Battery Operations in Electricity Markets: Strategic Behavior and Distortions

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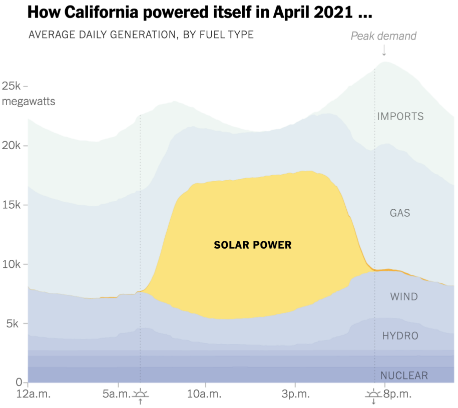
The Growth of Batteries in California



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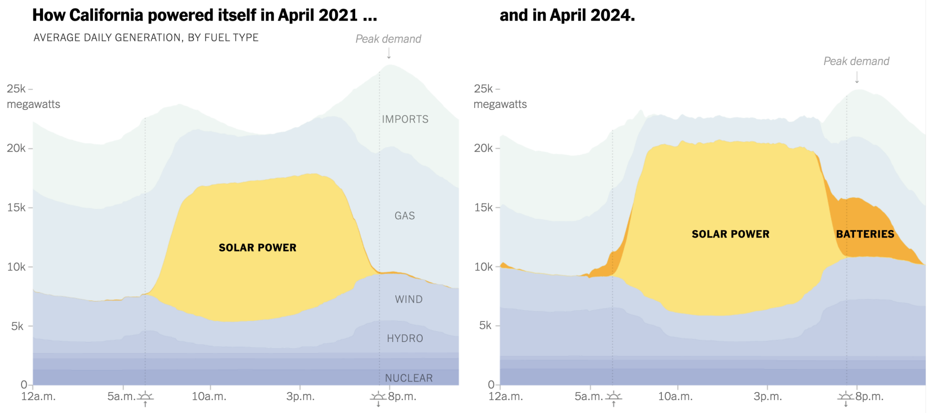

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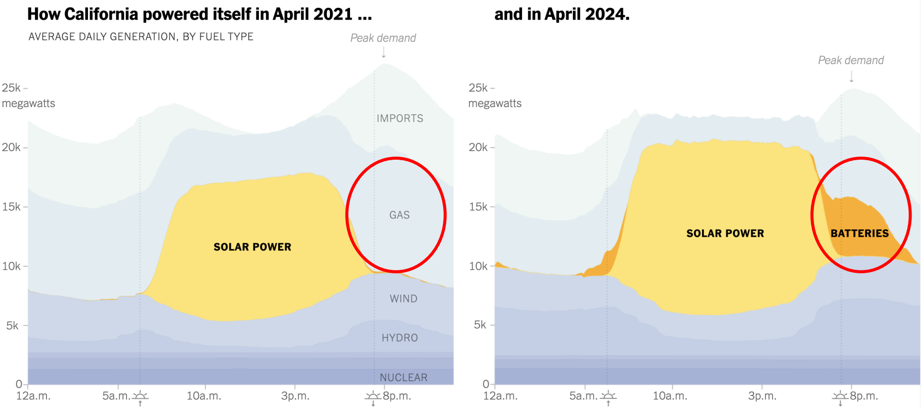
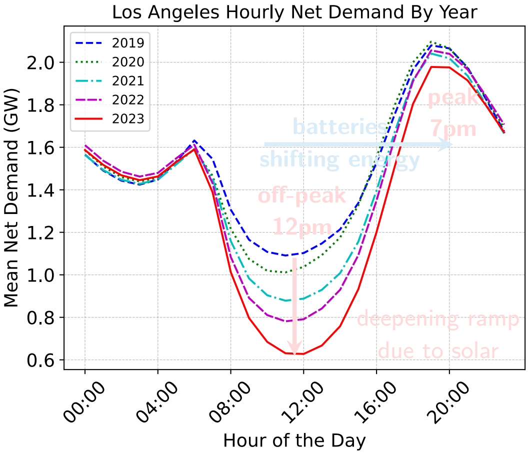


Los Angeles's "duck curve": supply-demand mismatch

$$\text{net demand} = \underbrace{\text{system demand}}_{\text{(constant)}} - \underbrace{\text{renewables}}_{\text{(increasing)}} = \text{conventional generators}$$



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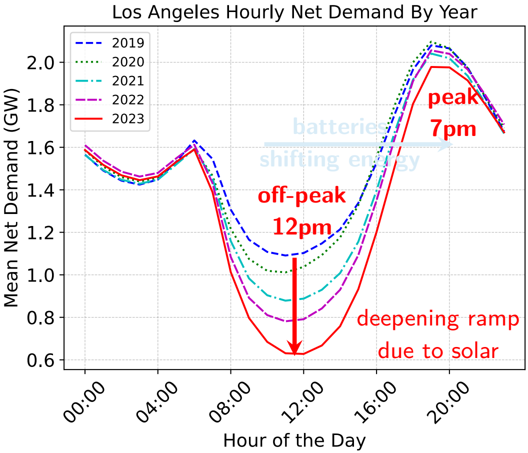

