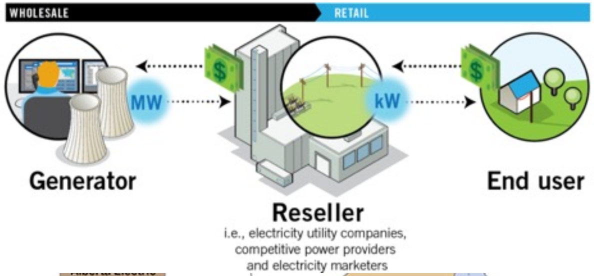
Energy Storage Integration in Electricity Markets: Model Design and Learning-aided Participation

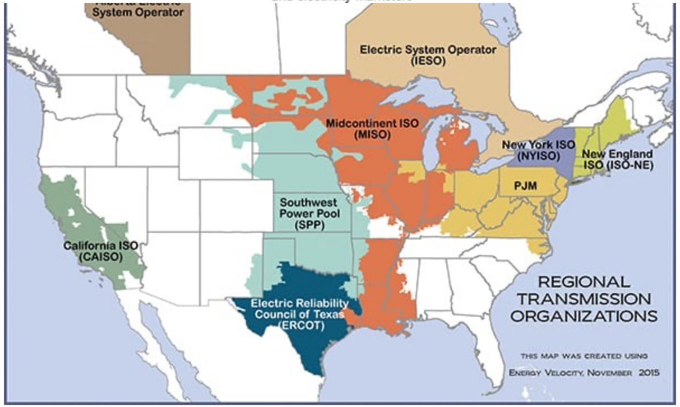
Bolun Xu
Assistant Professor, Earth and Environmental Engineering
Columbia University

Seminar at RWTH Aachen
July 12th , 2023

Power system
(pre 1900)

Electricity markets
(ca. 2000)



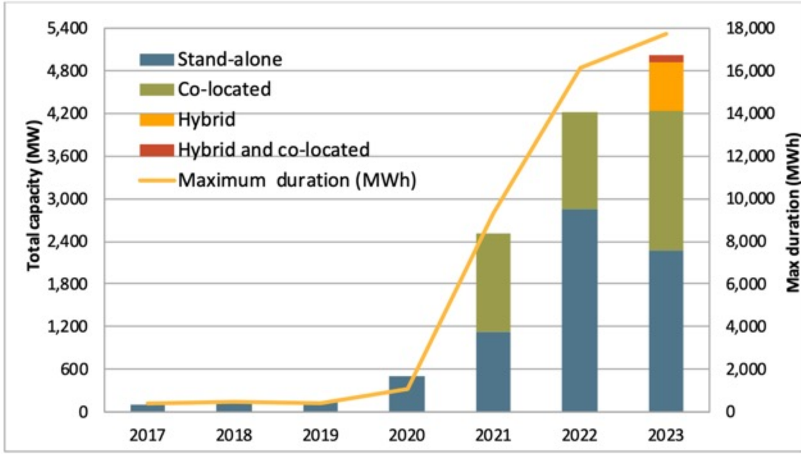


Battery energy storage
(ca. 2015)

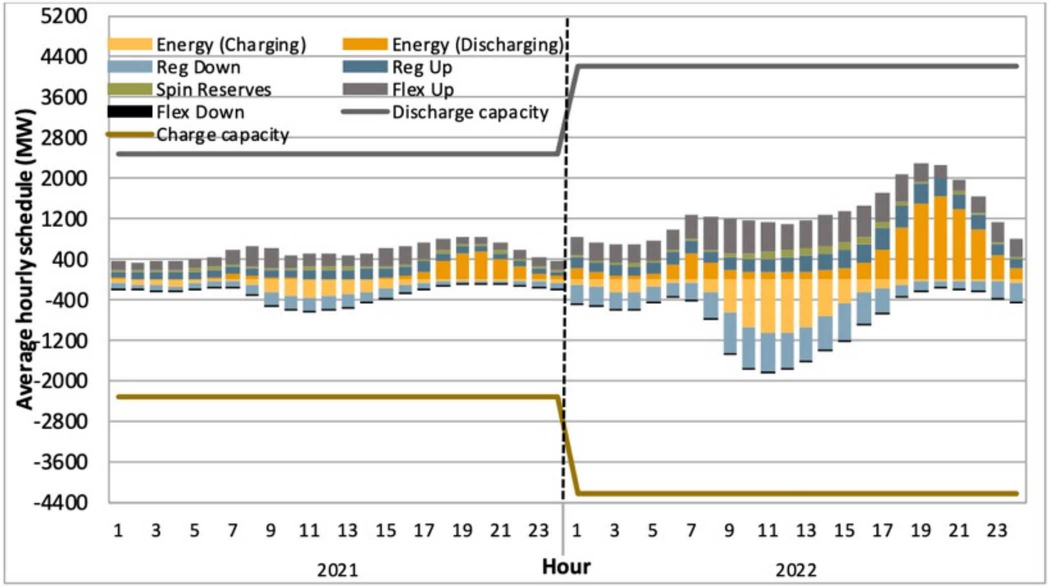
CAISO battery capacity exceeded 5GW

- >50GW battery on the interconnection queue (CAISO peak demand: 52GW)

Battery capacity reached 5GW



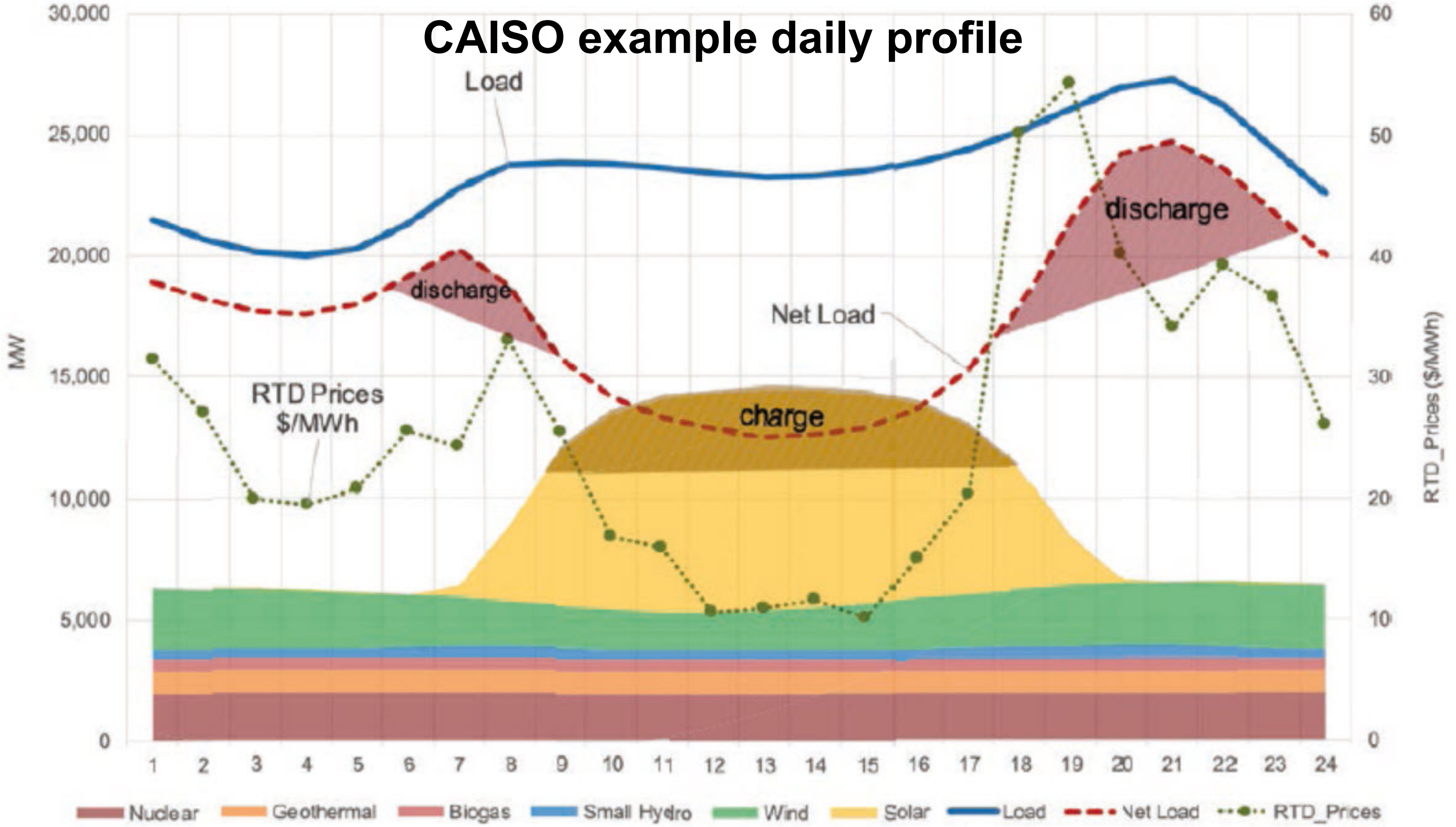
Main application: Energy market/Price arbitrage



