Electricity dispatch and pricing using agent decision rules

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The Economist

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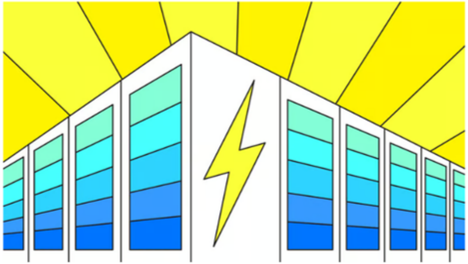
Business | Charging forward

Clean energy's next trillion-dollar business

Grid-scale batteries are taking off at last



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Sep 1st 2024

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Figure: Battery production boom [Economist: September 1, 2024.]

Energy & Environment Energy Transitions Renewables & Advanced Energy United States and Canada

New Atlanticist | May 13, 2024

California's battery boom is a case study for the energy transition

By Joseph Webster

California is the country's largest and most mature solar market, but it's also changing in important ways. On April 25, California marked a major milestone, as it became the first state to deploy 10 gigawatts (GW) of battery storage capacity. This large-scale deployment of lithium-ion storage batteries is leading to lower solar "curtailment," or when electricity generation is suppressed due to price signals or physical oversupply. Curtailment is a problem because it means solar power stations, for example, are producing less electricity than they could, contributing less to the overall energy mix than they otherwise might.

Figure: CAISO battery boom [New Atlanticist, May 2024]

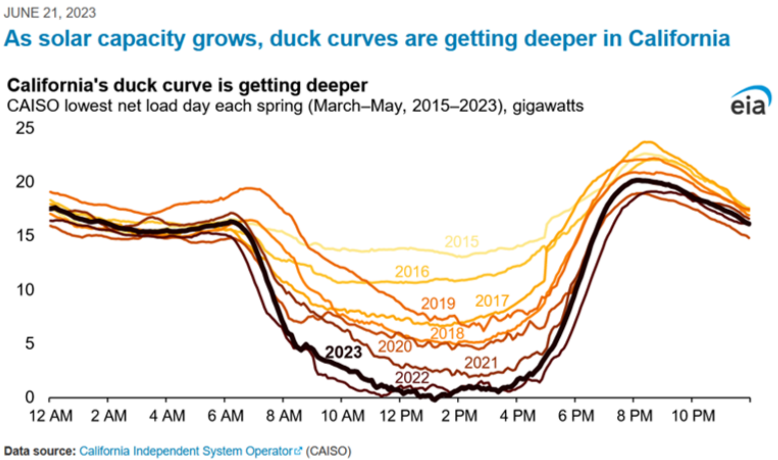

Figure: CAISO Duck curves [California Independent System Operator]

What is the problem with this?

- Renewable energy (wind and solar) are growing in scale.
- Net demand is difficult to forecast and can be volatile.
- Grid-connected storage is increasing to deal with this.
- System operators solve a multiperiod dispatch problem to schedule generators and batteries and compute prices.
- When dispatch problem is a mixed integer program, energy prices often need additional uplift payments.
- Uplift can be to make whole, and/or to compensate for lost opportunity cost.
- When convex dispatch model updated with a rolling horizon, prices also incur lost opportunity cost. [Hogan,2020; Biggar & Hesamzadeh,2022]

Can stochastic programming help?

- Two-stage stochastic dispatch and pricing have been proposed by various authors. [Wong & Fuller,2007; Pritchard et al,2010]
- System operator and all market agents assume the same probability distribution for second-stage events.
- Optimal dispatch gives first-stage decision and dispatch and price for each scenario.
- Generators recover costs in expectation. System operator is budget balanced in every scenario. [Cory-Wright et al,2018]

What about multistage stochastic programming?

- Multistage stochastic dispatch and pricing now being proposed.
  - Models formulated and solved in a scenario tree of random outcomes.
  - Assumes consensus on system operator's scenarios.
  - Uplift payments can be required for lost opportunity costs.
- This paper: Propose single-period dispatch, but use agent decision rules defined by a dynamic programming policy.

