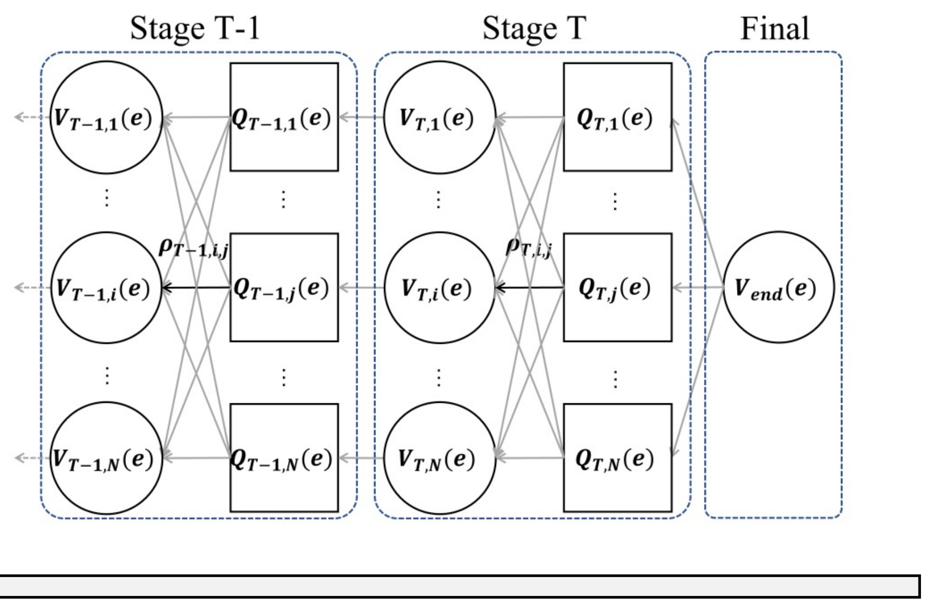
- Nonlinear storage models
  - SoC-dependent efficiencies
  - SoC-dependent power rating
  - SoC-dependent degradation cost

Local linearization

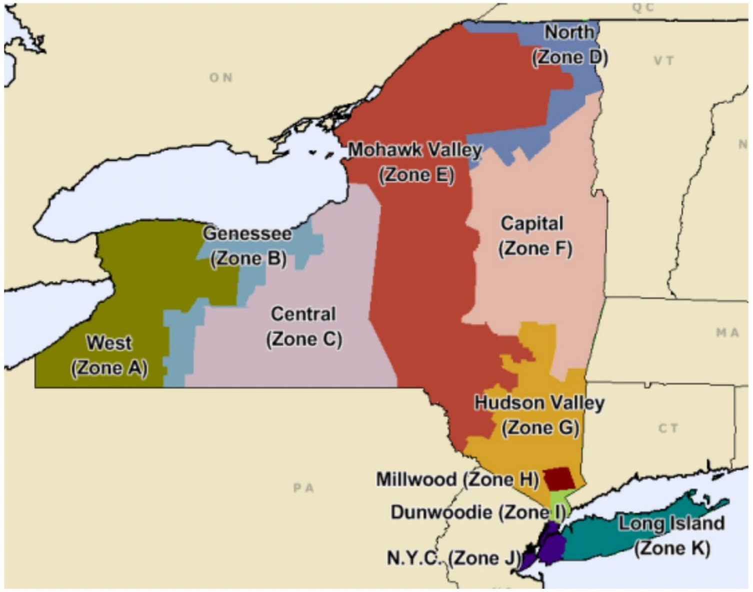
Uncertainty

Single-period optimization: $Q_{t-1}(e_{t-1} \mid \lambda_t) = \max_{b_t, p_t} \lambda_t \cdot (p_t - b_t) - c p_t + V_t(e_t \mid \lambda_t)$

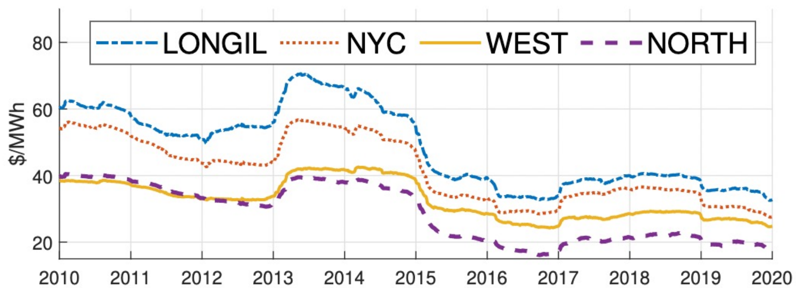
Value function updates: $V_t(e_t \mid \lambda_t) = \mathbb{E}_{\lambda_{t+1}} \left[Q_t(e_t \mid \lambda_{t+1}) \middle| \lambda_t \right]$



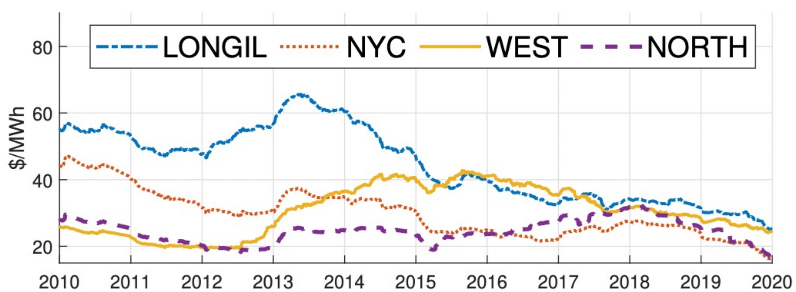
Solves using analytical value function update with one backwards sweep



(a) New York State Price Zones.



