Sequential Pricing of Electricity

Jacob Mays

PSERC Webinar

February 14, 2024

Acknowledgment: This project is being funded in part by the U.S. Department of Energy Solar Energy Technologies Office. Logo was developed by the U.S. Department of Energy to indicate receipt of DOE funding—not an endorsement by DOE.
Interconnection queues across the country are dominated by solar, storage, and wind.
Market reform backdrop

Variability, uncertainty, non-convexity, and intertemporal constraints present growing challenges for price formation.
“Some resource ... have low or no marginal costs ... This fact, in our opinion, poses an existential challenge to the continuing operation of single-clearing priced auction markets for energy and related services in RTOs.”

-Tony Clark (former FERC commissioner) and Vincent Duane (former PJM executive)
Pricing reforms, ERCOT edition

PUC Commissioners meet to discuss new proposal to improve power grid reliability

ERCOT market has contemplated many reforms following the 2021 disaster in Winter Storm Uri
As energy demand continues to grow in Texas, adding ECRS will support grid reliability and mitigate real-time operational issues to keep supply and demand balanced.
“We have evaluated the proposed AS methodology and find that it:
• Is not based on sound reliability criteria;
• ...
• Generated artificial shortages that produced massive inefficient market costs, totaling more than $12 Billion in 2023; and
• Diminished reliability by withholding units that are needed to manage transmission congestion.”
In long process, FERC approved changes to PJM reserve products, then changed its mind a year later
Motivation

1. Market reforms have significant consequences for cost, reliability, and climate impacts.

2. Market operators and regulators do not have tools capable of correctly assessing market reforms.
Return to first principles

What are we trying to accomplish with price formation?
Market design philosophy

Principle of competitive markets:

Transparent & Complete Price Signals

Efficient Investment and Operation

Want prices that support efficiency in both short-term operations and long-term investment
Outline

• Static picture
• Idealized stochastic benchmark
• Sequential decisions
• Pitfalls of price formation design and analysis
• Policies for sequential decisions and prices
• Short-term price formation and long-run efficiency
Outline

• Static picture
  • Idealized stochastic benchmark
  • Sequential decisions
• Pitfalls of price formation design and analysis
• Policies for sequential decisions and prices
• Short-term price formation and long-run efficiency
Static, single-period merit order curve

Marginal Cost

Quantity

Renewables

Baseload (nuclear, historically coal)

Gas and oil combustion turbines, steam turbines

Mid-merit (combined-cycle gas, coal now)

Generators, etc.
Clearing prices in the static picture

Units with marginal cost under the price earn a profit

Units with marginal cost above the price prefer not to operate

A marginal unit sets the price and breaks even

Demand

Supply

Marginal Cost

Clearing Price

Quantity
Dynamic questions

- Where do storage bids and offers fit?
- What happens if a plant is ramp-constrained?
- How do start-up/shut-down decisions alter the curve?

Need to move from a static to a dynamic view
Outline

• Static picture
• **Idealized stochastic benchmark**
• Sequential decisions
• Pitfalls of price formation design and analysis
• Policies for sequential decisions and prices
• Short-term price formation and long-run efficiency
Long-term goal is to find a collection of investments that maximizes value of operating the system minus the upfront cost

\[
\max_x \quad - \sum_{g \in G} C_{g \text{\tiny inv}} x_g + E[V(x; \xi)]
\]

Investment cost

Expected surplus from operations given uncertainty
Modeling idealized prices

Suppose we are solving the joint capacity expansion and operating problem of a risk-neutral social planner:

Capacity investment in node $n = 0$

Year-long (8760 stage) operation under uncertainty through nodes $\mathcal{N}^{OP} = \mathcal{N} \setminus \{0\}$
Capacity expansion on a tree

Cost of building generation

\[
\max_{y,p,k,d} \quad - \sum_{g \in \mathcal{G}} C_{g}^{INV} y_g - \sum_{b \in \mathcal{B}} C_{b}^{INV} y_b
\]

Cost of building storage

\[
+ \sum_{n \in \mathcal{N}^{OP}} \sum_{l \in \mathcal{L}} \phi_n V_{l}^{L} d_{ln} - \sum_{n \in \mathcal{N}^{OP}} \sum_{g \in \mathcal{G}} \phi_n C_{g}^{OP} p_{gn}
\]

