Electricity dispatch and pricing using agent decision rules

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Joint work with Michael Ferris and Jacob Mays

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New Zealand welcomes first big battery to national grid

New Zealand's transition to a renewable energy future has taken a significant step forward with the nation's first grid-scale battery energy storage project now offering injectable reserves to the electricity market for the first time.

MARCH 13, 2024 DAVID CARROLL

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Image: Wel Networks

Figure: Rotohiko BSS [PV Magazine: March 13, 2024.]

Consent granted for large solar power station at Ruakākā in Northland

12:38 pm on 30 September 2024

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Meridian's battery energy storage site (BESS) under construction at Marsden Point. Photo: Supplied / Meridian

Figure: Ruakaka BSS [RNZne: March 13, 2024.]

01 July 2024

Contact to develop a grid-scale 100 MW battery in Auckland

- **Contact's first renewable project in Auckland to start immediately.**
- **Tesla selected as battery energy storage system supplier, the first Megapack 2 XL project in New Zealand.**
- **The battery system will discharge stored energy at a split second to significantly improve security of energy supply to New Zealanders.**
- **The project will be operational by March 2026.**

Contact Energy (Contact) has answered calls for more energy storage by contracting with Tesla to build a 100-megawatt (MW) battery, which will provide enough electricity to meet peak demand over winter for 44,000 homes for over two hours.

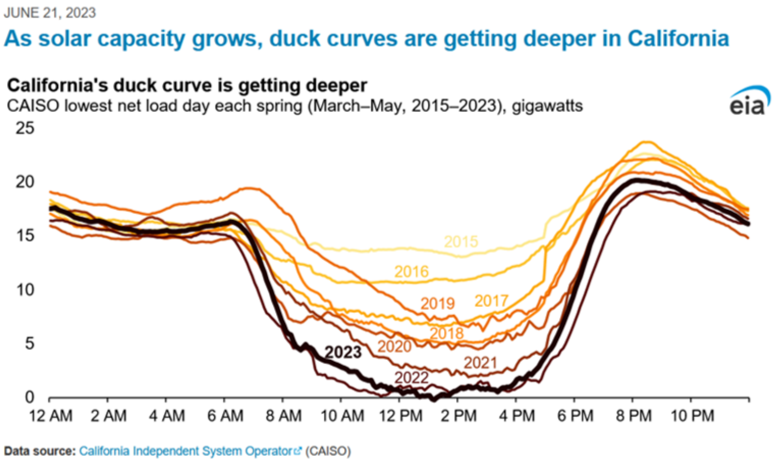

Figure: CAISO Duck curves [California Independent System Operator]

Self dispatch versus central dispatch

Self dispatch

- Battery forecasts/models prices and solves an optimization problem to maximize revenue from storage.
- System operator forecasts exogenous battery operation as part of net demand.

Central dispatch

- Battery provides supply/demand curve defining what battery will sell/buy as price increases.
- System operator co-optimizes SPD using endogenous battery operation

Supply curves are state dependent

- The marginal cost of battery charge/discharge in period t depends on the current level of charge, and (random) prices in $t+1, t+2, \ldots$.
- Optimal price-taking offer can be computed by each battery using stochastic dynamic programming.
- Predispatch SPD:
  - solves deterministic problem with forecast demand and offers in $t+1, t+2, \ldots$ and publishes prices and dispatch.
  - Batteries use deterministic prices and state of charge to update offers.
- Make this more efficient using agent decision rules (ADRs)

Agent decision rules (ADRs)

- An agent decision rule (ADR) is a mapping from any known parameter of the stage t problem, and a's state (storage) at end of t, to an energy offer in period t.
- An agent Bellman function (ABF) for agent a in period t is a function $W_a^t(y)$ that expresses the expected future benefit to a of being in state y at the end of period t.
- We can define an ADR for battery a using observed price $\pi(t)$ and its initial storage y_a and ABF W_a^t. Choose discharge u and charge v so as to:

$$\begin{aligned} \max_{u,v} \quad & \pi(t)(u - v) + W_a^t(y_a - u + \eta v) \\ \text{s.t.} \quad & 0 \leq y_a - u + \eta v \leq E_a \end{aligned}$$

Single-node electricty dispatch with ABFs

Given ABFs for battery agents $\mathcal{B}$, and state of charge $y(t-1)$:

$$\begin{aligned}
\mathrm{ADR}(t)\text{: min} \quad & \sum_{a\in\mathcal{G}} c_a x_a(t) + Lz(t) - \sum_{a\in\mathcal{B}} W_a^t(y_a) \\
\text{s.t.} \quad & \sum_{a\in\mathcal{G}} x_a(t) + \sum_{a\in\mathcal{B}} u_a(t) - \sum_{a\in\mathcal{B}} v_a(t) + z(t) = d(t), \quad [\pi(t)] \\
& x_a(t) \in \mathcal{X}_a(x_a(t-1)), \quad a \in \mathcal{G}, \\
& (y_a(t), u_a(t), v_a(t)) \in \mathcal{Y}_a(y_a(t-1)), \quad a \in \mathcal{B}, \\
& z(t) \in [0, d(t)].
\end{aligned}$$

New dispatch process with ADRs

- Generator agents provide system operator with marginal costs.
- Battery agent *a* provides system operator with ADR defined by increasing concave ABF W_a^t.
- System operator solves single-stage problem ADR(t) and computes dispatch and system marginal price $\$\pi(t)/$MWh.
- Generator is paid $\pi(t)$ per MWh
- Battery is paid $\pi(t)$(charge - discharge).

