Alternative Pricing Policies and Market Design in Electricity Markets

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Themes

• Electricity forward and spot markets are complicated by operating requirements (start-up costs, minimum run levels and times) and uncertainty in supply and demand

• Current market designs can create efficiencies

• Redesign to include consistency in incentives and explicit recognition of uncertainty can reduce inefficiency
Outline

• Renewable sources and their impact
• Current market
• Issues in market design
  – Evidence of market power
  – Issues with non-convexities
  – Price and quantity mismatches
  – Lack of pooling incentives
• Potential resolution with stochastic optimization
U.S. Wind Power Capacity Reaches 60 GW (282 GW Globally)

Source: AWEA, 2013 MISO 2012
Wind Variability

MISO Hourly Wind Power - January 2012

Hourly Wind Generation [MWh]
U.S. Solar PV Capacity Reaches 6.4 GW (over 100 GW Globally)

New U.S. Solar Electric Installations

Source: SEIA 2012
Solar Intermittency

Source: SEIA 2012
The Market: Independent System Operator (e.g., MISO)

- Coordinates and monitors the use of the electric transmission system by utilities and generators.

Color Key:
- **Blue:** Transmission
- **Green:** Distribution
- **Black:** Generation

- Provides a wholesale energy market.
MISO Wholesale Energy Market

Participants:
- Generators
- Load entities (demand)
- Virtual or financial participants

Market Operation:
1. Buyers and sellers submit bids at particular nodes (locations), interconnected by transmission lines with limited capacity.
2. MISO clears the market considering bids, transmission capacity and energy lost in transmission.

Prices:
- Cleared prices: Marginal cost of supplying 1 MW of electricity at each location
- 10% of the generation capacity is wind: transmission lines are congested and prices differ across locations.
- Current prices (LMPs): http://miso.org/
Market Efficiency

Timing

- Day-ahead market: schedules production and demand for the next day
- Real-time market: final adjustments are made.

Efficiency

- Ideally, the day-ahead market is the expected value of the real-time market.
- Only last minute shocks are adjusted in the real-time.
- Generation is cheaper when it is planned, as last minute changes in production are expensive.

Congestion:

- Creates market power by isolating nodes.
- Generators have incentives to withhold quantities in the day-ahead market.
• Generators have incentive to reduce day-ahead quantity and release in real-time
Market Power: Day-Ahead Price Premium

Cumulative day-ahead premium

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Barbaros Tansel Memorial Lecture, Bilkent U., March 2016
Reducing Market Power

• Demand adjustment:
  – Low incentive: Often regulated in retail market to margin above cost
  – Load sufficiency penalty: Face penalties for not meeting demand with the day-ahead market

• Virtual (financial) bidders:
  – Can enter market on either demand or supply
  – Face some penalties for incremental resources
  – Can enter energy and transmission markets
Virtual Bidder Anomaly: More Day-Ahead Buying than Selling
Virtual Bidder Behavior

• Demand bidding may increase the value of transmission right (FTR)
  – FTR for 100 MW for Hour h pays the difference in price between A and B
  – A-to-B transmission is binding with DA prices of $20/MWh at A and $30/MWh at B while real-time will be $18/MWh and $28/MWh
  – Excess demand bid of 1MW in Hour h at B raises price to $40/MWh at B

• Net to FTR holder/Virtual energy bidder:
  FTR: \((40-30)*100= $1000\)
  Energy: \((28-40)*1= $ -12\)
  Net: \($ 988\)
Additional Market Power Issue: Day-Ahead Commitment

- Generators have minimum run-time and level requirements (i.e., must produce at a given level for a period of time after start-up)
- Load-bearing entities (consumers) have limited flexibility to shed load
- Without commitment, a marginal flexible resource can push prices to high or low limits
Issues in Price Signals: Non-convex Costs

- Each generator has a startup cost, variable cost, and production range

- Example:

<table>
<thead>
<tr>
<th>Gen</th>
<th>G1</th>
<th>G2</th>
<th>G3</th>
</tr>
</thead>
<tbody>
<tr>
<td>fixed cost ($)</td>
<td>50</td>
<td>300</td>
<td>100</td>
</tr>
<tr>
<td>Pmin (MW)</td>
<td>0</td>
<td>10</td>
<td>50</td>
</tr>
<tr>
<td>Pmax (MW)</td>
<td>20</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>variable cost ($/MW)</td>
<td>40</td>
<td>10</td>
<td>20</td>
</tr>
</tbody>
</table>
Example Costs

Total Cost:

Marginal Cost:
Effect of Low Prices (LMP)

• Prices from marginal costs cannot support the total cost of production
• Typical market adjustment is an uplift charge (make-whole payment) to cover fixed costs
• Distortion can lead to inefficiency
  – Gen3 in example has additional incentive to reduce output to include Gen1
Alternatives

• Restricted model (standard LMP):
  Fix commitments in optimization and use multipliers for prices

• Dispatchable model:
  Relax the 0-1 commitments to fractions

• Convex hull model:
  Find the convex hull or dual (Gribik, Pope, Hogan 07)

• Restrict outcomes to have no uplift (Reguant 11)
Additional Issue: Uncertainty

- If (residual) demand is uncertain, expected price and quantity is in convex hull of supply curve.