Source: CAISO: Special Report on Battery Storage July 7, 2023

COLUMBIA | ENGINEERING
The Fu Foundation School of Engineering and Applied Science

Energy storage earns revenue while helping the grid to integrate renewable energy



Source: Energy Storage: Perspectives from California and Europe, CAISO & RGI, Nov 2019

Research questions

- What happens when storage capacity continues to increase?

- How to manage a **power system** with high **energy storage** share through **electricity markets** – 3 criteria
  - **Market design** reflects (storage's) physical characteristics

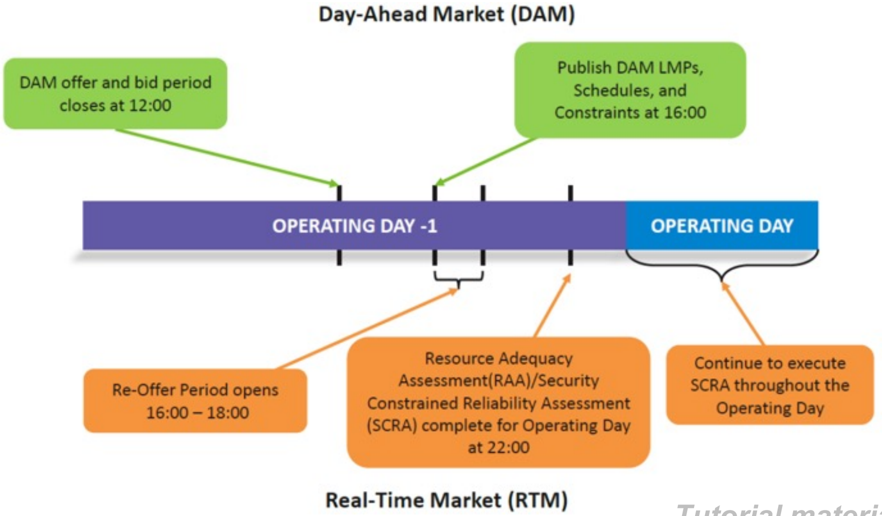
  - Participants are **rational** and profit-driven

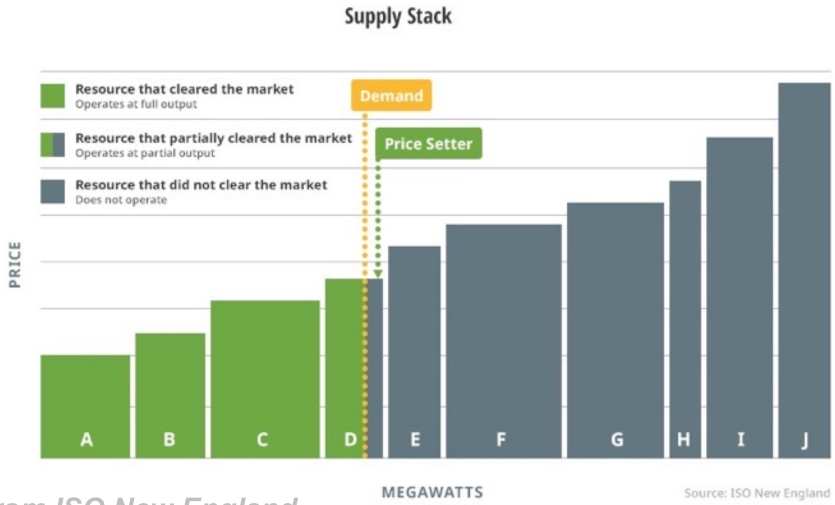
  - Market is **competitive**

- How to evaluate battery technologies for grid services

Why problematic for storage to participate in markets

- Electricity markets were designed solely based on thermal generators



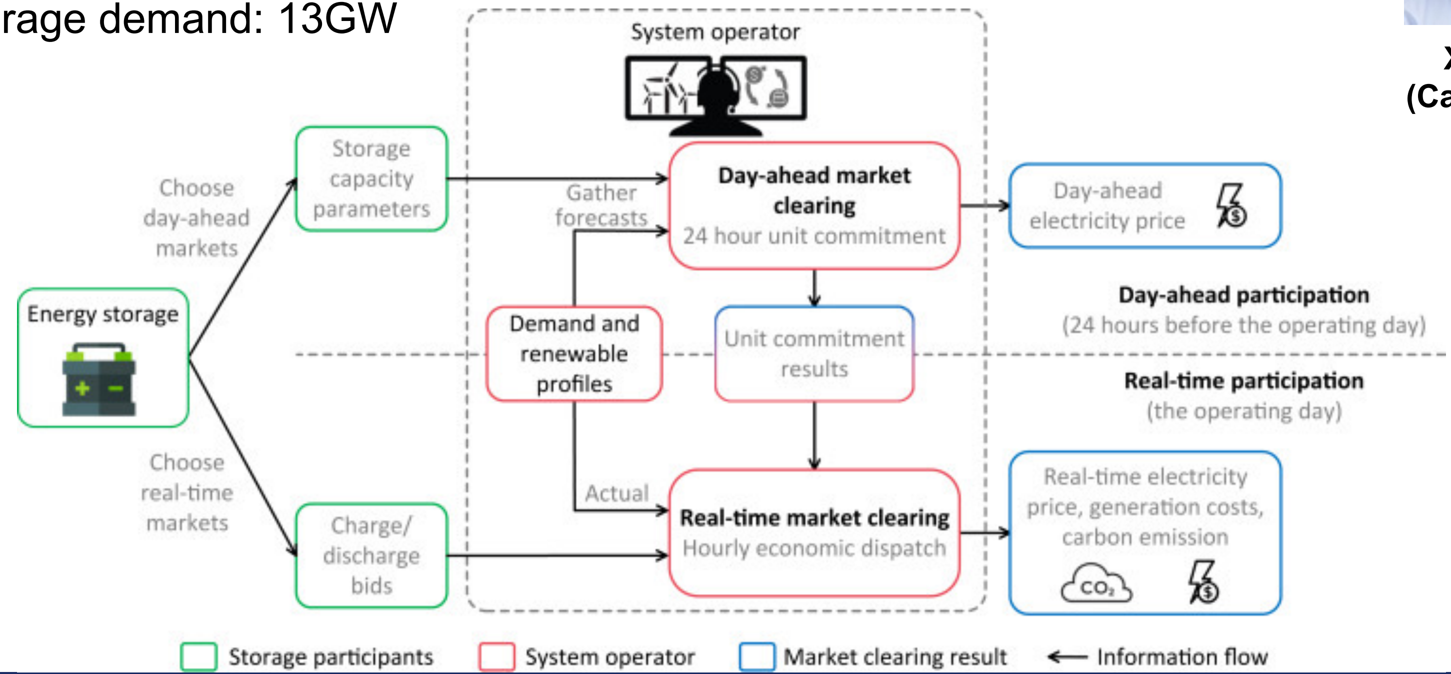


Tutorial materials from ISO New England

- No systematic ways to
  - Manage storage state-of-charge to recharge from cheap and renewable sources
  - Unique degradation and efficiency characteristics