Operating cost of generation

\[
s.t. \quad \sum_{l \in \mathcal{L}} d_{ln} - \sum_{g \in \mathcal{G}} p_{gn} - \sum_{b \in \mathcal{B}} k_b = 0 \quad \forall n \in \mathcal{N}^{OP}
\]

Value of served load

\[
p_g \in \mathcal{X}_g(y_g) \quad \forall g \in \mathcal{G}
\]

Power balance

\[
k_b \in \mathcal{X}_b(y_b) \quad \forall b \in \mathcal{B}
\]

Resource-specific constraints

\[
d_l \in \mathcal{X}_l \quad \forall l \in \mathcal{L}
\]

© 2024 Jacob Mays
Long-run equilibrium

- Assume convexity and perfect competition
- Allow generic constraints between nodes
  - State of charge
  - Ramping limits
- Setting prices equal to dual of system-wide power balance constraint supports a long-run equilibrium at the socially optimal capacity mix
  - All agents maximize expected profit given individual constraints
  - All generation and storage have zero expected profit
Market design philosophy

Principle of competitive markets:

Transparent & Complete Price Signals ➔ Efficient Investment and Operation

Idealized prices can be derived from an arbitrarily large stochastic program

© 2024 Jacob Mays
Outline

• Static picture
• Idealized stochastic benchmark
• **Sequential decisions**
  • Pitfalls of price formation design and analysis
  • Policies for sequential decisions and prices
  • Short-term price formation and long-run efficiency

© 2024 Jacob Mays
Real-world implementations

• Impossible to construct and solve the idealized stochastic program
  – Limits on information
  – Limits on computation
• Instead, real-world operators solve a problem of sequential decisions under uncertainty
• Dual values from algorithms used in practice are unlikely to replicate duals from the idealized stochastic program

How do algorithmic choices in the design of policies for the sequential decision problem affect prices?
Operators solve a sequential decision problem (e.g., covering one year with hourly time steps)

We are searching for the best policy mapping states to decisions

$$\max_{\pi} \mathbb{E}\left[ \sum_{t=1}^{\infty} C_t(S_t, X_t^\pi(S_t), W_{t+1}) | S_0 \right]$$  (1)

We sum over all of the operational time periods, given our starting state $S_0$

Function $C_t$ tells us how much cost we incur in time period $t$ given our state and decision

Policy $\pi$ gives us a function that maps states $S_t$ to decisions $x_t$
Assume at each time $t$ we solve a deterministic lookahead model to determine our actions:

$$X_t^{DLAC}(S_t \mid H, F) \in \arg\max_{\tilde{x}_t} \sum_{l \in L} \sum_{t' \in T_t^{H,F}} V_t^L \tilde{a}_{ltt'} + \sum_{t' \in T_t^{H,F}} V_t^R \tilde{z}_{tt'}$$

Look-ahead model covering $F$ periods of the future and accounting for $H$ periods of history

- Value of load
- Value of reserves
- No-load cost
- Start-up cost
- Energy cost

Provisional decisions $\tilde{x}_t$ for all periods $t' \in T_t^{H,F} = \{t - H, t + F\}$ as well as binding decisions $x_t = \tilde{x}_{tt}$
Constraints in the deterministic lookahead commitment model:

\[ s.t. \sum_{l \in \mathcal{L}} \tilde{d}_{ltt'} - \sum_{g \in \mathcal{G}} \tilde{p}_{gtt'} - \sum_{b \in \mathcal{B}} \tilde{k}_{btt'} = 0 \quad \forall t' \in \mathcal{T}_t^{H,F} \quad (2b) \]

\[ \sum_{l \in \mathcal{L}} \tilde{z}_{ltt'} - \sum_{g \in \mathcal{G}} \tilde{r}_{gtt'} - \sum_{b \in \mathcal{B}} \tilde{r}_{btt'} = 0 \quad \forall t' \in \mathcal{T}_t^{H,F} \quad (2c) \]

We will derive provisional prices $\tilde{\lambda}_{tt'}$ and $\tilde{\mu}_{tt'}$ for all periods $t' \in \mathcal{T}_t^{H,F} = \{t - H, t + F\}$ as well as binding prices $\lambda_t = \tilde{\lambda}_{tt}$ and $\mu_t = \tilde{\mu}_{tt}$
Lookahead commitment constraints (2)