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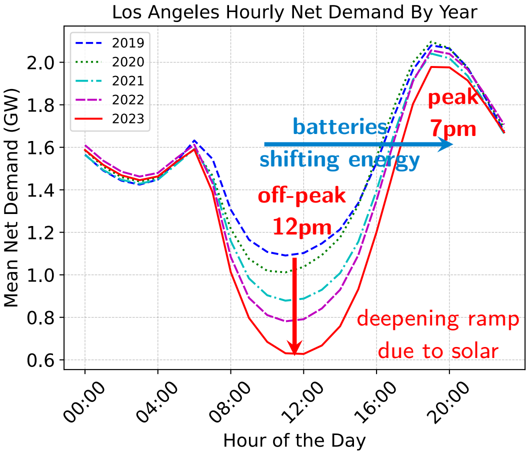

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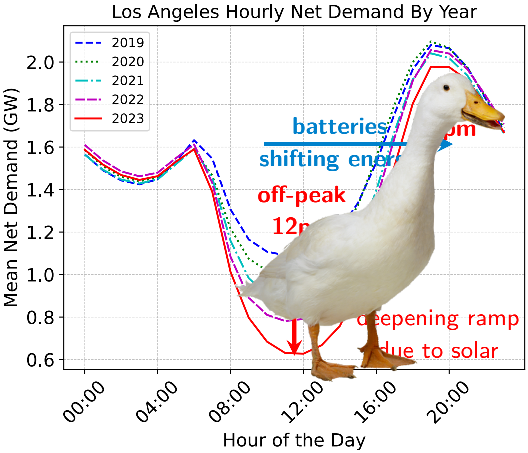

Research Questions

Batteries are no longer price takers, so ...

How do batteries operate in electricity markets?

How does the strategic behavior of decentralized batteries distort decisions compared to centralized batteries?

Electricity markets are highly complex.

Our contribution: a **tractable analytical model**
= economic intuition + rich enough to capture salient features.

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Three Operating Regimes

No Battery (NB)

"Status quo" benchmark.

Centralized Battery (CN)

Minimizing generation cost.

Decentralized Battery (DCN)

Maximizing battery profit.

Electricity Markets Clear in Two Stages

Day-Ahead Market (DA)

Real-Time Market (RT)

based on forecast

based on realized demand

(1) forward market reduces uncertainty

(2) slow generators take time to start and ramp up

demand must equal supply at all times

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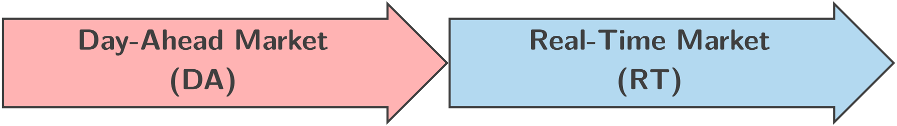

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THE BATTERY DECIDES DISCHARGES z IN DA AND RT

	Day-Ahead Market (DA)	Real-Time Market (RT)
T periods		
demand	$\underbrace{\mathbb{E}[D_1], \ldots, \mathbb{E}[D_T]}_{\text{DA demand (forecast)}}$	$\underbrace{D_1 - \mathbb{E}[D_1], \ldots, D_T - \mathbb{E}[D_T]}_{\text{RT residual demand}}$
decisions	$z_1^{DA}, \ldots, z_T^{DA}$	$\underbrace{z_1^{RT}(\cdot), \ldots, z_T^{RT}(\cdot)}_{\text{depending on realized demand history}}$

Discharge ($z > 0$) or charge ($z < 0$)

Constraints: net discharge is zero. $\sum_t z_t^{DA} = \sum_t z_t^{RT} = 0$.

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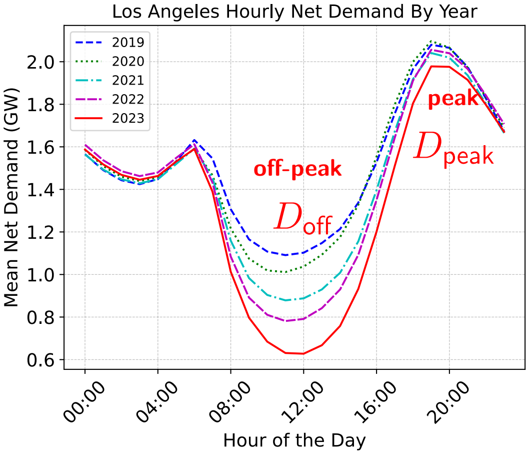
$T = 2$ Periods Captures the Duck Curve

$$(D_{\mathsf{peak}}, D_{\mathsf{off}}) \sim \pi$$



Market Clearing: Day-Ahead (DA) + Real-Time (RT)

Let p^{DA} = DA price, p^{RT} = RT price.