Establishing a baseline understanding

- An agent-based framework to simulate storage in **day-ahead (DA)** and/or **real-time (RT)** markets
- ISO-NE system model *(Krishnamurthy et al, TPWRS, 2015)*
  - Average demand: 13GW



Xin Qin
(Cambridge)

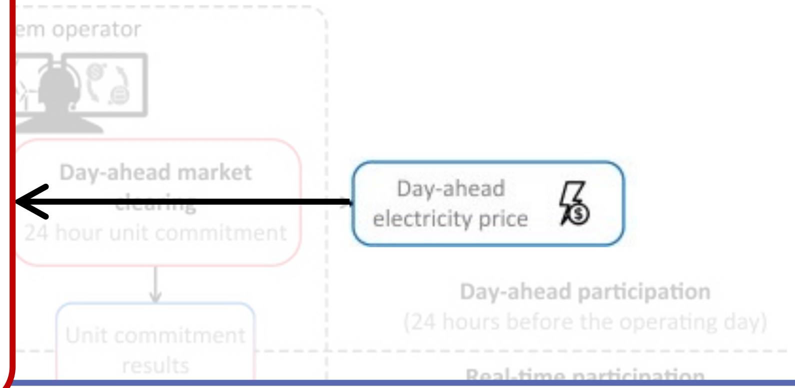
Columbia Engineering
The Fu Foundation School of Engineering and Applied Science

Generate RT bids from DA prices

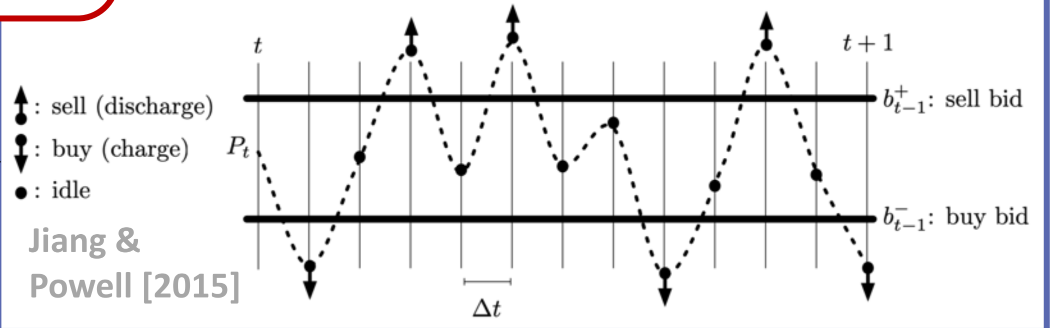
Bid generation algorithm

Xu et al, CDC, 2020

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



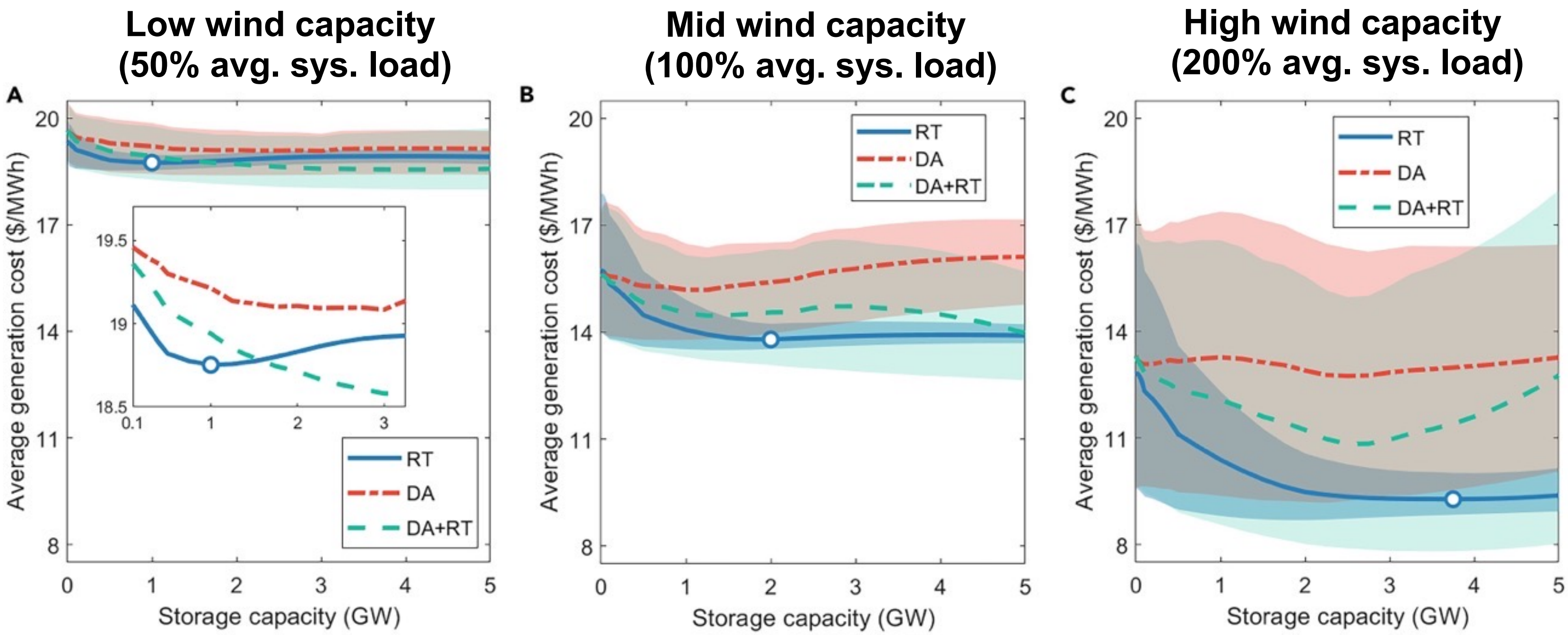
Charge/ discharge bids



Jiang & Powell [2015]