Constraints in the deterministic lookahead commitment model (continued):

\[ s.t. \quad \tilde{d}_{l,t',t} \leq \tilde{D}_{l,t'} \quad \forall l \in L, \forall t' \in T_t^{H,F} \quad (2d) \]

\[ \tilde{p}_{g,t',t} + \tilde{r}_{g,t',t} \leq \tilde{P}_{g,t'} \quad \forall g \in G, \forall t' \in T_t^{H,F} \quad (2e) \]

"Non-revisionist" constraints covering historical periods

\[ p_{g,t',t} = p_{g,t} \quad \forall g \in G, t' \in T_t^{H} \quad (2f) \]

Ramping, state-of-charge, other resource-specific constraints

Binary commitment variables introducing non-convexity

\[ \tilde{u}_{g,t',t}, \tilde{v}_{g,t',t}, \tilde{q}_{g,t',t} \in \{0,1\} \quad \forall g \in G, t' \in T_t^{H,F} \quad (2g) \]

© 2024 Jacob Mays
Specifying a price formation policy

1. Specifying the decision model (e.g., deterministic vs stochastic, robust, chance-constrained, etc.)

2. Specifying the parameterization (e.g., how forecasts for wind, solar, and load are updated)

3. Specifying treatment of binary variables (and any other modifications to the decision model)
Outline

• Static picture
• Idealized stochastic benchmark
• Sequential decisions

• Pitfalls of price formation design and analysis
• Policies for sequential decisions and prices
• Short-term price formation and long-run efficiency
Implications for literature and practice

• Viewing price formation through the lens of sequential decisions has several implications
• In general, price formation literature has focused on step 3 above, taking the formulation and parameterization as a given
• Implicitly provides guarantees on the provisional prices instead of the underlying problem and the actual prices
• I will focus on two implications in this section
  – Arbitrage, price convergence, and modeling day-ahead markets
  – Implementing and interpreting strategies for non-convexity
Price convergence

• Recall that we calculated provisional prices $\tilde{\lambda}_{tt'}$ at time $t$ for our entire lookahead horizon.

• Law of iterated expectations (or a no-arbitrage condition) suggests that we should have

$$
\tilde{\lambda}_{tt'} = \mathbb{E}_{w_{t+1},...,w_{t'}}[\lambda_{t'}]
$$

• In other words, ideally the provisional price generated by our three-step process should relate to the potential values that might arise given uncertainty (wind, solar, load, etc.)
Day-ahead markets

- In the sequential description above, prices were only binding for a single period
- Day-ahead markets result in 24 hours of binding prices from a single unit commitment model
- Day-ahead markets also include virtual bidders that drive convergence between day-ahead and expected real-time prices

Very common issue in production cost modeling is to produce day-ahead market prices with a persistent bias relative to real-time market prices
Strategies for non-convexity

• Recall that we have binary variables in the decision problem, complicating the calculation of market-clearing prices

• Most FERC-jurisdictional markets have introduced logic to “allow the commitment costs of fast-start resources to be reflected in prices”
  – Extended LMP in MISO
  – Fast-start pricing in ISO-NE, NYISO, PJM, SPP

• In academic literature, convex hull pricing often described as an “ideal”

• Analysis typically performed on a multi-period market with all periods binding
Implementing schemes for non-convexity

• Calculating prices from alternative schemes in the day-ahead market is not valid
  – Virtual bidders will drive prices back to expected real-time prices
• Instead, need to specify how the desired policy is instantiated in real-time price formation

Many academic proposals (e.g., convex hull pricing) are underspecified relative to what is required in the full sequential decision problem
Recall the constraints in the deterministic lookahead commitment model:

\[ \tilde{d}_{ltt'} \leq \tilde{D}_{ltt'} \quad \forall l \in L, \forall t' \in T_t^{H,F} \quad (2d) \]

\[ \tilde{p}_{gtt'} + \tilde{r}_{gtt'} \leq \tilde{P}_{gtt'} \quad \forall g \in G, \forall t' \in T_t^{H,F} \quad (2e) \]

\[ P_{gtt'} = p_{gt} \quad \forall g \in G, t' \in T_t^H \quad (2f) \]

\[ \tilde{u}_{gtt'}, \tilde{v}_{gtt'}, \tilde{q}_{gtt'} \in \{0,1\} \quad \forall g \in G, t' \in T_t^{H,F} \quad (2g) \]