Remarks

- ADR(t) is a deterministic convex optimization problem (assuming no unit commitment).
- This means price $\pi(t)$ gives budget balance for system operator (i.e. revenue adequacy).
- Price $\pi(t)$ defines a perfectly competitive equilibrium for stage t, so agents recover costs.
- Does dispatch problem ADR(t) yield social optimum?
- If all agents and system operator agree on probability distribution of future demand then ADRs can recover social optimum.

How agents might choose an ADR

- SDDP defines (approximate) system Bellman function $C^t(y)$ at stage t (using cuts).
- Suppose given $y(t-1)$ the optimal dispatch with $C^t(y)$ yields state of charge $y^*(t)$.
- Given $y(t-1)$ agent a makes a forecast $\tilde{y}^t$ of $y^*(t)$.
- Propose that each agent $a \in \mathcal{B}$ offers ADR:

$$\tilde{W}_a^t(y_j) = -C^t(y_j, \tilde{y}_{-j}^t).$$

ADRs can be system optimal

Theorem

Suppose given $y(t-1)$, that each agent a makes a perfect forecast $\tilde{y}^t$ of $y^*(t)$ (for example they might all solve SDDP model with the same shared data). Then

1. the solution for ADR(t) using $\sum_a \tilde{W}_a^t(y_a)$ is optimal for EP(t) with $C^t(y)$;
2. prices from EP(t) and the solution to ADR(t) defines a perfectly competitive equilibrium where all agents optimize profit in period t at system prices accounting for their ADR.

Example: one battery, one ramping generator

$x(t)$ = dispatch of generator in period t;

$\bar{x}$ = dispatch of generator in period $t-1$;

$y(t)$ = storage in battery at end of period t;

$\bar{y}$ = storage in battery at end of period $t-1$;

u = discharge from battery in period t;

v = charge input to battery in period t;

$$\mathcal{X}(\bar{x}) = \{x \mid 0 \le x \le q, x - \bar{x}_i \le \rho_i, \bar{x} - x \le \sigma_i\},$$

$$\begin{aligned}\mathcal{Y}(\bar{y}) = \{(y,u,v) | 0 \le y \le E, 0 \le u \le r, 0 \le v \le s, \\ y = \bar{y} - u + \eta v\}.\end{aligned}$$

An example: one battery, one ramping generator

Assume $T = 24$, $c_i(x) = 70.0x$, $\sigma = \infty$. Other parameters are as follows.

$q = 70.0$	$E = 30.0$	$\eta = 0.8$
$r = 10.0$	$s = 10.0$	$\rho = 10.0$
$L = 500.0$	$x^0 = 35.0$	$y^0 = 4.0$

Table: Parameter values for example

Example demand

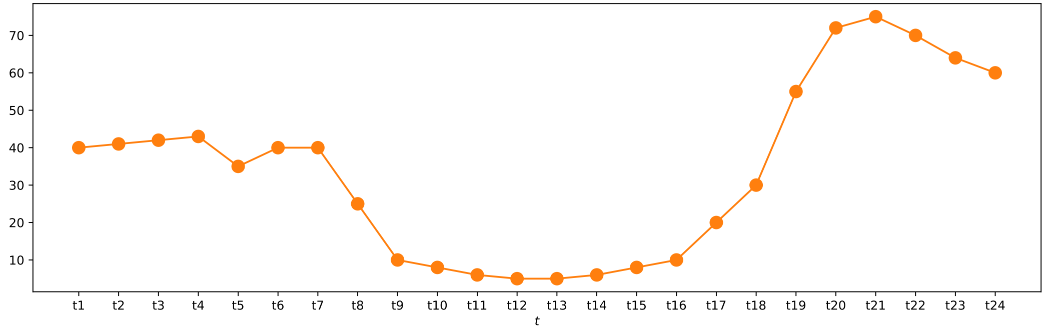

Figure: Example values of $d(t)$ for $t = 1, 2, \ldots, 24$. We add stagewise independent random noise chosen from -4.0, -2.0, 0.0, 2.0, 4.0 with equal probabilty

Experiment with imperfect forecast

- In battery example, suppose we solve SDDP, and simulate over many sample paths. This gives expected cost $=57{,}148 \pm 21$.
- Let $(\tilde{x}^t, \tilde{y}^t)$ denote average values of generation and average values of battery storage at each stage.
- We then simulate the solution of ADR(t) using the system Bellman function approximation:

$$\tilde{V}^t(x) + \tilde{W}^t(y)$$

- Simulated policy gives $58{,}082 \pm 76$. Some social optimality is lost since $(\tilde{x}^t, \tilde{y}^t) \neq (x^*(t), y^*(t))$ (varying with each sample path).

“To do” list

- Dispatch must also meet many side constraints (e.g. reserve).
- Agents can hold a portfolio of technologies.
- Agents have different views of the future.
- Agents have different risk preferences.
- Agents may be strategic: i.e. not reveal their true future costs.

The End

Any questions?

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For the paper go to https://www.epoc.org.nz/papers/ADRv2.pdf