Outline

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Example of multiperiod dispatch and pricing

Example of stochastic dispatch and pricing

Agent decision rules

Economic dispatch example

$x_i(t)$ = dispatch of generator i in period t;

$\bar{x}_i$ = dispatch of generator i in period $t \quad 1$;

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

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

u_j = discharge from battery j in period t;

v_j = charge input to battery j in period t;

$$X_i(\bar{x}) \quad = \quad fx \, j \, 0 \quad x \quad q_i, x \quad \bar{x}_i \quad r_i, \bar{x}_i \quad x \quad s_i g,$$

$$Y_j(\bar{y}) \quad = \quad f(y, u, v) j 0 \quad y \quad E_j, 0 \quad u \quad r_j, 0 \quad v \quad s_j,$$
$$y = \bar{y}_j \quad u + h_j v g.$$

Economic dispatch and pricing: period t

$$\mathrm{EP}(t): \min \sum_{i \in G} c_i(t) x_i(t) + L z(t)$$

$$\text{s.t.} \quad \sum_{i \in G} x_i(t) + \sum_{j \in J} u_j(t) - \sum_{j \in J} v_j(t) + z(t) = d(t) + w(t),$$

$$x_i(t) \in X_i(x(t-1)), \quad i \in G,$$

$$(y_j(t), u_j(t), v_j(t)) \in Y_j(y(t-1)), \quad j \in J,$$

$$w(t) \geq 0, z(t) \in [0, d(t)].$$

Multiperiod economic dispatch

$$\text{EP: } \min \sum_{t=1}^{T} \left(\sum_{i \in G} c_i(t) x_i(t) + L z(t) \right)$$

$$\text{s.t. } \sum_{i \in G} x_i(t) + \sum_{j \in J} u_j(t) - \sum_{j \in J} v_j(t) + z(t) = d(t) + w(t),$$

$$x_i(0) = x^0, \quad x_i(t) \in X_i(x(t-1)), \quad i \in G,$$

$$y_j(0) = y^0, \quad (y_j(t), u_j(t), v_j(t)) \in Y_j(y(t-1)), \quad j \in J,$$

$$w(t) \geq 0, z(t) \in [0, d(t)], \quad t = 1, 2, \ldots, T.$$

An example: one battery, one generator

Assume $T = 24$, $c(t) = 7.0$, $s = ¥$. Other parameters are as follows.

$q = 70.0$	$E = 8.0$	$h = 0.8$
$r = 10.0$	$s = 10.0$	$r = 10.0$
$L = 35.0$	$x^0 = 35.0$	$y^0 = 4.0$

Table: Parameter values for example

Example demand

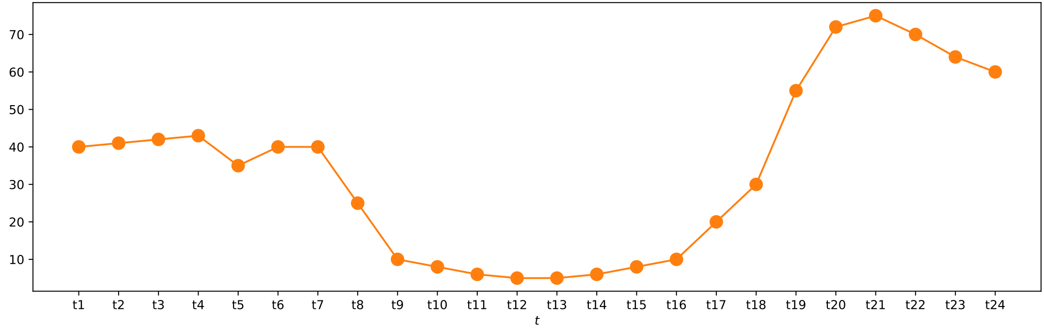

Figure: Values of $d(t)$ for $t = 1, 2, \ldots, 24$.

Example solution

The optimal solution to EP has cost 6062, with optimal dispatch and battery charge shown in Figure 5.

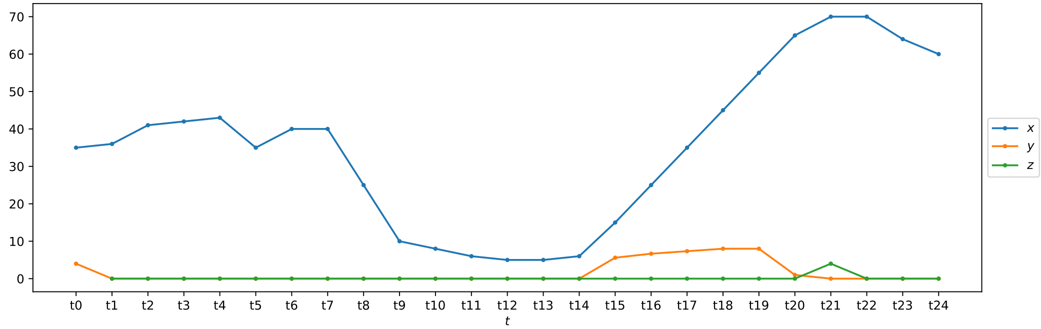

Figure: Solution of DP showing generation x, battery charge y and lost load z for $t = 1, 2, \ldots, 24$.