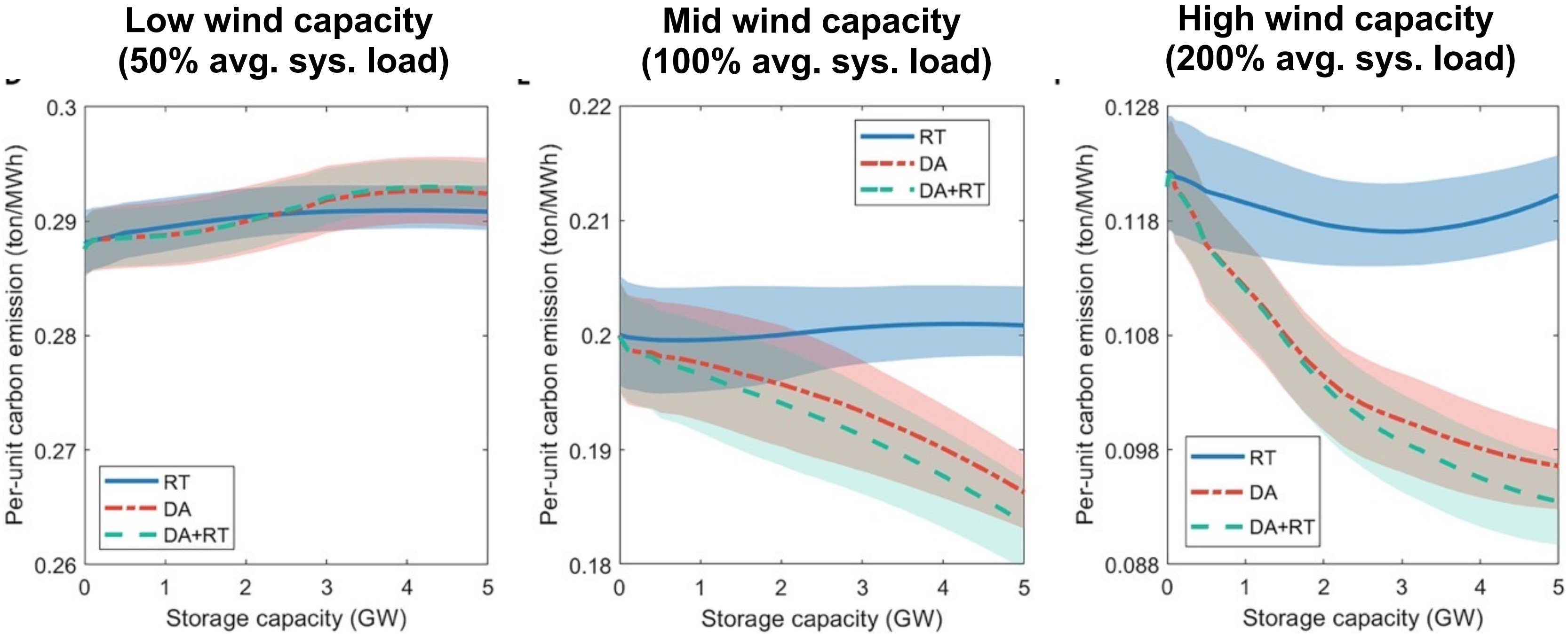
Comparison of system cost

- Real-time participation achieves the lowest system cost in all mid to high wind scenarios



Comparison of system emission

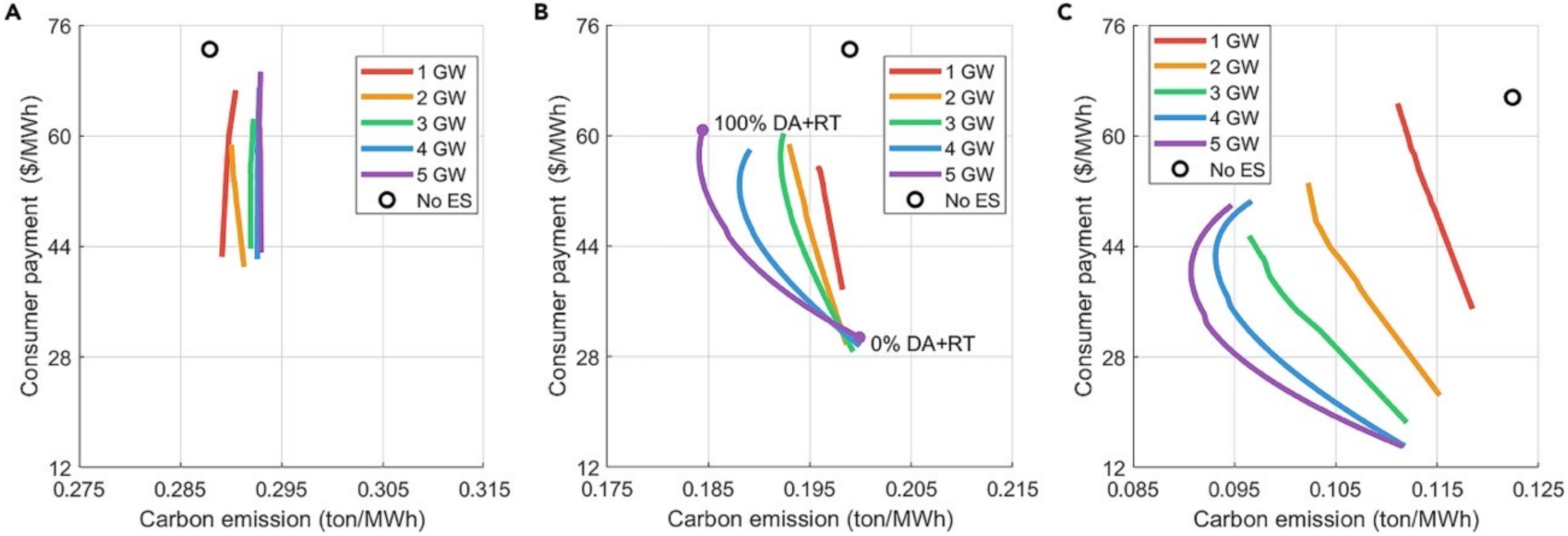
- Day-ahead participation is more effective to reduce system carbon emission



Pareto analysis of all participation options

- Storage market participation options affect up to 53% of consumer cost and 16% of emission reduction

Low wind capacity (50% avg. sys. load) | **Mid wind capacity (100% avg. sys. load)** | **High wind capacity (200% avg. sys. load)**



Improving market design for storage

- Market design must reflect storage's **physical** and **economic** characteristics – FERC Order 841

Physical - Degradation

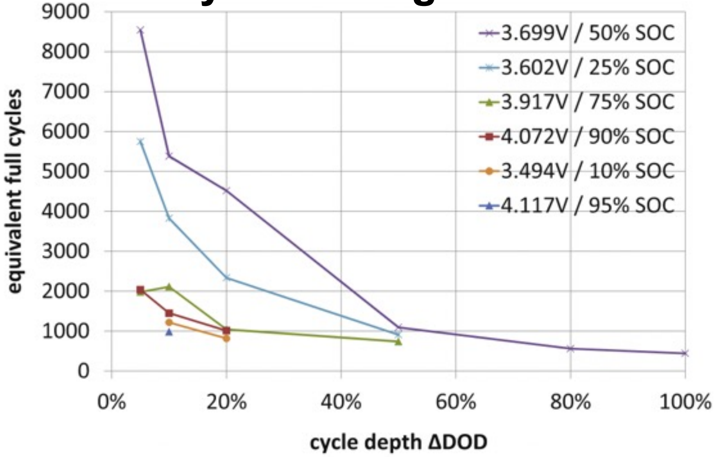
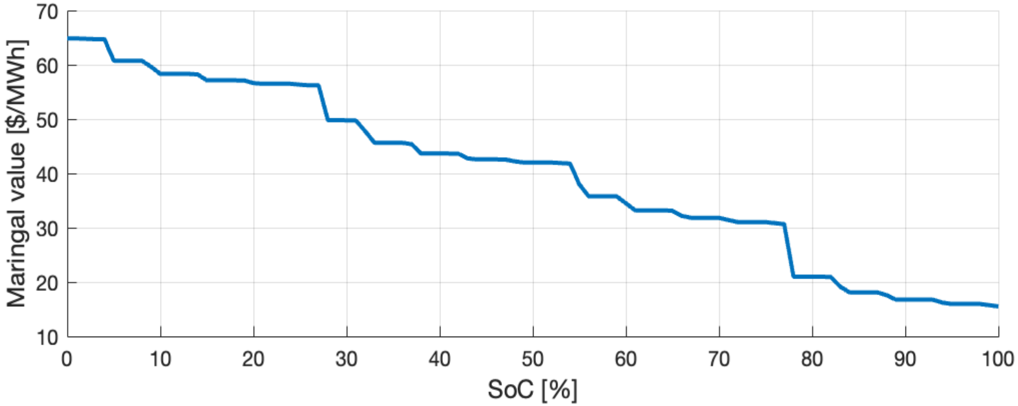


Fig. 14. Wöhler curves for cells cycled with 1 C at 35 °C around different average voltages. Number of equivalent full cycles until capacity reaches 80% of the initial value vs. cycle depth is shown.