(b) 30 day moving average price.



(c) 30 day moving average daily price deviations.

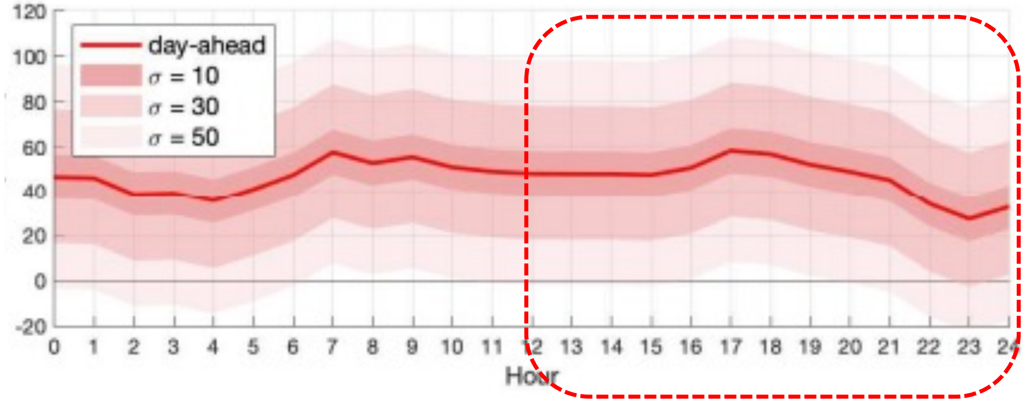
Profit in New York State

P2E – power to energy ratio
MC – marginal cost of discharge
Trained using 2017-2018
Tested on 2019

Zone	P2E	Prorated Profit Ratio [%]			
		0 MC	10 MC	30 MC	50 MC
NYC	1	59.9	66.1	71.8	78.5
	0.5	67.2	72.0	78.7	84.3
	0.25	76.2	78.9	85.3	90.8
LONGIL	1	56.0	59.0	62.1	62.3
	0.5	63.5	65.1	66.7	67.4
	0.25	72.7	72.5	71.7	72.0
NORTH	1	58.4	63.5	70.1	75.3
	0.5	69.5	74.6	81.1	83.6
	0.25	79.4	83.7	90.2	88.0
WEST	1	67.1	70.9	75.2	78.2
	0.5	74.1	77.3	80.1	81.8
	0.25	82.2	84.2	85.8	86.7