$\Rightarrow$ No deterministic day-ahead market can match both expected price and quantity.

$F(q) = p(q) \cdot q$; Jensen’s inequality for $F$ concave and $p(q)$ convex.

$E[F(q)] < F(E(q)) = p(E(q)) \cdot E(q) \leq E(p(q)) \cdot E(q) = (E(p), E(q))$
Uncertainty Issues

• With a fixed (deterministic) model of the day ahead, nonlinearity in the cost of supply implies that matching expected prices and expected quantities between day-ahead and real-time markets is not possible.

• Deterministic models cannot capture the advantages of diversification and cannot be modified to produce an efficient solution in expectation.
Potential Resolutions

• Approximate convex hull prices:
  – Allocate fixed charges across minimum uptimes and levels of each unit

• Commit units with prices based on the expected outcomes in the real-time market
  – Solving for commitments based on day-ahead scenarios of demand and renewable output

• Reduces incentives for market power and market manipulation between energy and transmission
Basic Model: Stochastic Unit Commitment

Objective: Determine units to commit and levels of generation to meet load and to maximize expected total surplus

• Recognizing uncertainty in availability of renewable resources, demand, and other supply

• Requires generation of many future scenarios
Why Stochastic Programming?

- Weather-driven renewables are hard to forecast and increase the uncertainty in the electric power grid

- Stochastic programming could serve as a tool to address the increased uncertainty in power system and electricity market operations

- Stochastic programming is a powerful tool in dealing with uncertainty, but it has advantages and disadvantages
  
  **Pluses**
  - is based on axioms of foundational decision theory
  - considers uncertainty holistically rather than focusing on worst case scenarios
  - can effectively hedge against randomness

  **Minuses**
  - requires probabilistic inputs which may be hard to obtain or estimate
  - can be computationally hard to solve stochastic programming models
Scenario Generation

• Focus on wind power uncertainty with scenarios
  – Stochastic unit commitment model requires scenario representation of wind power forecast
  – Scenario generation from Markov chain model (where some values may be unobserved)
  – May attempt to reduce scenarios but…

• Random scenario selection performs better than both scenario reduction algorithms
  – Scenario reduction reduces scenario variance and level of hedging in UC strategy

• Increasing the number of scenarios improves performance
  – Computational burden also increases
Stochastic Unit Commitment

Minimize \{\text{fuel cost} + \text{start-up cost} + \text{load shedding penalty}\}

<table>
<thead>
<tr>
<th>Decision Variables</th>
<th>Constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>First stage:</strong></td>
<td>• Load balance</td>
</tr>
<tr>
<td>Unit on/off</td>
<td>• Min up-time/down-time</td>
</tr>
<tr>
<td><strong>Second stage:</strong></td>
<td>• Ramp up/down</td>
</tr>
<tr>
<td>Thermal dispatch</td>
<td>• Transmission limits</td>
</tr>
<tr>
<td>Wind dispatch</td>
<td>• Generation capacity limits</td>
</tr>
<tr>
<td>Transmission flow</td>
<td>• Spinning reserves</td>
</tr>
</tbody>
</table>
Simplified Finite Sample Model

• Assume \( p \) is fixed and random variables represented by sample \( \xi^i_t \) for \( t=1,2,..,T, \ i=1,\ldots,N_t \) with probabilities \( p^i_t \), \( a(i) \) an ancestor of \( i \), then model becomes (no chance constraints):

\[
\text{minimize} \quad \sum_{t=1}^{T} \sum_{i=1}^{N_t} p^i_t f_t(x^{a(i)}_t, x^i_{t+1}, \xi^i_t)
\]

s.t. \( x^i_t \in X^i_t \)

Observations?

