Electricity dispatch and pricing using agent decision rules

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EPRG, Cambridge, October 15, 2024.

Preamble

Business | Charging forward

Clean energy's next trillion-dollar business

Grid-scale batteries are taking off at last

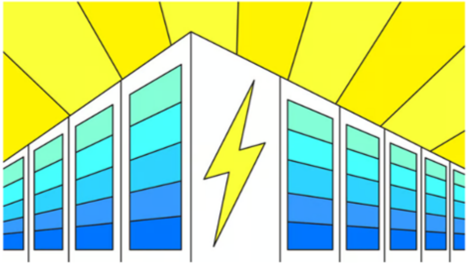

ILLUSTRATION: ROSE WONG

Sep 1st 2024

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Figure: Economist: September 1, 2024.

Preamble

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.

Preamble

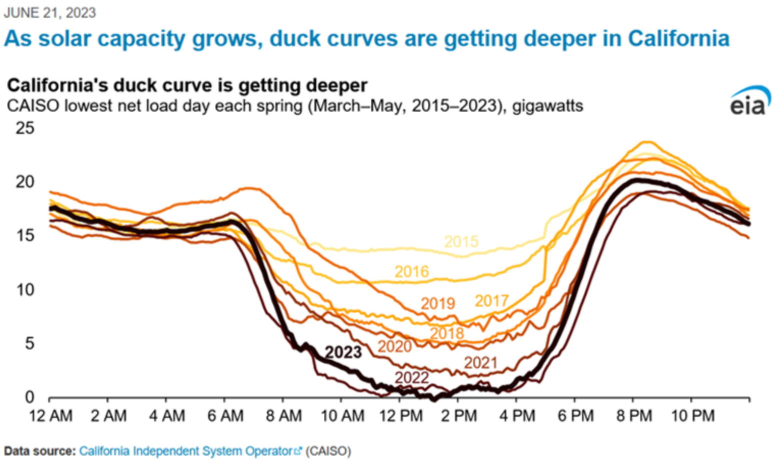

Figure: CAISO Duck curves.

Preamble

- Renewable energy (wind and solar) growing in scale.
- Grid-connected storage increasing.
- Stochastic multiperiod dispatch and pricing being proposed.
  - Pricing rules for minimizing uplift payments.
  - Pricing the option value of storage.
  - Consistency of prices from multiperiod solutions.
  - Consensus on system operator's scenarios?
- Proposal: return to single-period dispatch but use decision rules.

Outline

Stochastic dispatch and pricing

Agent decision rules

Extensions

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Economic dispatch: notation

$x_i(t)$ = 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;

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

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

Economic dispatch and pricing: period t

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

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

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

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

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

Multiperiod economic dispatch

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

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

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

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

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

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

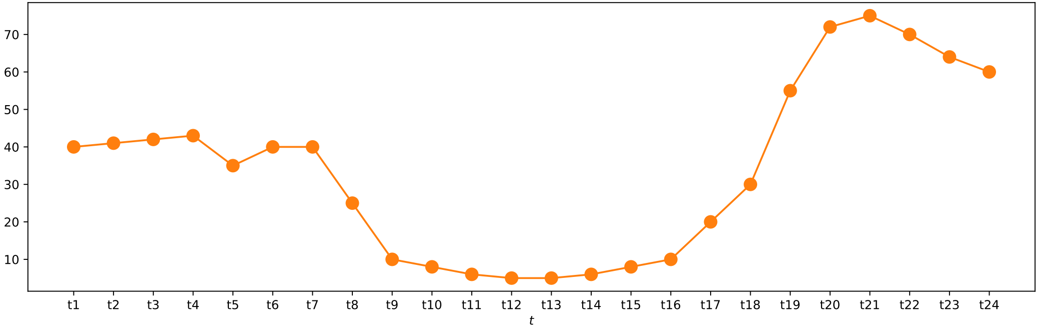

Figure: Values of $d(t)$ for $t = 1, 2, \ldots, 24$.