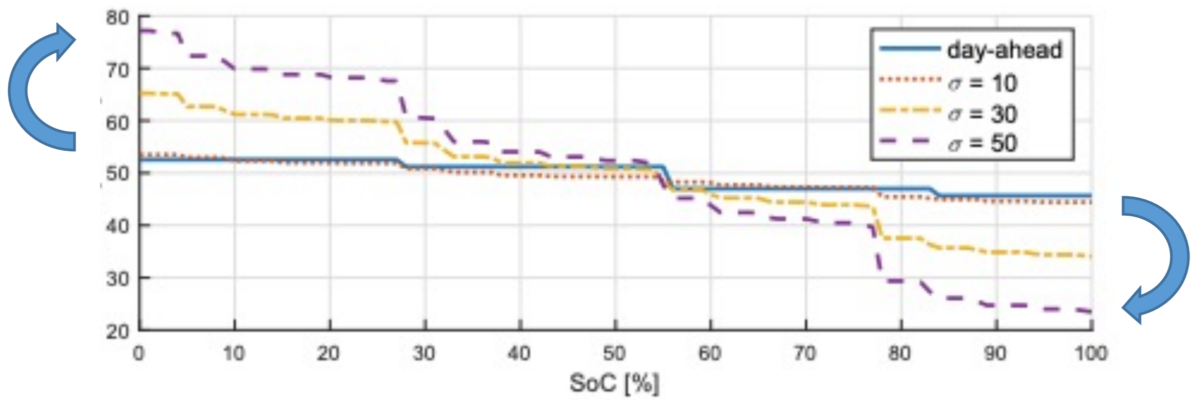
Uncertainties

Price prediction with uncertainties



Storage value at hour 12

Marginal SoC value at Hour 12



Value slope increases with uncertainty

Variable efficiency

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

$$0 \le b_t \le P,\ 0 \le p_t \le P$$

$$p_t = 0 \text{ if } \lambda_t < 0$$

$$e_t - e_{t-1} = -p_t / \boxed{\eta^p(e_{t-1})} + b_t \boxed{\eta^b(e_{t-1})}$$

$$0 \le e_t \le E$$

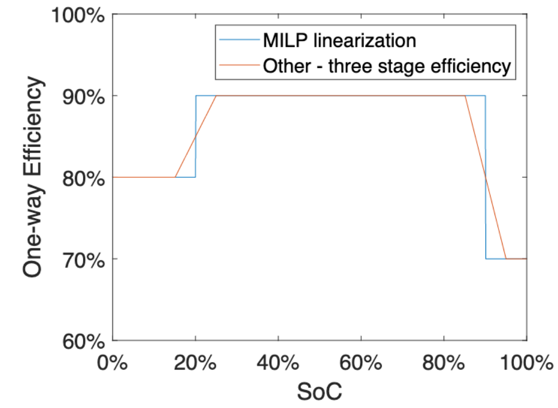
Efficiency depends on SoC

Look up efficiency values based on input SoC during valuation – local linearization

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

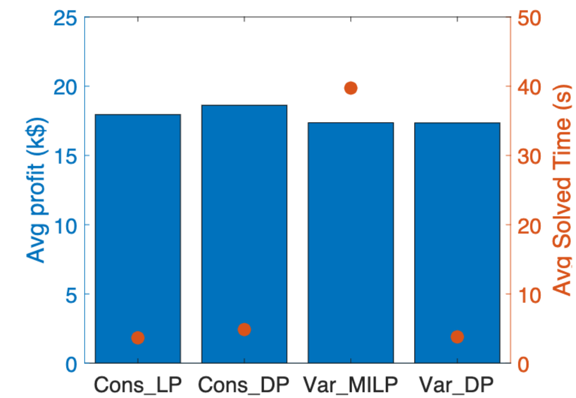
Variable efficiency

3 segment variable efficiency model

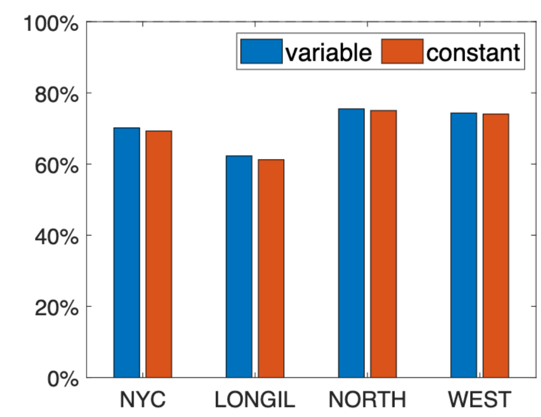


Comparison to Gurobi in deterministic arbitrage

- Cons_LP – constant efficiency using linear programming
- Cons_DP – constant efficiency using dynamic programming
- Var_MILP – variable efficiency using MILP
- Var_DP – variable efficiency using dynamic programming



MILP model:
$$\max_{p_{k,t},b_{k,t}} \sum_{t}^{T}\sum_{k}^{K} \pi_t \cdot (p_{k,t} - b_{k,t}) - c p_{k,t}$$
$$\textbf{s.t.} \quad 0 \le \sum_{k}^{K} b_{k,t} \le P, \; 0 \le \sum_{k}^{K} p_{k,t} \le P$$
$$e_{k,t} - e_{k,t-1} = -p_{k,t}/\eta_k^p + b_{k,t}\eta_k^b$$
$$E_1 u_{1,t} \le e_{1,t} \le E_1$$
$$E_k u_{k,t} \le e_{k,t} \le E_k u_{k-1,t}, \quad \forall k \in \{2, ..., K-1\}$$
$$0 \le e_{K,t} \le E_K u_{K-1,t}$$



Stochastic arbitrage comparison

- Valuation using constant or variable efficiency model
- Simulate control over a variable efficiency storage model

Nonlinear storage model

Update value based on input SoC e

- P – power rating
- η – efficiency
- c – degradation cost

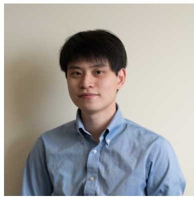
No impact on computation speed to consider nonlinear models

- Full year solution time (100k time steps): < 5 seconds

May need to increase time granularity for better local linearization

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

Collaborators and References



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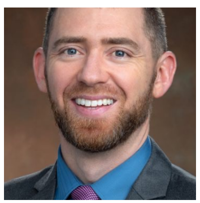

Gabe Murtaugh
Storage Sector Manager, CAISO

References:

CAISO new market model:
http://www.caiso.com/InitiativeDocuments/Presentation-EnergyStorageEnhancements-RevisedStrawProposal-Mar21-2022.pdf

N. Zheng, J. J. Jaworski and B. Xu, "Arbitraging Variable Efficiency Energy Storage using Analytical Stochastic Dynamic Programming," in *IEEE Transactions on Power Systems*, doi: 10.1109/TPWRS.2022.3154353.

Impact of Bidding and Dispatch Models over Energy Storage Utilization in Bulk Power Systems
https://arxiv.org/abs/2201.03421

Thanks!

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https://bolunxu.github.io/