• Problems for different \( i \) are similar – solving one may help to solve others
• Problems may decompose across \( i \) and across \( t \) yielding
  • smaller problems (that may scale linearly in size)
  • opportunities for parallel computation.
Stochastic Unit Commitment

\[
\min_{u,x,f,w} \sum_{s \in S} \sum_{t=1}^{T} \sum_{i \in I} \left[ g(x^s_{it}) \cdot u_{it} + h(u_{it}, u_{i,t-1}) \right]
\]

\[
s.t. \quad u, x, f, w \in C_s, s \in S
\]

\[
\forall i, \forall s \in S, t \in T
\]

\[u^s_{it} = u_{it}\]

- \(u\): Unit on/off
- \(x\): Generation output
- \(f\): Flow
- \(w\): Wind dispatch
- \(P_s\): Probability of scenario \(s\)
- \(P_s\): Scenario set
- \(S\): Set of thermal generators
- \(I\): Number of periods
- \(T\): Technological constraints
- \(C_s\):
Example:

6-Bus system* with
- 2 thermal generators
- 3 loads

<table>
<thead>
<tr>
<th>Bus No.</th>
<th>Unit Cost Coefficients</th>
<th>Pmax (MW)</th>
<th>Pmin (MW)</th>
<th>Ini. State (h)</th>
<th>Min Off (h)</th>
<th>Min On (h)</th>
<th>Ramp (MW/h)</th>
<th>Start Up (MBtu)</th>
<th>Fuel Price ($/MBtu)</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td>1</td>
<td>176.95</td>
<td>13.51</td>
<td>0.0004</td>
<td>220</td>
<td>100</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>G2</td>
<td>2</td>
<td>129.98</td>
<td>32.63</td>
<td>0.001</td>
<td>100</td>
<td>10</td>
<td>3</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

* The details of the system and parameters are available at:
http://motor.ece.iit.edu/data/
Wind Power Day-Ahead Forecast Scenarios

- 10 wind scenarios
- Derived from EWITS data with KDF, MC sampling, and scenario reduction
- Wind unit capacity is set so that it can satisfy 30% of the daily load
Basic UC Model

Unit 1 is always on.

Unit 2 is on when the wind generation is low.

Wind is dispatched down (curtailed) early morning and late night.


\[
\min \sum_{s \in S} p_s \sum_{i \in I} \sum_{t=1}^{T} \left\{ g_i(x_{it}^s) u_{it}^s + h_i(u_{it,t-1}^s, u_{it}^s) \right\}
\]

subject to:

<table>
<thead>
<tr>
<th>Constraint</th>
<th>∀t, s</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \sum_{i \in I} f_{it}^s + \sum_{i \in I} x_{it}^s + \sum_{j \in J} w_{jt}^s = \sum_{i \in I} f_{it}^s + D_t )</td>
<td></td>
<td>Load balance</td>
</tr>
<tr>
<td>( f_{it}^s = B_i(\theta_{it}^s - \theta_{mt}^s) )</td>
<td>∀l = (m,n) ∈ L,t,s</td>
<td>Flow computation</td>
</tr>
<tr>
<td>(-F_i \leq f_{it}^s \leq F_i )</td>
<td>∀l,t,s</td>
<td>Flow limits</td>
</tr>
<tr>
<td>( w_{jt}^s \leq W_{jt} )</td>
<td>∀j,t,s</td>
<td>Wind curtailment</td>
</tr>
<tr>
<td>( \sum_{i \in I} r_{it}^s \geq R_t )</td>
<td>∀t,s</td>
<td>Spinning reserve requirement</td>
</tr>
<tr>
<td>( x_{it}^s + r_{it}^s \leq Q_i u_{it}^{s,b} )</td>
<td>∀i,t,s</td>
<td>Maximum output</td>
</tr>
<tr>
<td>( x_{it}^s \leq q_i u_{it}^{s,b} )</td>
<td>∀i,t,s</td>
<td>Minimum output</td>
</tr>
<tr>
<td>( x_{it}^s - x_{it-1}^s + r_{it}^s \leq u_{it-1}^{s,b} \Delta_i + (1 - u_{it-1}^{s,b}) \Delta_i^{SU} )</td>
<td>∀i,t ≥ 2,s</td>
<td>Ramp-up/Start-up</td>
</tr>
<tr>
<td>( x_{it-1}^s - x_{it}^s \leq u_{it}^{s,b} \Delta_i + (1 - u_{it}^{s,b}) \Delta_i^{SP} )</td>
<td>∀i,t ≥ 2,s</td>
<td>Ramp-down/Shutdown</td>
</tr>
<tr>
<td>( u_{it}^{s,b} - u_{it-1}^{s,b} \leq u_{it}^{s,b} )</td>
<td>∀t ≥ 2,s,t, t = t + 1,..., min{t + L_t - 1,T}</td>
<td>Minimum up-time</td>
</tr>
<tr>
<td>( u_{it}^{s,b} - u_{it}^{s,b} - 1 \leq u_{it}^{s,b} )</td>
<td>∀t ≥ 2,s,t, t = t + 1,..., min{t + L_t - 1,T}</td>
<td>Minimum down-time</td>
</tr>
<tr>
<td>( u_{it}^q = u_{it} )</td>
<td>∀t, i, s</td>
<td>Non-anticipativity</td>
</tr>
<tr>
<td>( x_{it}^q r_{it}^q \geq 0 )</td>
<td>∀t,i,s</td>
<td>Non-negativity</td>
</tr>
<tr>
<td>( w_{jt}^s \geq 0 )</td>
<td>∀t,j,s</td>
<td></td>
</tr>
<tr>
<td>( u_{it}, u_{it} \in {0,1} )</td>
<td>∀t,i,s</td>
<td>Integrality</td>
</tr>
</tbody>
</table>
The Expected Value of Perfect Information (EVPI)