Example solution

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

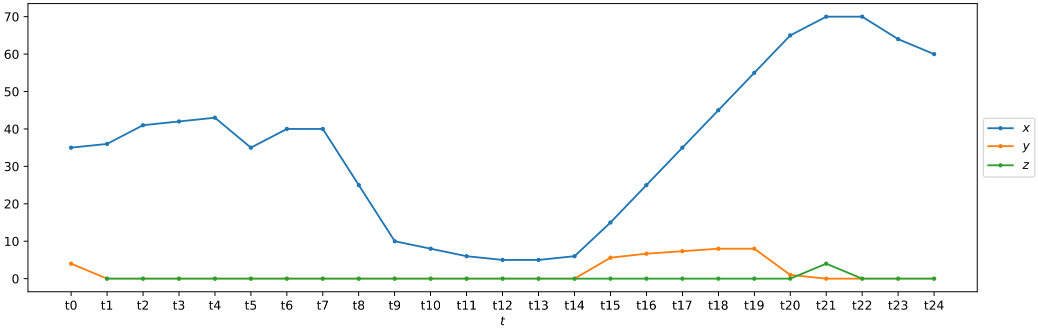

Figure: Solution of DP showing generation x, battery charge y and lost load z for $t = 1, 2, \ldots, 24$.

A scenario tree.

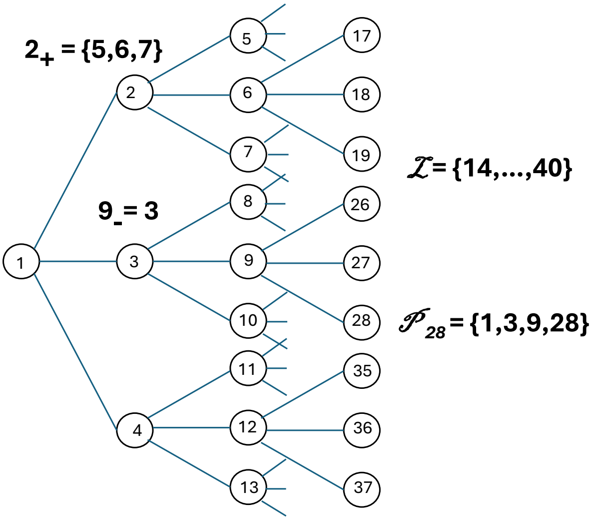

Figure: Scenario tree. Here n_- is the parent of n, and $\mathcal{L}$ is the set of leaf nodes.

Stochastic economic dispatch in scenario tree

$$\min \sum_{n \in N} P(n) \left(\sum_{i \in G} c_i(n) x_i(n) + L z(n) \right)$$

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

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

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

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

Pricing in scenario tree

- Dual variables give prices p that decouple system problem into agent problems.

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

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

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

Use SDDP.jl to compute prices

- SDDP.jl is an open source Julia implementation of SDDP.
- built on `JuMP.jl` modelling language.
- supports a number of open-source and commercial solvers.
- support for:
  - infinite horizon problems
  - convex risk measures
  - mixed-integer state and control variables
  - partially observable stochastic processes

`[Dowson and Kapelevich, 2021]`
`https://odow.github.io/SDDP.jl/stable/`

Example problem with random demand

Figure: Stagewise independent demand realizations for example.