Ecker et al, *Journal of Power Sources*, 2014

Economic – Opportunity cost



Marginal opportunity cost of storage decreases monotonically with SoC – **diminishing returns**

Xu et al, *Conference on Decision and Control, 2020*

Opportunity cost depends on SoC

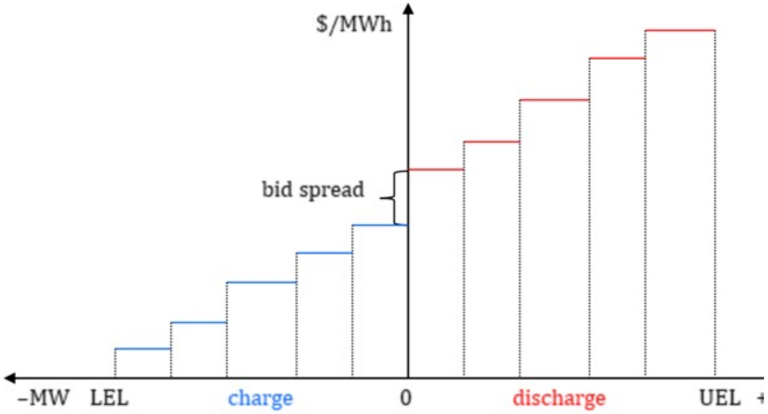
Zheng et al. TEMPR. 2023

- Proposal: SoC-dependent bidding model for storage
  - Charge and discharge bids changes with SoC (monotonic decrease)

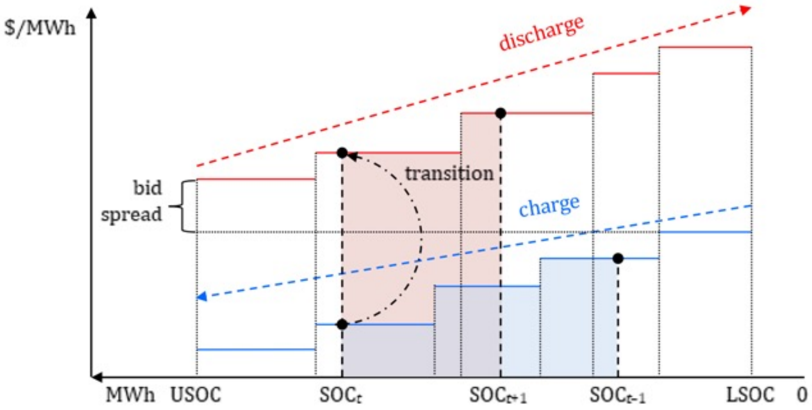
Ningkun Zheng

Xin Qin (Cambridge)

Existing power-based model:



Proposed SoC-based model:



CAISO energy storage enhancement proposal, March 21, 2022

Our model improves profit and reduces costs

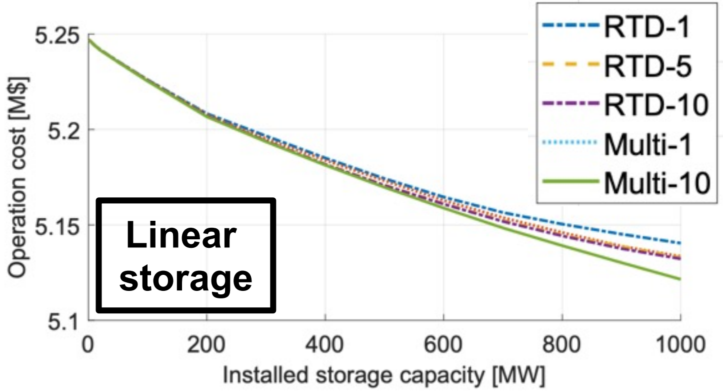
Zheng et al. TEMPR. 2023

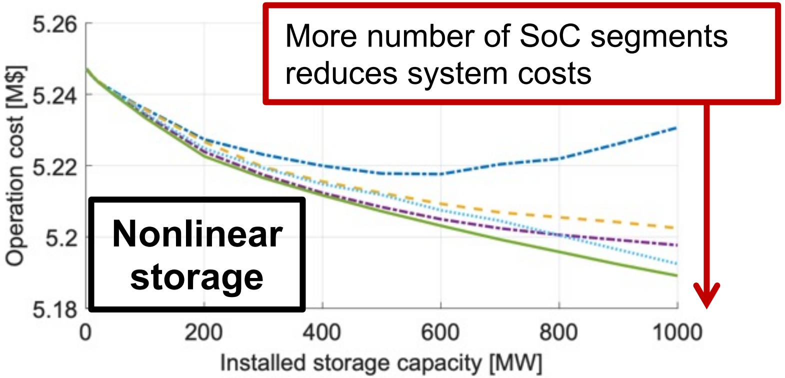
Price-taker arbitrage results show SoC-based bidding model improves storage profits

TABLE III
ARBITRAGE SIMULATION RESULTS WITH CAISO WALNUT 2016 PRICE DATA WITH SOC DEPENDENT STORAGE MODELS

Storage Model	Market Model	Revenue [$]	Cost [$]	Profit [$]	Profit Ratio [%]	Solution Time (s)
DPA	Multi	20803	3228	17575	100	283
	RTD-5	17328	2707	14621	83.2	22
	RTD-1	12468	2389	10079	57.3	16
DPB	Multi	21233	3148	18085	100	193
	RTD-5	20372	2995	17377	96.1	19
	RTD-1	17544	2834	14710	81.3	11
DPC	Multi	22081	3310	18772	100	97
	RTD-5	21450	3382	18068	96.2	18
	RTD-1	18529	3056	15472	82.4	11
DPF	Multi	21905	3470	18435	100	170
	RTD-5	20174	3299	16875	91.5	18
	RTD-1	17261	2851	14410	78.2	11
DPL	Multi	21833	3236	18598	100	172
	RTD-5	19898	3282	16616	89.3	18
	RTD-1	14462	2893	11569	62.2	11