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Probability</th>
<th>Total cost ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>0.10</td>
<td>61,306</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>0.06</td>
<td>64,503</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>0.09</td>
<td>59,321</td>
</tr>
<tr>
<td>Scenario 4</td>
<td>0.07</td>
<td>61,067</td>
</tr>
<tr>
<td>Scenario 5</td>
<td>0.11</td>
<td>61,996</td>
</tr>
<tr>
<td>Scenario 6</td>
<td>0.19</td>
<td>58,074</td>
</tr>
<tr>
<td>Scenario 7</td>
<td>0.13</td>
<td>61,944</td>
</tr>
<tr>
<td>Scenario 8</td>
<td>0.10</td>
<td>59,577</td>
</tr>
<tr>
<td>Scenario 9</td>
<td>0.08</td>
<td>58,850</td>
</tr>
<tr>
<td>Scenario 10</td>
<td>0.07</td>
<td>53,268</td>
</tr>
</tbody>
</table>

Perfect information solution 59,913
Stochastic solution 60,427

The expected value of perfect information (EVPI) 515
The Value of a Stochastic Solution (VSS)

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Load Curtailment</th>
<th>Total cost ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>0.00</td>
<td>61,306</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>3.90</td>
<td>77,523</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>0.00</td>
<td>59,321</td>
</tr>
<tr>
<td>Scenario 4</td>
<td>1.72</td>
<td>66,755</td>
</tr>
<tr>
<td>Scenario 5</td>
<td>0.46</td>
<td>62,950</td>
</tr>
<tr>
<td>Scenario 6</td>
<td>0.00</td>
<td>58,074</td>
</tr>
<tr>
<td>Scenario 7</td>
<td>0.00</td>
<td>61,944</td>
</tr>
<tr>
<td>Scenario 8</td>
<td>0.00</td>
<td>59,577</td>
</tr>
<tr>
<td>Scenario 9</td>
<td>0.00</td>
<td>58,850</td>
</tr>
<tr>
<td>Scenario 10</td>
<td>0.00</td>
<td>53,526</td>
</tr>
<tr>
<td>Expected value solution</td>
<td>0.00</td>
<td>61,247</td>
</tr>
<tr>
<td>Stochastic solution</td>
<td>0.00</td>
<td>60,427</td>
</tr>
</tbody>
</table>

*The value of stochastic solution (VSS)* 880
Alternative Approach with Bundling of Scenarios

• Stochastic programming models tend to give better results with more scenarios, capturing the full range of uncertainty.

• Unit commitment is a multi-stage decision problem in electricity market operations (day-ahead, reliability, real-time).

• To solve the problem with a large number of scenarios and to capture the multi-stage decision process we consider bundling. We observe that:
  – the scenarios can be bundled according to their deviation from the average forecast.
  – the bundles might be different across the time horizon.

• The idea is:
  – to enforce the non-anticipativity constraints for the bundles only
Bunching Form

\[
\min_{u,x,f,w} \sum_{s \in S} \sum_{t=1}^{T} \sum_{i \in I} [g(x^s_{it}) \cdot u^s_{it} + h(u^s_{it}, u^s_{i,t-1})]
\]

s.t. \( u, x, f, w \in C_s, s \in S \)

\[
u^s_{it} = u^b_{it} \ \forall \ i, \forall b \in B, \forall s \in S_b, t \in T_{block}, T_{block} \subset \{1, \ldots, T\}
\]

- \( B \): Set of bundles
- \( S_b \): Set of scenarios in bundle \( b \)
- \( T_{block} \): Time periods in a time block
Bundling Approach