Plot of prices from SDDP

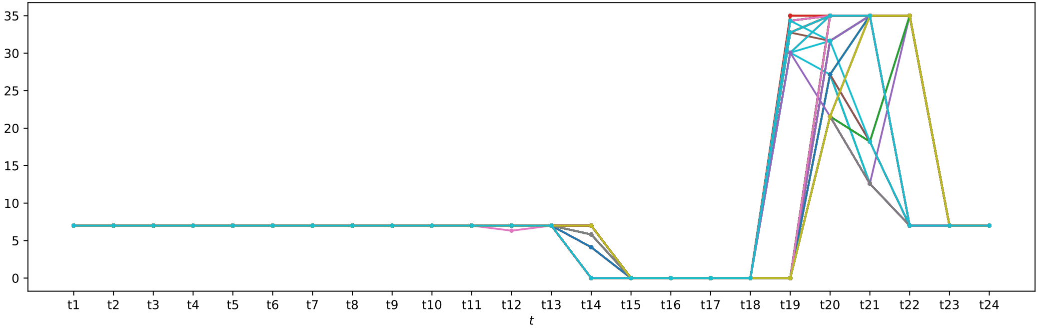

Figure: System marginal prices from 100 simulations of optimal stochastic policy.

Why these prices won't work

- The prices (dual variables) derived from a scenario tree are difficult to optimize with;
- For computation, scenario tree problem is formulated as a look-ahead model solved in rolling horizon mode;
- 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";
- The future will (almost surely) not be a scenario in the tree;
- Even if the future matches a scenario perfectly the prices computed from a rolling horizon implementation might be inconsistent with perfect foresight ;

* [Hogan,2020],[Cho and Papavasiliou,2023]

Outline

Agent decision rules

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

System stage problem and expected future benefit

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

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

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

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

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

Separable approximation using ADRs

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

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

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

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

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

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 $p(t)(u_j(t) - v_j(t))$.

How to compute an ADR from system value function

- 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 $(x(t), y(t))$.
- Suppose agents make a forecast $(\tilde{x}^t, \tilde{y}^t)$ of $(x(t), y(t))$.
- Agents $i \in G$ and $j \in J$ then offer

$$V_i^t(x_i) = \hat{V}^t(x_i, \tilde{x}^t{}_{-i}, \tilde{y}^t) - (1 - \frac{1}{2|G|})\hat{V}^t(\tilde{x}^t, \tilde{y}^t),$$

$$W_j^t(y_j) = \hat{V}^t(\tilde{x}^t, y_j, \tilde{y}^t{}_{-j}) - (1 - \frac{1}{2|J|})\hat{V}^t(\tilde{x}^t, \tilde{y}^t).$$

Separable ADRs can be system optimal

Theorem

If all agents make perfect forecasts of $(x(t), y(t))$ then optimal dispatch with

$$\sum_{i \in G} V_i^t(x_i) + \sum_{j \in J} W_j^t(y_j)$$

yields the same outcome as optimal dispatch with $\hat{V}^t(x, y)$.

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

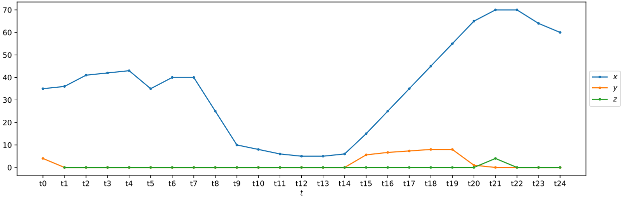

Figure: Generation x, battery charge y and lost load z for deterministic ADR.

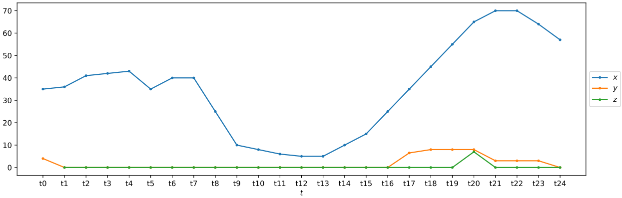

Figure: Generation x, battery charge y and lost load z for crude stochastic ADR.

Remarks

- Assuming perfect competition and complete markets, ADRs recover system optimum under separability and stagewise independence assumptions.
- ADRs seem to perform well even when separability assumptions do not hold.
- ADRs are easy to implement, and can build in some system operator look-ahead.
- ADRs enable agents to put “money where their mouths are”.

Outline

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?

The End

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