Price-influencer dispatch results



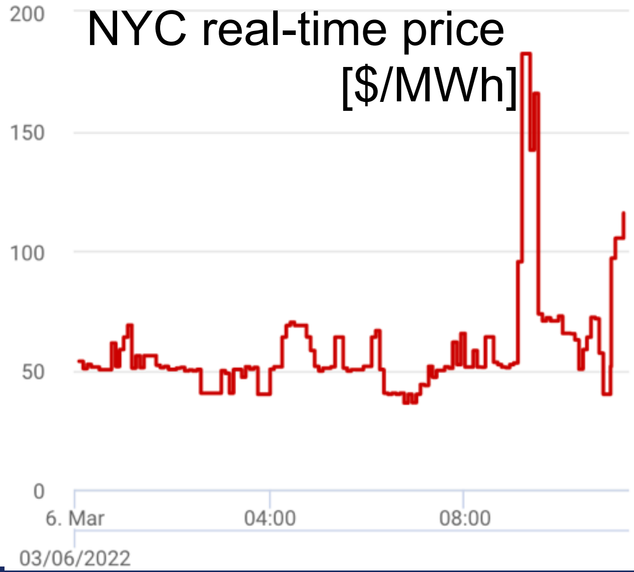


Energy storage bidding

- Various rules regarding how storage can arbitrage electricity prices

- Utility-scale (front of the meter)
  - Submit hourly bids one hour before market clearing (**HA-1**)
  - Market clears every 5 minutes
  - Bids may depend on SoC (**HA-10**)

- Behind the meter storage
  - Can response after observing prices (**PR-10**)
  - Battery size has to be small enough



Combine DP with Neural Network

Arbitrage objective:

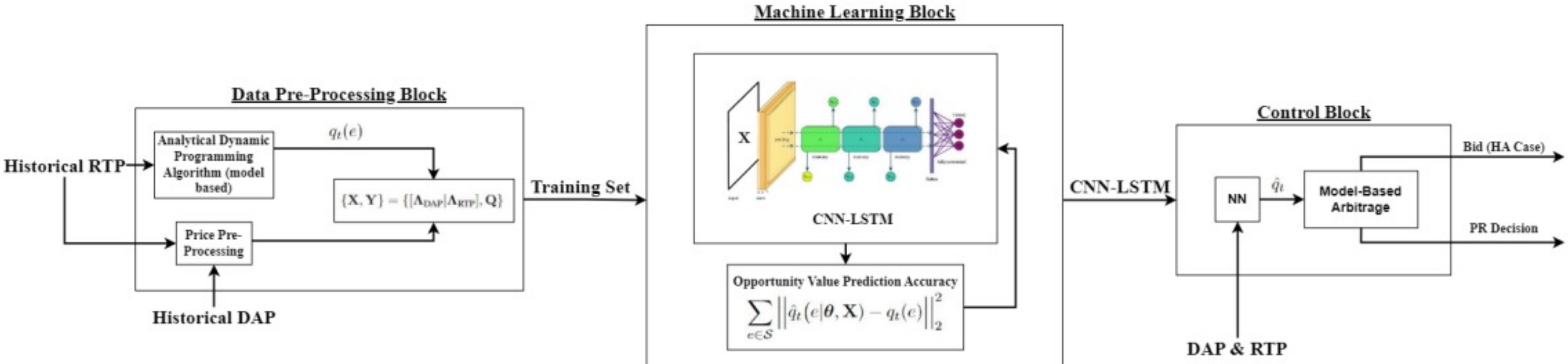
$$\max_{\substack{b_t,p_t,e_t \\ \in \mathcal{E}(e_{t-1})}} \lambda_t(p_t-b_t) - cp_t + \boxed{\hat{Q}(e_t|\boldsymbol{\theta},\mathbf{X})}$$

Constraints:

$$0 \le b_t \le P,\ 0 \le p_t \le P$$
$$p_t = 0 \text{ if } \lambda_t < 0$$
$$e_t - e_{t-1} = -p_t/\eta + b_t\eta$$
$$0 \le e_t \le E$$

Yousuf Baker

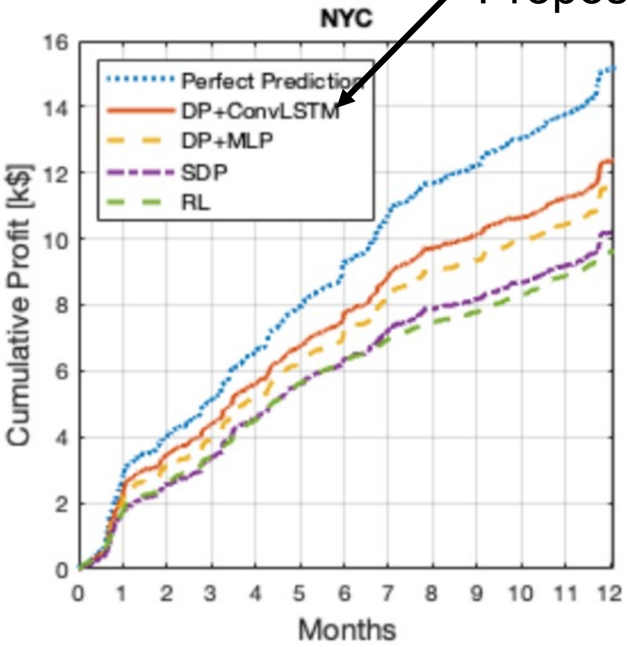
Use supervised learning to predict value function with the help of an off-line dynamic programming algorithm (Xu et al, CDC 2020)



Achieving 70% to 90% profit ratio

Profit ratio – percentage of profit captured compared to perfect forecast

Proposed

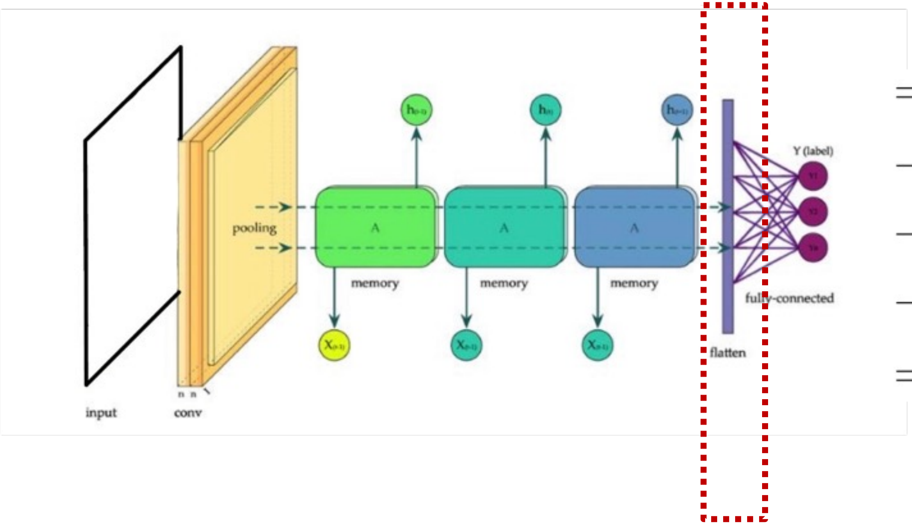


	Hour-ahead bidding			**Hour-ahead SoC-based**			**BTM Response**		
Zone	HA-1			HA-10			PR-10		
	2hr	4hr	12hr	2hr	4hr	12hr	2hr	4hr	12hr
NYC	73.99	74.82	77.00	78.79	80.61	74.47	83.69	83.63	75.67
LONGIL	74.26	76.56	82.01	75.30	79.63	81.89	82.98	83.94	82.38
NORTH	73.22	71.71	70.17	75.83	77.21	73.16	79.52	79.96	74.29
WEST	78.79	80.13	84.17	83.12	83.94	84.60	87.97	87.44	84.43

Use transfer learning for new markets

- Transfer learning – only train the last layer using new data inputs
- Simulation – pre-train the network using NYC data and test in Queensland, Australia

Transfer learning illustration



Update the output layer using new data

Profit ratio percentage results

Duration	Training	No Data	3 Days	HA-1 1 Week	1 Month	1 Year
2hr	T.L.	77.24	82.76	82.85	81.30	85.35
	No T.L.	X	48.22	51.36	78.59	83.88
4hr	T.L.	81.21	81.29	81.31	78.11	79.12
	No T.L.	X	62.40	65.45	74.92	80.42
12hr	T.L.	92.43	83.96	81.32	78.74	82.73
	No T.L	X	74.79	75.53	74.39	75.43