• Tradeoff
  – More variables versus ability to capture uncertainty

• Advantages of bundling
  – Captures multi-stage decision process
    • no need to enforce formal tree structure
  – Reduces the need for scenario reduction
    • can take into account extreme scenarios
  – May reduce computational burden
    • relaxation of traditional 2-stage formulation

• Three approaches
  – Non-anticipativity constraints across scenarios
  – Non-anticipativity constraints across bundles
  – Non-anticipativity constraints across bundles at the end of the blocks
Bundles for 100 Scenarios (Day-Ahead Forecast)

According to the deviations from the average forecast

- < 25% quantile -> Bundle 1
- < 50% quantile -> Bundle 2
- < 75% quantile -> Bundle 3
- < 100% quantile -> Bundle 4
Bundle UC Model: Objective Function and Run-time

<table>
<thead>
<tr>
<th>Extensive Form</th>
<th>“Across scenarios”</th>
<th>“Across bundles”</th>
<th>“Across bundles at the end of time blocks”</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objective</td>
<td>62,401</td>
<td>62,162</td>
<td>61,860</td>
</tr>
<tr>
<td>Execution time (sec)</td>
<td>18.15</td>
<td>23.37</td>
<td>23.29</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Progressive Hedging*</th>
<th>“Across scenarios”</th>
<th>“Across bundles”</th>
<th>“Across bundles at the end of time blocks”</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objective</td>
<td>62,401</td>
<td>62,162</td>
<td>61,846</td>
</tr>
<tr>
<td>Execution time (sec)</td>
<td>635.29</td>
<td>400.56</td>
<td>399.19</td>
</tr>
<tr>
<td>Number of PH iterations</td>
<td>50</td>
<td>26</td>
<td>29</td>
</tr>
</tbody>
</table>

The bundling approach gives:
- Lower expected operating cost
- Improved run-time and fewer iterations (under PH)

*rho = 200
IEEE RTS-96 24-Bus

• 24-Bus
• 32 generators – thermal, hydro
• 34 lines
• 17 loads
Solution Approaches – Computational efficiency
– 24 Bus, 100MW and 250MW wind farms located in Nodes 7, 8.
– 10 Scenarios

<table>
<thead>
<tr>
<th></th>
<th>Solution Time (secs)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EF</td>
</tr>
<tr>
<td>Across scenarios</td>
<td>31</td>
</tr>
<tr>
<td>Across bundles</td>
<td>89</td>
</tr>
<tr>
<td>Bundles at end of time blocks</td>
<td>2418</td>
</tr>
</tbody>
</table>
### Larger Example

- **IEEE 118-Bus Example**

<table>
<thead>
<tr>
<th></th>
<th>Deter. Standard</th>
<th>Stochastic Standard</th>
<th>Deterministic Modified</th>
<th>Stochastic Modified</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Commitment Cost</td>
<td></td>
<td></td>
<td></td>
<td>150,511</td>
</tr>
<tr>
<td>Total Dispatch Cost</td>
<td></td>
<td></td>
<td></td>
<td>747,960</td>
</tr>
<tr>
<td>Total Load Payment</td>
<td>1,826,560</td>
<td>1,956,710</td>
<td>2,355,710</td>
<td>2,252,460</td>
</tr>
<tr>
<td>Total Uplift Payment</td>
<td>50,529</td>
<td>38,615</td>
<td>11,055</td>
<td>17,906</td>
</tr>
<tr>
<td>Total Payment</td>
<td>1,877,089</td>
<td>1,995,325</td>
<td>2,366,765</td>
<td>2,270,366</td>
</tr>
<tr>
<td>Total Generation Revenue</td>
<td>1,681,040</td>
<td>1,802,740</td>
<td>2,183,630</td>
<td>2,087,550</td>
</tr>
<tr>
<td>Total Congestion Rent</td>
<td>145,519</td>
<td>153,968</td>
<td>172,077</td>
<td>164,908</td>
</tr>
</tbody>
</table>
Price Effects

• Stochastic model produces smoother price responses
Example Implications

- Modified cost (like convex hull) provides lower uplift payments
- Stochastic model can smooth price responses with small increases in uplift payments
- Note: the commitment decisions and bids were not affected by market design in this test
Some Remaining Questions

• What is the effect of strategic bidding and changing commitment on efficiency in the stochastic market model?
• Should bidders also bid for adjustments?
• How does the convex hull (dual) pricing model compare to a no-uplift model?

Conjecture: With some assumptions, both are equivalent and efficient.

• How to run counter-factuals on ISO data?
Summary

• Electricity markets present challenges due to operating requirements and uncertainties
• Current market designs can create inefficiencies
• Allocating fixed charges or restricting uplift payments and including stochastic scenarios may improve efficiency
Thank you!

• Questions?