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Stochastic model uses a scenario tree.

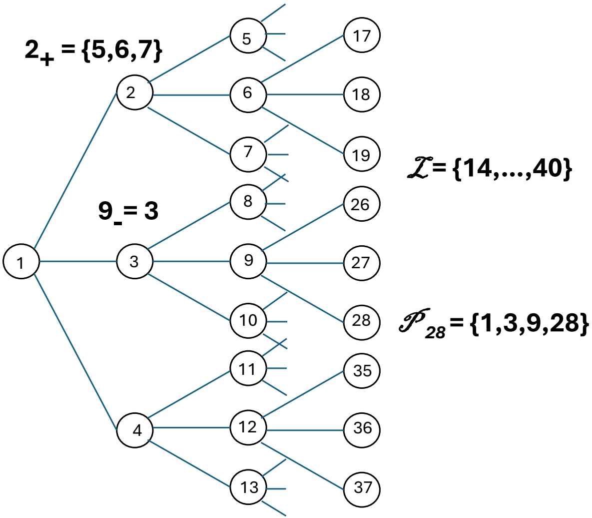

Figure: Scenario tree. Here n is the parent of n, and L is the set of leaf nodes.

Stochastic economic dispatch in scenario tree

$$\text{SP:}\quad \min \sum_{n\in N} P(n)\left(\sum_{i\in G} c_i(n)x_i(n) + Lz(n)\right)$$

$$\text{s.t.}\quad \sum_{i\in G} x_i(n) + \sum_{j\in J} u_j(n) - \sum_{j\in J} v_j(n) + z(n) = d(n) + w(n), n \in N,$$

$$x_i(1) = x_0, \quad x_i(n) \in X_i(x(n^-)), \quad \forall i, n \in N \setminus \{1\},$$

$$y_j(1) = y_0, \quad (y_j(n), u_j(n), v_j(n)) \in Y_j(y(n^-)), \forall j, n \in N \setminus \{1\},$$

$$w(n) \ge 0, z(n) \in [0, d(n)], \quad n \in N.$$

Optimal dispatch gives energy prices p

Dual variables on demand constraints are $P(n)p(n)$ that decouple SP into agent problems. [Ferris & P., 2022]

$$\text{GP}(i): \quad \max \sum_{n \in N} P(n)(p(n) - c_i(n))x_i(n))$$
$$\text{s.t.} \quad x_i(1) = x_0, \quad x_i(n) \in X_i(x(n_-)), \forall i, n,$$

$$\text{CO}: \quad \max \sum_{n \in N} P(n)(p(n) - L)z(n)$$
$$\text{s.t.} \quad 0 \le z(n) \le d(n), \forall n.$$

$$\text{BP}(j): \quad \max \sum_{n \in N} P(n)p(n)(u_j(n) - v_j(n))$$
$$\text{s.t.} \quad y_j(1) = y_0, \quad (y_j(n), u_j(n), v_j(n)) \in Y_j(y(n_-)), \forall j, n.$$

Drawbacks of scenario trees

- The scenario tree reflects the system operator view of the future and is not a consensus of market participant views, who prefer to "put their money where their mouths are";
- Even with a shared view, the future will (almost surely) not be a scenario in the tree;
- Solving scenario-based problems is impossible at scale;
- With stagewise independent or Markov noise we can use SDDP [SDDP.jl: Dowson and Kapelevich,2021];
- Prices p from SDDP models are not stagewise independent: agents can't use dynamic programming.[Barty et al, 2010]

Rolling-horizon dispatch

Tractability dictates limited lookahead. System operator updates scenario trees using a rolling horizon.

Set $n = 1$ and repeat:

1. Create scenario tree with root node n.
2. Solve SP in tree with root node n.
3. Dispatch from node n is implemented.
4. Agents pay (are paid) $p(n)$ for energy in node n.
5. Child node m 2 n_+ is realized.
6. Set $n = m$.