Assume **two types** of generators:

	cost CDF (mass of gens w/ cost $\leq p$)
"slow" (DA only, e.g. coal & nuclear)	$G_s(p) = (1 - k_f)G(p)$
"fast" (DA + RT, e.g. gas)	$G_f(p) = k_f G(p)$
	$k_f \equiv$ fraction of fast generators

For each time period t,

$$G_s(p_t^{DA}) + G_f(p_t^{DA}) = \mathbb{E}[D_t] - z_t^{DA} \quad \text{(DA)}$$

$$G_s(p_t^{DA}) + G_f(p_t^{RT}) = D_t - z_t^{DA} - z_t^{RT}(\cdot) \quad \text{(RT)}$$

supply from "slow" supply from "fast" net demand − battery discharge

This gives prices p_t^{DA}, p_t^{RT} in terms of battery decisions $z_t^{DA}, z_t^{RT}(\cdot)$.

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Generation Cost From DA+RT Supply Curves

Slow generators clear in DA at price p_t^{DA}.

Fast generators clear in RT at price p_t^{RT}.

$$\text{generation cost} = \sum_t \left(\int_{p \le p_t^{DA}} p dG_s(p) + \mathbb{E}\left[\int_{p \le p_t^{RT}} p dG_f(p) \right] \right)$$

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Battery Profit - from Energy Arbitrage

Decentralized battery chooses $z^{DA}, z^{RT}(\cdot)$ to maximize profit:

$$\text{profit} = p^{DA}_{\text{peak}}\, z^{DA}_{\text{peak}} + p^{DA}_{\text{off}}\, z^{DA}_{\text{off}} + \mathbb{E}\left[p^{RT}_{\text{peak}}\, z^{RT}_{\text{peak}} + p^{RT}_{\text{off}}\, z^{RT}_{\text{off}}\right]$$

Related Literature

- forward markets
  - Allaz and Vila (1993), Ito and Reguant (2016), You et al. (2019)
- batteries and renewables operations
  - investments, locations, intermittency, ownership models, ...
  - Sioshansi (2010, 2014), Kaps et al. (2023), Peng et al. (2021), Peura and Bunn (2021), Acemoglu et al. (2017), Wu et al. (2023), ...
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Results: Battery Behavior

Both the centralized and decentralized problems are quadratic infinite-dimensional problems.

We prove that both problems are **convex** and solve them in **closed-form**.

The DCN solution shows 3 types of distortions from the CN solution:

- quantity withholding
- shift from day-ahead to real-time
- reduction in real-time responsiveness

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Results: Battery Behavior

quantity withholding, shift to real-time, reduction in RT responsiveness.

Centralized Battery Discharge

$$z^{DA}_{\text{peak}} = \boxed{\frac{1}{2}(\mu_{\text{peak}} - \mu_{\text{off}})}$$

$$z^{RT}_{\text{peak}}(D_{\text{peak}}) = \frac{1}{2}(D_{\text{peak}} - \mu_{\text{peak}}) - \frac{1}{2}(\mu_{\text{off}|D_{\text{peak}}} - \mu_{\text{off}})$$

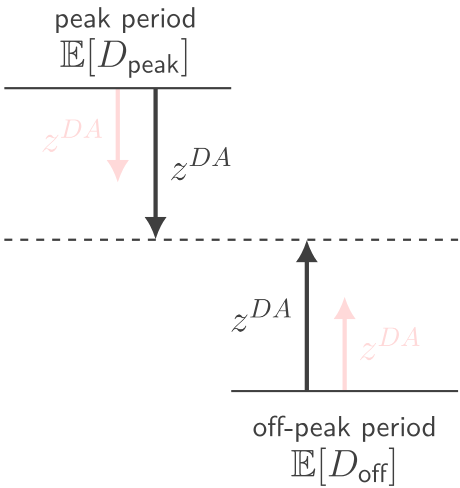
Decentralized Battery Discharge

$$z^{DA}_{\text{peak}} = \boxed{\frac{(2-k_f)}{2(4-k_f)}(\mu_{\text{peak}} - \mu_{\text{off}})}$$

$$z^{RT}_{\text{peak}}(D_{\text{peak}}) = \boxed{\frac{k_f}{2(4-k_f)}(\mu_{\text{peak}} - \mu_{\text{off}})} + \frac{1}{4}(D_{\text{peak}} - \mu_{\text{peak}}) - \frac{1}{4}(\mu_{2|D_{\text{peak}}} - \mu_{\text{off}})$$