Maintain market competitiveness

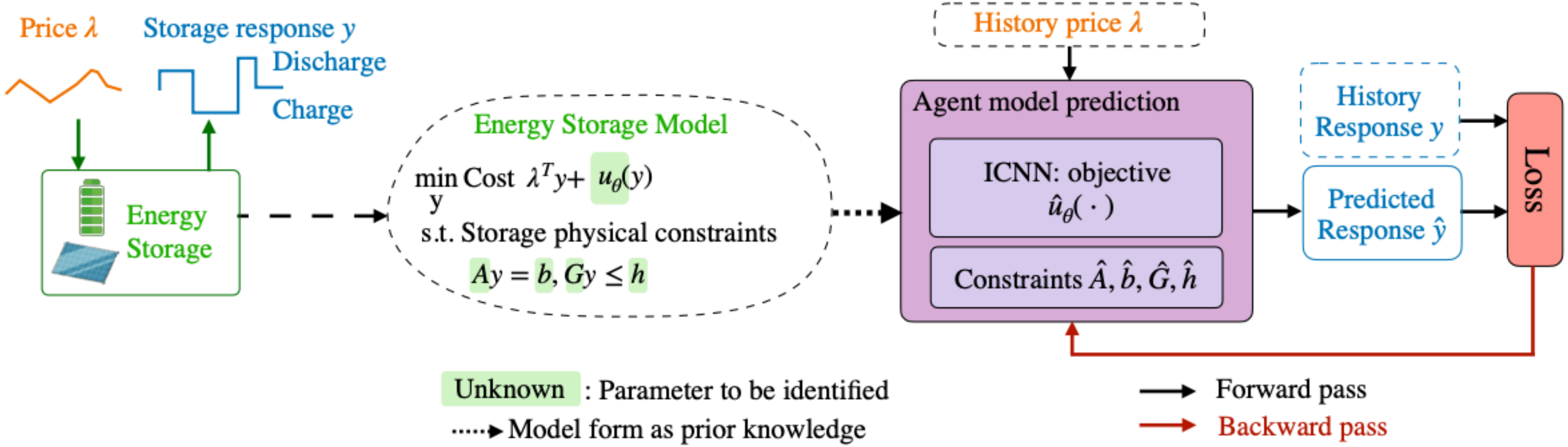
Bian et al. TSG 2023 (2nd review)

- System operator must understand storage's arbitrage behaviors
- We propose an inverse model-based/free approach to learn the storage arbitrage decision making model from observed operations

Yuexin Bian (UCSD)

Ningkun Zheng

Input data **Storage model** **Model regression (inverse optimization)**



Validated using real-world data

Obj: minimize prediction loss

$$\min_{\Theta} \quad L := \frac{1}{N}\sum_{i=1}^{N}\left(\|p_i^\star - p_i\|^2 + \|d_i^\star - d_i\|^2\right)$$

s.t. storage model

To learn: storage's utility function

$$\min_{p,d} \quad \sum_{t=1}^{T}\lambda_t(p_t - d_t) + u_\theta(p,d)$$

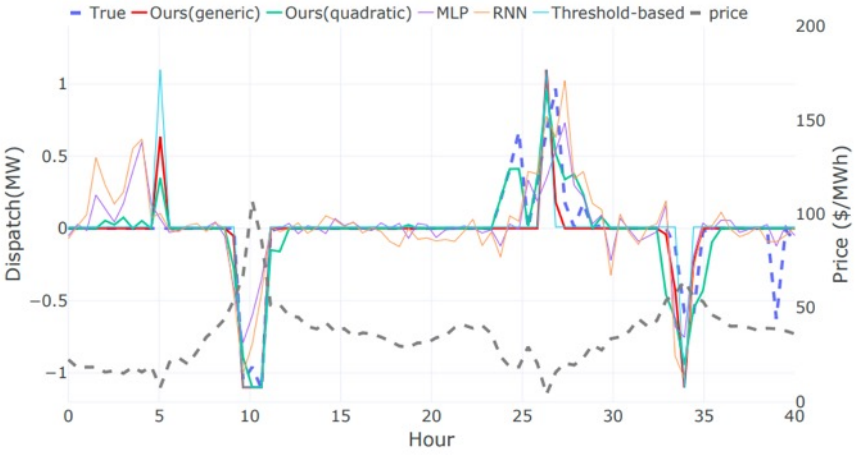
$$\text{subject to} \quad \underline{P} \le d_t, p_t \le \overline{P},$$

$$e_t = e_0 + \sum_{\tau=1}^{t} p_\tau \eta_c - \frac{d_\tau}{\eta_d},$$

$$\underline{E_m} \le e_t \le \overline{E_m},$$

Optional: storage physical models

Test using real data from UQ Tesla project



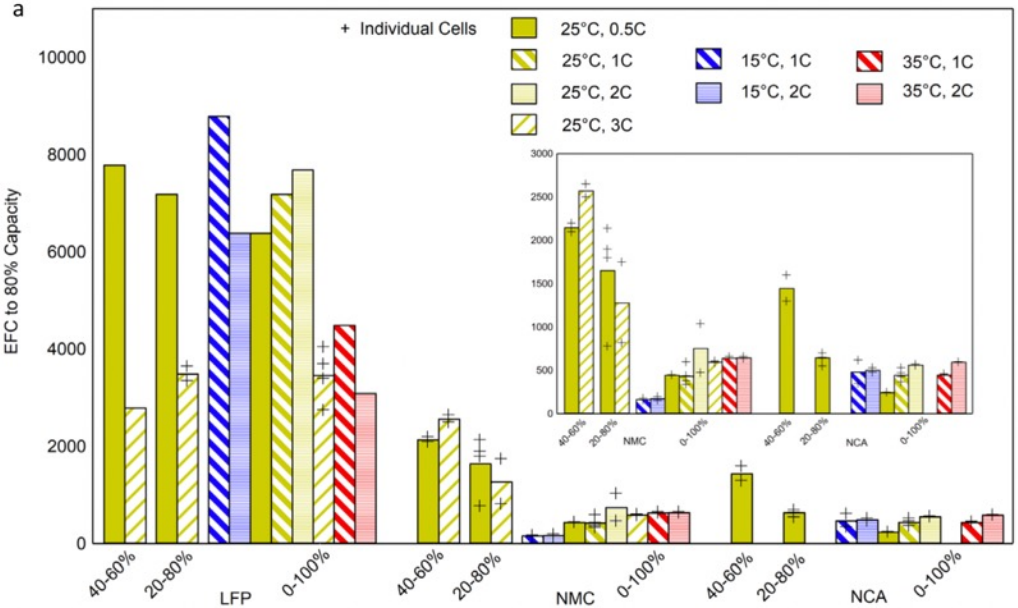
MEAN SQUARE ERROR (MSE) AND CORRELATION SCORE.