Problems with rolling-horizon prices

- Even in single scenario case, the prices computed from a rolling horizon implementation might be inconsistent. [Hogan,2020]
- This means the dispatch and prices we record do not form a competitive equilibrium in a perfect foresight model.
- Allowing variation of previous dispatch (in each model run) gives prices and quantities that yield an equilibrium. [Hua et al,2019]
- Inconsistency persists in scenario tree model. [Cho and Papavasiliou,2023]

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Example of multiperiod dispatch and pricing

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Agent decision rules

Agent decision rules

- In social planning problem, SDDP gives a socially optimal decision rule defined by cutting planes.
- Each stage problem has a solution with future cost function defined by these cuts.
- Decompose system optimal solution into agent stage problems with agent decision rules (ADRs).
- An ADR for agent a in period t is a function of any parameter of the stage t problem, and a's dispatch (storage) at end of t.
- An ADR for agent a expresses the expected future benefit to a of being in a given state at the end of each period.

System stage problem and expected future benefit

$$\mathrm{EP}(t):\ \min \sum_{i\in G} c_i(t)x_i(t) + Lz(t) + \hat{V}^{t}(x,y)$$

$$\text{s.t.}\ \sum_{i\in G} x_i(t) + \sum_{j\in J} u_j(t) - \sum_{j\in J} v_j(t) + z(t) = d(t) + w(t),$$

$$x_i(t) \in X_i(x(t-1)),\quad i \in G,$$

$$(y_j(t), u_j(t), v_j(t)) \in Y_j(y(t-1)),\quad j \in J,$$

$$w(t) \ge 0,\ z(t) \in [0, d(t)].$$

Expected future benefit as ADRs

$$\text{ADR}(t): \min \sum_{i \in G} c_i(t) x_i(t) + Lz(t) - \sum_{i \in G} V_i^t(x_i) - \sum_{j \in J} W_j^t(y_j)$$

$$\text{s.t.} \sum_{i \in G} x_i(t) + \sum_{j \in J} u_j(t) - \sum_{j \in J} v_j(t) + z(t) = d(t) + w(t),$$

$$x_i(t) \in X_i(x(t-1)), \quad i \in G,$$

$$(y_j(t), u_j(t), v_j(t)) \in Y_j(y(t-1)), \quad j \in J,$$

$$w(t) \geq 0, z(t) \in [0, d(t)].$$

Dispatch process for generators and batteries

- Generator agents $i \in G$ provide system operator with marginal costs $c_i(t)$.
- Generator agents $i \in G$ provide system operator with ADR defined by V_i^t.
- Battery agents $j \in J$ provide system operator with ADR defined by W_j^t.
- System operator solves single-stage problem ADR(t) and computes dispatch and system marginal price $p(t)$.
- Generator is paid $p(t)x_i(t)$.
- Battery is paid $p(t)(u_j(t) - v_j(t))$.

Remarks

- Dispatch problem is a deterministic convex optimization problem.
- This means prices give budget balance for system operator.
- Prices define a perfectly competitive equilibrium, so agents recover costs.
- Does dispatch problem ADR(t) yield social optimum?
- Depends on the ADRs used...

ADRs and system value function (deterministic case)

- SDDP produces cuts defining $\hat{V}^t(x, y)$ for system optimum.
- Given $(x(t-1), y(t-1))$, system optimal dispatch with $\hat{V}^t(x, y)$ yields $(x(t), y(t))$.
- Agent a makes a forecast $(\tilde{x}^t{}_{-a}, \tilde{y}^t{}_{-a})$ of $(x_{-a}(t), y_{-a}(t))$.
- Agents $i \in G$ and $j \in J$ then can offer ADRs:

$$\tilde{V}_i^t(x_i) = \hat{V}^t(x_i, \tilde{x}^t{}_{-i}, \tilde{y}^t),$$

$$\tilde{W}_j^t(y_j) = \hat{V}^t(\tilde{x}^t, y_j, \tilde{y}^t{}_{-j}).$$

ADRs can be system optimal (deterministic case)

Theorem

If given $(x(t-1), y(t-1))$, each agent a makes a perfect forecast $(\tilde{x}^t{}_{-a}, \tilde{y}^t{}_{-a})$ of $(x_{-a}(t), y_{-a}(t))$ then

1. the solution for ADR(t) using $\sum_{i \in G} \tilde{V}_i^t(x_i) + \sum_{j \in J} \tilde{W}_j^t(y_j)$ is optimal for EP(t) with $\hat{V}^t(x, y)$;
2. prices from EP(t) and the solution to ADR(t) defines a perfectly competitive equilibrium where all agents make non-negative return in period t accounting for their ADR;

Example problem with random demand

Figure: Stagewise independent demand realizations for example.