Distortion 1: Quantity Withholding

centralized battery
equates net demands
from two periods
BUT THEN
two periods have the
same price
$=$ zero battery profit



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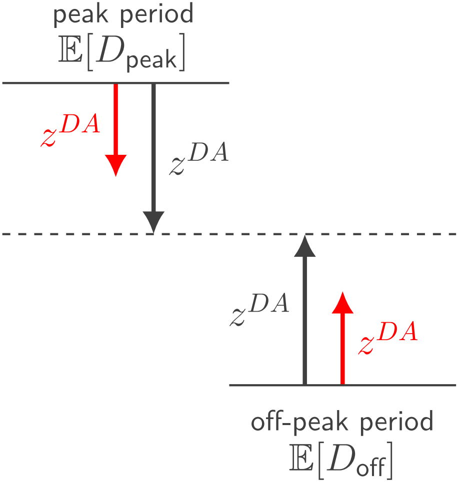

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Distortion 2: Shift from Day-Ahead to Real-Time

Structural consequence of **sequential market clearing**.

Simplest case: no randomness, identical markets with price function $P(\cdot)$.

Maximize profit $= z^{DA}P(z^{DA}) + z^{RT}P(z^{DA} + z^{RT})$.

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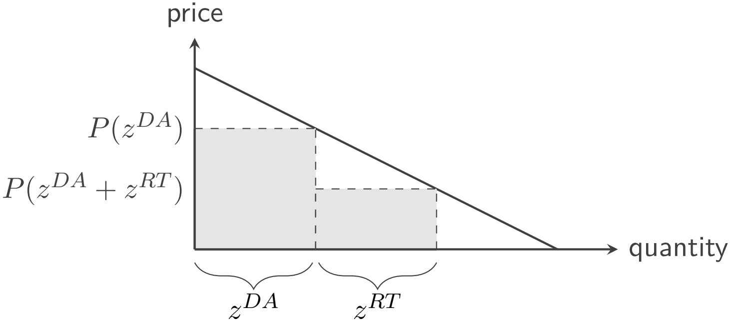
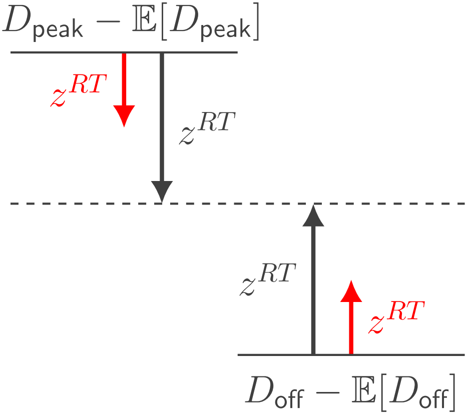


Distortion 3: Reduction in Real-Time Responsiveness

Same kind of tension between **centralized** and **decentralized** regimes, except the "quantity withholding" is on *real-time residual demand*.



Results: Generation Costs

Define the Price of Anarchy (PoA) as an incentive misalignment metric:

$$\text{PoA} = \frac{\text{GenCost}(\text{NoBattery}) - \text{GenCost}(\text{Centralized})}{\text{GenCost}(\text{NoBattery}) - \text{GenCost}(\text{Decentralized})}$$

PoA ≥ 1. Lower PoA means better alignment.

Theorem

Assume the demand is jointly normal, then

- PoA $\in [9/8, 4/3]$ for every market parameter. (12.5% to 33.3%)
- PoA is decreasing in k_f.

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Calibration with Los Angeles and Houston

If a battery achieves local monopoly, distortions can be significant!

e.g. Los Angeles batteries (Apr'24): **355 MW**, 40 MW, fringe $\sim$27 MW

	PoA	distortion types		
		quantity withholding	shift from DA to RT	reduction in RT responsiveness
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$$\text{quantity withholding} = 1 - \frac{\text{total DCN discharge}}{\text{total CN discharge}}$$

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	PoA	distortion types		
		quantity withholding	shift from DA to RT	reduction in RT responsiveness
Los Angeles	**15%**	35%	47%	50%
Houston	**25%**	40%	33%	50%

$$\text{shift from DA to RT} = \frac{\text{RT DCN discharge}}{\text{total (DA+RT) DCN discharge}}$$

Calibration with Los Angeles and Houston

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$$\text{reduction in RT responsiveness} = 1 - \frac{\text{RT “random” DCN discharge}}{\text{RT “random” CN discharge}}$$

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- We develop a **tractable analytical model** quantifying different forms of battery behavior in terms of market fundamentals.
- Incentive misalignment (PoA) from 3 forms of distortions
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  - shift from day-ahead to real-time
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- We **calibrate** the model to Los Angeles and Houston and show that *incentive misalignment* is **practically significant**.
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