Not clear which if any convex hull prices could be considered ideal
Outline

• Static picture
• Idealized stochastic benchmark
• Sequential decisions
• Pitfalls of price formation design and analysis
• Policies for sequential decisions and prices
• Short-term price formation and long-run efficiency
• Above, presented deterministic lookahead commitment as a “base policy” due to correspondence with current practice

• Here we consider three modifications:
  – Net load biasing
  – Reserve tuning
  – Stochastic programming
Common practice is to adjust parameterization of deterministic model to account for uncertainty:

\[ \tilde{d}_{ltt}, \leq \tilde{D}_{ltt}' \quad \forall l \in L, \forall t' \in T_t^{H,F} \quad (2d) \]

\[ \tilde{p}_{gtt}, + \tilde{r}_{gtt}, \leq \tilde{P}_{gtt}' \quad \forall g \in G, \forall t' \in T_t^{H,F} \quad (2e) \]

Adjust estimated wind/solar availability time \( t' \) downwards

Adjust demand forecast in period \( t' \) upwards (i.e., do not use expected value)

Can induce additional commitments for future periods, but may not affect prices in binding period

© 2024 Jacob Mays
Another strategy is to increase willingness to pay for reserves (e.g., through creating a new product):

$$X_t^{DLAC}(S_t|H,F) \in$$

$$\arg\max_{\tilde{x}_t} \sum_{l \in \mathcal{L}} \sum_{t' \in T_t^{H,F}} V_l^L \tilde{a}_{ltt'} + \sum_{t' \in T_t^{H,F}} V_R \tilde{z}_{tt'} \quad (2a)$$

$$- \sum_{g \in \mathcal{G}} \sum_{t' \in T_t^{H,F}} (C_g^{NL} \tilde{u}_{gtt'} + C_g^{SU} \tilde{v}_{gtt'} + C_g^{EN} \tilde{p}_{gtt'})$$

Similarly increases demand, but attaches a payment for the reserve product (plus higher energy prices)
Stochastic programming may better approximate the benchmark prices:

\[ X_t^{SLAC}(S_t | H, F) \in \]

\[ \arg \max_{x_t, \tilde{x}_t} \sum_{\omega \in \tilde{\Omega}_t} \tilde{\rho}_\omega \left( \sum_{l \in L} \sum_{t' \in T_{t,H,F}^L} V_l^L d_{ltt'} \omega \\
+ \sum_{t' \in T_{t,H,F}^R} V^R \tilde{z}_{tt'} \omega \right) \quad (3a) \]

\[ - \sum_{g \in G} \sum_{t' \in T_{t,H,F}^H} (C_{gNL}^N \tilde{u}_{gtt'} \omega + C_{gSU}^S \tilde{v}_{gtt'} \omega + C_{gEN}^E \tilde{p}_{gtt'} \omega) \]

Construct scenario set \( \tilde{\Omega}_t \) and solve stochastic program with nonanticipativity in binding period
Opportunity cost bidding

Alternative used in some markets: do not use lookahead at all, just use participant bids/offers

<table>
<thead>
<tr>
<th>Opportunity costs</th>
<th>Stochastic programming</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Storage (and others) forecast future prices</td>
<td>• Endogenously calculates an estimated opportunity cost for storage</td>
</tr>
<tr>
<td>• Calculate bids and offers based on opportunity costs</td>
<td>• Dispatches the system consistent with this endogenous opportunity cost</td>
</tr>
<tr>
<td>• Submits curves to system operator</td>
<td>• More useful for analysis since we do not have access to participant offers</td>
</tr>
<tr>
<td>• System operator uses in dispatch</td>
<td></td>
</tr>
</tbody>
</table>
Outline

• Static picture
• Idealized stochastic benchmark
• Sequential decisions
• Pitfalls of price formation design and analysis
• Policies for sequential decisions and prices

