Stochastic Programming for Improved Electricity Market Operations with Renewable Energy

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Outline

- Introduction
  - Renewable energy in the United States
  - Stochastic Programming

- Scenario generation and reduction
  - Scenarios from probabilistic wind power forecasts
  - Implications for stochastic unit commitment problem

- Stochastic unit commitment experiments
  - Basic model formulation
  - Scenario bundling and non-anticipativity
  - Alternative model formulation with bundles
  - Illustrative examples

- Concluding Remarks
U.S. Wind Power Capacity Reaches 60 GW (282 GW Globally)

MISO Hourly Wind Power - January 2012

Source: AWEA, 2013 MISO 2012
U.S. Solar PV Capacity Reaches 6.4 GW (over 100 GW Globally)

New U.S. Solar Electric Installations

Solar Radiation

Source: SEIA 2012
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:
  
  +
  -

  +
  -

  • is based on axioms of foundational decision theory
  • considers uncertainty holistically rather than focusing on worst case scenarios
  • can effectively hedge against randomness

  -
  • requires probabilistic inputs which may be hard to obtain or estimate
  • can be computationally hard to solve stochastic programming models
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Background: Scenario Generation and Reduction

- We use statistical methods to produce probability density functions for the wind power forecast
  - Kernel Density Forecasting (KDF) [Bessa et al. 2012]

- Stochastic unit commitment model requires scenario representation of wind power forecast → account for the temporal correlation of forecast errors
  - A large number of scenarios generated with Monte-Carlo simulation based on quantile distribution (multivariate Gaussian error variable, covariance matrix) [Pinson et al. 09]

- In previous work, we investigated three scenario reduction methods [Botterud et al. 2011]
  - SR1: Random selection
  - SR3: Scenario clustering approach [Sumaili et al. 2011]
Scenario Generation and Reduction - Illustration

A. Probabilistic forecast (KDF)

B. Large scenario set

C. Reduced scenario set (scenarios with different probabilities)
Scenario Selection is Important for Stochastic UC

- 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, 15-20 times longer run-time with 100 scenarios

Total operating costs from “out-of-sample” simulations:

- Unserved load
- Unserved reserve
- Start-up
- Fuel

SR1 - Random selection
SR2 - SCENRED (GAMS)
SR3 - Scenario clustering

[Botterud et al. 2011]
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Basic UC Model Formulation

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

subject to:

<table>
<thead>
<tr>
<th>Constraint</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>[ \sum_{l \in I_{in}} f_{it}^s + \sum_{i \in I_{in}} x_{it}^s + \sum_{j \in J_{in}} w_{jt}^s = \sum_{i \in I_{out}} f_{it}^s + D_t ]</td>
<td>Load balance</td>
</tr>
<tr>
<td>[ f_{it}^s = B_l(\theta_{nt}^s - \theta_{mt}) ]</td>
<td>Flow computation</td>
</tr>
<tr>
<td>[ -F_t \leq f_{it}^s \leq F_t ]</td>
<td>Flow limits</td>
</tr>
<tr>
<td>[ w_{jt}^s \leq W_{jt}^s ]</td>
<td>Wind curtailment</td>
</tr>
<tr>
<td>[ \sum_{i=1}^{L} r_{it}^s \geq R_t ]</td>
<td>Spinning reserve requirement</td>
</tr>
<tr>
<td>[ x_{it}^s + r_{it}^s \leq Q_i u_{it}^{s,b} ]</td>
<td>Maximum output</td>
</tr>
<tr>
<td>[ x_{it}^s \leq q_i u_{it}^{s,b} ]</td>
<td>Minimum output</td>
</tr>
<tr>
<td>[ x_{it}^s - x_{it,t-1}^s + r_{it}^s \leq u_{it,t-1}^{s,b} \Delta_i + (1 - u_{it,t-1}^{s,b}) \Delta_i^{SU} ]</td>
<td>Ramp-up/Start-up</td>
</tr>
<tr>
<td>[ x_{it,t-1}^s - x_{it}^s \leq u_{it}^{s,b} \Delta_i + (1 - u_{it}^{s,b}) \Delta_i^{SD} ]</td>
<td>Ramp-down/Shutdown</td>
</tr>
<tr>
<td>[ u_{it}^{s,b} - u_{it,t-1}^{s,b} \leq u_{it}^{s,b} \forall t \geq 2, s, \tau = t + 1, ..., \min{t + L_i - 1, T} ]</td>
<td>Minimum up-time</td>
</tr>
<tr>
<td>[ u_{it}^{s,b} - u_{it,t-1}^{s,b} \leq 1 - u_{it}^{s,b} \forall t \geq 2, s, \tau = t + 1, ..., \min{t + l_i - 1, T} ]</td>
<td>Minimum down-time</td>
</tr>
<tr>
<td>[ u_{it}^s = u_{it} ]</td>
<td>Non-anticipativity</td>
</tr>
<tr>
<td>[ x_{it}^s, r_{it}^s \geq 0 ]</td>
<td>Non-negativity</td>
</tr>
<tr>
<td>[ w_{jt}^s \geq 0 ]</td>
<td>Non-negativity</td>
</tr>
<tr>
<td>[ u_{it}^s, u_{it} \in {0,1} ]</td>
<td>Integrality</td>
</tr>
</tbody>
</table>
We use Sandia National Laboratories’ optimization tool Coopr, in particular PySP (*Python-based Stochastic Programming*) modeling and solver library (Watson et al. 2012). The tool can solve the problem in two ways:

- Extensive form
- Progressive Hedging

  - *Scenario-based decomposition scheme*
  - *Relaxation of non-anticipativity constraints*
  - *Has been used for unit commitment (e.g. Takriti et al. 1996)*
Illustrative 6-Bus System

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

<table>
<thead>
<tr>
<th>Bus No.</th>
<th>U</th>
<th>b (MBtu/MW)</th>
<th>c (MBtu/MW^2)</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>55</td>
<td>10</td>
<td>1</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>50</td>
<td>200</td>
<td>1</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: Dispatch Results**

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.
## 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>

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Perfect info.</td>
<td>59,913</td>
</tr>
<tr>
<td>Stoch. info.</td>
<td>60,427</td>
</tr>
</tbody>
</table>

*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>60,427</td>
<td></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
Alternative Model Formulation with Bundles

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

subject to:

- Load balance:
  \[\sum_{i \in \text{IN}_{in}} f_{it}^s + \sum_{i \in \text{IN}_{out}} x_{it}^s + \sum_{j \in J_{t}} w_{jt}^s = \sum_{i \in \text{OUT}} f_{it}^s + D_t\]
  \[\forall t, s\]

- Flow computation:
  \[f_{it}^l = B_l (\theta_{ni}^s - \theta_{mt}^s)\]
  \[\forall l = (m, n) \in L, t, s\]

- Flow limits:
  \[-F_{it} \leq f_{it}^l \leq F_{it}\]
  \[\forall l = (m, n) \in L, t, s\]

- Wind curtailment:
  \[w_{jt}^s \leq W_{ji}^s\]
  \[\forall j, t, s\]

- Spinning reserve requirement:
  \[\sum_{i=1}^I r_{it}^s \geq R_t\]
  \[\forall t, s\]

- Maximum output:
  \[x_{it}^s + r_{it}^s \leq Q_i u_{it}^{s,b}\]
  \[\forall i, t, s\]

- Minimum output:
  \[x_{it}^s \leq q_i u_{it}^{s,b}\]
  \[\forall i, t, s\]

- Ramp-up/Start-up:
  \[x_{it}^s - x_{i, t-1}^s \leq u_{it}^{s,b} \Delta_i + (1 - u_{it}^{s,b}) \Delta_i^{SD}\]
  \[\forall i, t \geq 2, s\]

- Ramp-down/Shutdown:
  \[u_{it}^{s,b} - u_{i,t-1}^{s,b} \leq u_{it}^{s,b}\]
  \[\forall t \geq 2, s, \tau = t + 1, ..., \min\{t + L_i - 1, T\}\]

- Minimum up-time:
  \[u_{it}^{s,b} - u_{it}^{s,b} \leq 1 - u_{it}^{s,b}\]
  \[\forall t \geq 2, s, \tau = t + 1, ..., \min\{t + l_i - 1, T\}\]

- Non-anticipativity:
  \[u_{it}^{s,b} = u_{it}^b\]
  \[\forall t, i, s\]

- Non-negativity:
  \[r_{it}^s, r_{it}^s \geq 0\]
  \[\forall t, i, s\]

- Integrality:
  \[u_{it}^{s,b}, u_{it}^b \in \{0,1\}\]
  \[\forall t, i, s\]

What if we divide the time horizon into time blocks, and enforce the non-anticipativity constraints across bundles only?

→ If the scenarios in the bundles behave similarly, we could get the same solution with LESS non-anticipativity constraints by enforcing them at the end of the blocks only.
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 50 Scenarios (Day-Ahead Forecast)

Bundling

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: Dispatch Result Comparison

- Unit 1 is always on for the three approaches.
- Unit 2 decision may change depending on the scenario.

"Across bundles"

"Across bundles at the end of time blocks"

"Across all scenarios"
### 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
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Conclusions and Future Work

- Stochastic programming is a powerful tool in solving problems with uncertainty
  - Has the potential to address uncertainty from renewables in operational decisions

- Computational effort is a challenge
  - We propose addressing this by bundling forecast scenarios and reducing the number of non-anticipativity constraints within a progressive hedging framework
  - The formulation also captures some of the multi-stage nature of the unit commitment problem

- Future work includes
  - Developing methods for more effective bundling of scenarios
  - Solving larger problems with more scenarios and stochastic variables
  - Investigate potential for improved pricing and financial incentives under stochastic scheduling
References and Acknowledgement


Acknowledgement

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