	Training MSE	Test MSE	Test Correlation
Ours(quadratic)	**0.044**	**0.042**	**0.74**
Ours(generic)	0.054	0.053	0.68
Threshold-based	0.088	0.070	0.57
MLP	0.047	0.096	0.34
RNN	0.092	0.109	0.27

Technology comparison

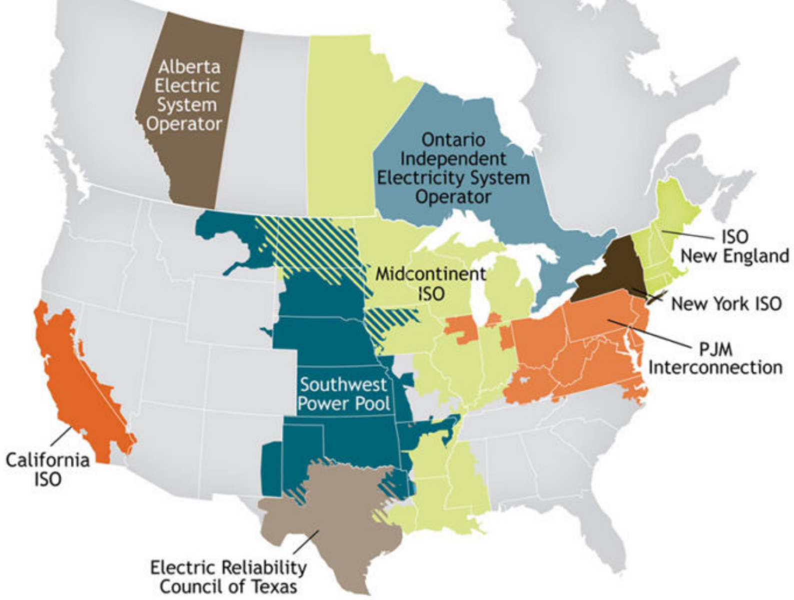
- Monetize value of different batteries (LFP, NMC, NCA) in grid services

Battery characteristics



Preger et al, *JES, 2020*

Market locations



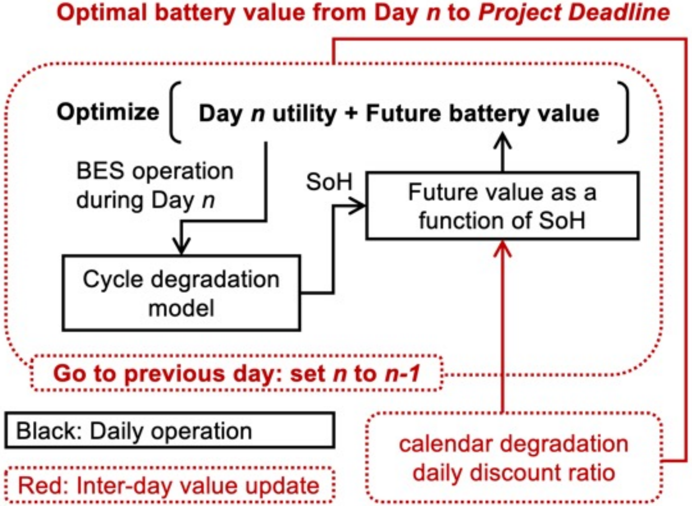
Dynamic valuation framework

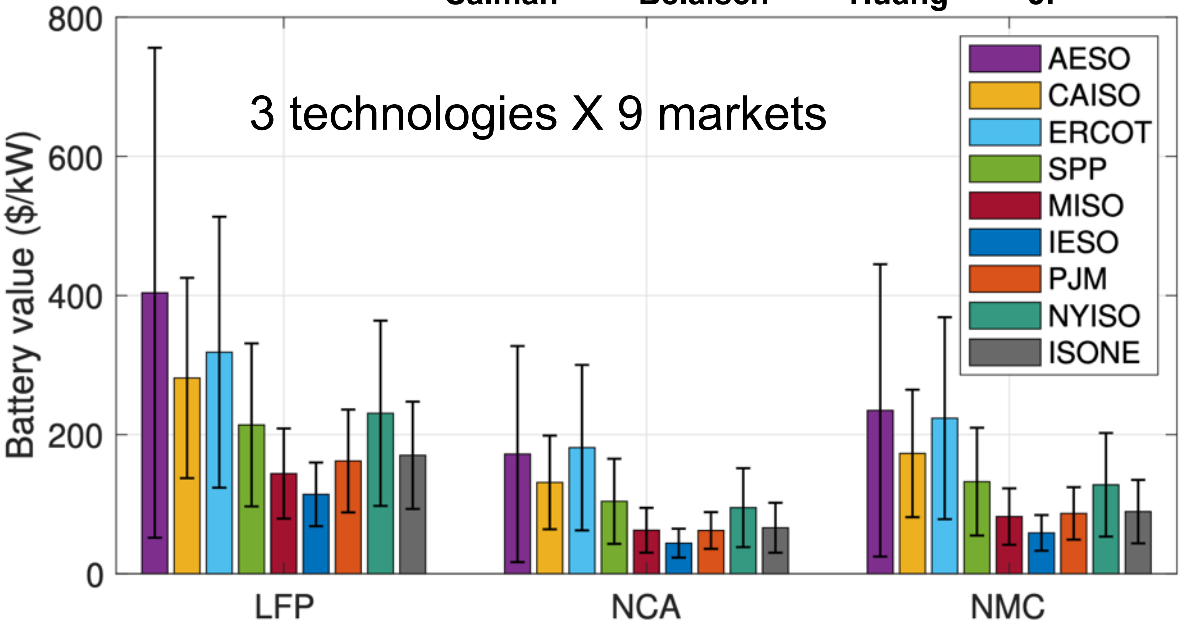
Salman et al, iEnergy, 2022

- Price battery technologies solely based on physical characteristics and market outcomes

Umar Salman | Sacha Belaisch | Danyi Huang | Zekun Ji

DP framework





Conclusions and ongoing/future works

- Energy storage integration requires multiple innovations on market design, participation solutions, monitoring, and valuation.
  - Storage market participation options have significant impact on system outcomes
  - Algorithmic and AI-assisted solutions are critical to understand and facilitate storage

- System/Market perspective:
  - More works are needed to understand more complex storage behaviors and their market impacts

- Storage perspective:
  - Better bidding algorithms considering changing market landscape
  - Accurate techno-economic analysis for emerging technologies

References – More at bolunxu@github.io

- **Storage market participation:**

Qin, X., Xu, B., Lestas, I., Guo, Y., & Sun, H. (2023). The role of electricity market design for energy storage in cost-efficient decarbonization. *Joule, 7(6)*.

- **Market design:**

Zheng, N., Qin, X., Wu, D., Murtaugh, G., & Xu, B. (2023). Energy storage state-of-charge market model. *IEEE Transactions on Energy Markets, Policy and Regulation*, *1*(1), 11-22.

- **Participation/bidding:**

Baker, Y., Zheng, N., & Xu, B. (2023). Transferable Energy Storage Bidder. *IEEE Transactions on Power Systems*.

- **Market monitoring:**

Bian, Y., Zheng, N., Zheng, Y., Xu, B., & Shi, Y. (2023). Predicting Strategic Energy Storage Behaviors. *arXiv preprint arXiv:2306.11872*.

- **Storage technology evaluation:**

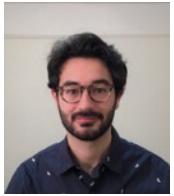
Salman, U., Belaish, S., Ji, Z., Huang, D., Zheng, N., & Xu, B. (2022). Comparing the economic value of lithium-ion battery technologies in the nine wholesale electricity markets in North America. *iEnergy*, *1*(3), 363-373.

Collaborators and Supports

Thank you!

Questions?





UC San Diego

UNIVERSITY OF CAMBRIDGE

Pacific Northwest NATIONAL LABORATORY

California ISO

清華大學 Tsinghua University

COLUMBIA UNIVERSITY DATA SCIENCE INSTITUTE

NSF

DEPARTMENT OF ENERGY · UNITED STATES OF AMERICA