System optimum has (est.) expected cost 6109.51 10.85.
Deterministic optimum has (est.) expected cost 6226.37 10.809.
(Crude) ADR optimum has (est.) expected cost 6208.27 9.17.

Solutions simulated in expected demand

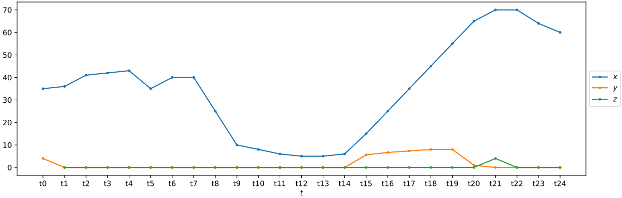

Figure: Generation x, battery charge y and lost load z for deterministic ADR.

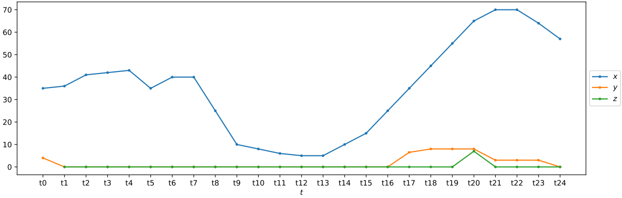

Figure: Generation x, battery charge y and lost load z for crude stochastic ADR.

Remarks

- Assuming perfect competition and complete markets, there exist ADRs that recover system optimality.
- Crude ADRs seem to perform well even when based on poor forecasts.
- ADRs enable agents to put “money where their mouths are”.
- ADRs are easy to implement, and can build in some system operator look-ahead in nonconvex settings.
- Questions remain about ADRs if agents exercise market power.

The End

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

Extensions

- Supply functions offers are simple ADRs.
- Transmission system can be included in dispatch.
- Pumped storage is same as a battery.
- Dispatchable demand is a demand function bid ADR.
- Flexible demand can shift a task in time.
- Reserve offers as ADRs.
- Hydroelectric reservoirs?
- Frequency regulation?
- Unit commitment?

Example problem with random demand

Figure: Stagewise independent demand realizations for example.

Plot of prices from optimal policy

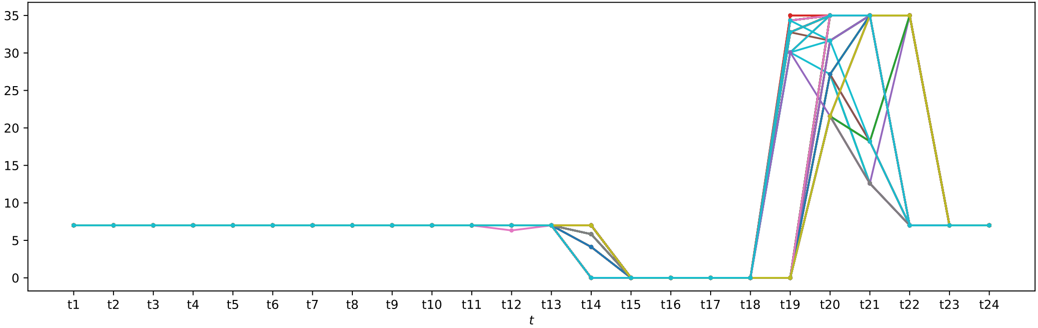

Figure: System marginal prices from 100 simulations of optimal stochastic policy computed using SDDP.jl.

ADR from Cournot game between storage and thermal plant

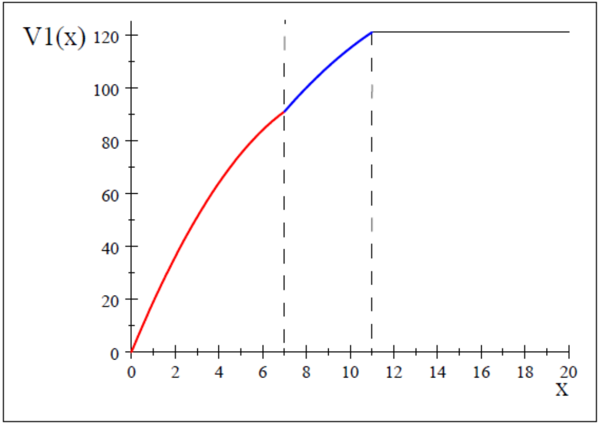

Figure: ADR from Cournot game [Crampes & Moreaux, 2001]