• **Short-term price formation and long-run efficiency**
Large-scale test system

- Set of 456 generators mimicking installed capacity of ERCOT in 2018
- 5 GW of 4-hr batteries added to system
- Scenarios constructed from distributional forecasts for July 18 and 19, 2018 (48 hours)
- All tests include all 48 hours in each time period’s problem
- Simulations conducted to compare three policies
  - Net load biasing (at varying levels)
  - Reserve tuning (at varying levels)
  - Stochastic programming
### Production cost of competing policies

Tested policies result in similar operating cost…

<table>
<thead>
<tr>
<th>Policy</th>
<th>Cost</th>
<th>Relative to SLAC</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Net Load Biasing</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50(^{th}) percentile</td>
<td>$833.5M</td>
<td>103.1%</td>
</tr>
<tr>
<td>65(^{th}) percentile</td>
<td>$806.6M</td>
<td>99.7%</td>
</tr>
<tr>
<td>95(^{th}) percentile</td>
<td>$819.9M</td>
<td>101.4%</td>
</tr>
<tr>
<td><strong>Reserve Tuning</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>40(^{th}) percentile</td>
<td>$816.3M</td>
<td>100.9%</td>
</tr>
<tr>
<td>60(^{th}) percentile</td>
<td>$832.2M</td>
<td>102.9%</td>
</tr>
<tr>
<td><strong>Stochastic Program</strong></td>
<td>$808.8M</td>
<td>100.0%</td>
</tr>
</tbody>
</table>
Revenue under competing policies

…but very different prices

<table>
<thead>
<tr>
<th>Policy</th>
<th>Cost</th>
<th>Total Charges</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Net Load Biasing</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50th percentile</td>
<td>$833.5M</td>
<td>$4,076M</td>
</tr>
<tr>
<td>65th percentile</td>
<td>$806.6M</td>
<td>$3,633M</td>
</tr>
<tr>
<td>95th percentile</td>
<td>$819.9M</td>
<td>$5,034M</td>
</tr>
<tr>
<td><strong>Reserve Tuning</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>40th percentile</td>
<td>$816.3M</td>
<td>$4,071M</td>
</tr>
<tr>
<td>60th percentile</td>
<td>$832.2M</td>
<td>$4,092M</td>
</tr>
<tr>
<td><strong>Stochastic Program</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$808.8M</td>
<td>$4,214M</td>
</tr>
</tbody>
</table>
Now have a modeling framework to explain this and (in principle) perform a cost-benefit analysis
Incentives for capacity

Choice of pricing policy affects resource compensation and incentives for investment

- Widely understood that energy market prices in most markets are too low to support resource adequacy ("missing money" problem)

Have a modeling framework to assess how algorithmic choices contribute to missing money
Less recognized that suppressing volatility could have long-run consequences:

- Too low volatility
- Insufficient flexibility

Suppressing volatility weakens incentive for flexibility and assets with uncorrelated failures
Storage in particular could be remunerated at very different levels under different policies.

**Profit relative to that under stochastic lookahead:**

<table>
<thead>
<tr>
<th>Policy</th>
<th>Steam</th>
<th>All</th>
<th>Storage</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Net Load Biasing</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50&lt;sup&gt;th&lt;/sup&gt; percentile</td>
<td>96.6%</td>
<td>96.7%</td>
<td>81.7%</td>
</tr>
<tr>
<td>70&lt;sup&gt;th&lt;/sup&gt; percentile</td>
<td>84.9%</td>
<td>84.4%</td>
<td>68.5%</td>
</tr>
<tr>
<td>95&lt;sup&gt;th&lt;/sup&gt; percentile</td>
<td>120.0%</td>
<td>119.5%</td>
<td>114.8%</td>
</tr>
<tr>
<td><strong>Reserve Tuning</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>40&lt;sup&gt;th&lt;/sup&gt; percentile</td>
<td>95.7%</td>
<td>96.6%</td>
<td>114.4%</td>
</tr>
<tr>
<td>60&lt;sup&gt;th&lt;/sup&gt; percentile</td>
<td>95.8%</td>
<td>97.1%</td>
<td>116.4%</td>
</tr>
</tbody>
</table>
Closing thoughts

Main points of this talk:

1. Need a shift to dynamic models in the design and analysis of price formation in electricity markets

2. Need to be aware of the long-term consequences of different price formation choices

3. One area of concern is ensuring efficient compensation of flexibility (e.g., storage)