Stochastic Look-ahead Dispatch with Intermittent Renewable Generation via Progressive Hedging and L-shaped Method

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Key Questions

- Is it necessary to conduct a stochastic economic dispatch for the *(near-)* real-time operation?
- How to formulate a stochastic look-ahead economic dispatch?
- How to decide when and where in the horizon to apply stochastic programming?
- How to implement an efficient algorithm for real-time operations?
Increasing Renewable Penetration

**WIND POWER**

Source: The global status of renewable energy

**FIGURE 18. WIND POWER GLOBAL CAPACITY, 1996-2012**

Source: Solar Energy News

**Renewable Portfolio Standard Policies**

Source: renewableportfolio.org / January 2013

29 states + Washington DC and 2 territories have Renewable Portfolio Standards (8 states and 2 territories have renewable portfolio goals)

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Challenge of Uncertainty

Load Forecast vs Actual
Current-Day Forecast Peak: 47,956 MW
Current System Load: 34,981 MW
Day-Ahead Forecast Peak: 45,335 MW

Wind Forecast vs. Actual

Source: ERCOT Grid Information
Stochastic Programming

\[
\begin{align*}
\text{minimize} & \quad c \cdot x_s \\
\text{subject to:} & \quad x_s \in Q_s
\end{align*}
\]

[Birge, et. al., 2011]

Stochastic Programming Problem

\[
\begin{align*}
\text{minimize} & \quad (c \cdot x) + \sum_{s \in S} \Pr(s)(f_s \cdot y_s) \quad (\text{EF}) \\
\text{subject to:} & \quad (x, y_s) \in Q_s \quad \forall s \in S
\end{align*}
\]

Multi-Stage Stochastic Programming

Two-Stage Stochastic Programming

\[
\begin{align*}
\text{minimize} & \quad c \cdot x \\
\text{subject to:} & \quad (x, y_s) \in Q_s \quad \forall s \in S
\end{align*}
\]
Necessary Condition

Uncertainty Response

Net Load Uncertainty: 0% → 100%
Economic Risks: 0.00% → 160.00%

Stochastic Programming is Needed

Security Zone

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Dynamic Look Ahead Scheduling

Conventional Power System Scheduling (Economic Dispatch):

\[
\text{min } \sum \text{generation cost} \\
\text{s.t.} \\
\text{system security constraints.}
\]

Dynamic Look-ahead Scheduling:

\[
\text{min } \sum \sum \text{generation cost over a look-ahead window} \\
\text{s.t.} \\
\text{system security constraints at each stage.} \\
\text{Multi-stage ramping constraints.}
\]

Source: [Xie et. al., 2011]
Look-ahead Operation Horizon

Source: [Gu et. al., 2012]
Although the uncertainties in the longer run are higher, their impacts on system economic risks behave much smaller than in the shorter run.
Mathematical Criterion

Whether to do SLAED? horizon division?

Mathematical Criterion

\[ Risk_{total} \approx \sum_{k}^{T} \beta_k Risk_k \]

SLAED: Stochastic Look-ahead Economic Dispatch

\( \beta_k \): Adjustment weighting factors
Hybrid Deterministic and Stochastic Horizon

- **Deterministic Portion**
  - Net Load Level and Distribution (MW)
  - Current Step
  - Confidence Interval: 95%, 90%, 80%

- **Stochastic Portion**
  - Future

 dispatch intervals in look-ahead plan (5 mins)
Stochastic Look Ahead Dispatch

\[
\min \ f = \sum_{k \in T_I} \sum_{i \in G} C_{G_{i,s_0}} P_{i,s_0}^k + \sum_{s \in S} \rho_s \left[ \sum_{k \in T_{II}} \sum_{i \in G} C_{G_{i,s_0}} P_{i,s}^k + R_s^k \right]
\]

Objective Function

\[
\sum_{i \in G} P_{i,s}^k = L_s^k, k \in T_I \cup T_{II}, s \in S \cup \{s_0\}
\]

Energy Balancing Equations

\[
\sum_{i \in G} P_{SU_{i,s}}^k \geq SU_s^k, k \in T_I \cup T_{II}, s \in S \cup \{s_0\}
\]

Upward/Downward Short Term Dispatchable Capacity (STDC) Requirement

\[
\sum_{i \in G} P_{SD_{i,s}}^k \geq SD_s^k, k \in T_I \cup T_{II}, s \in S \cup \{s_0\}
\]

\[
-F_s^{k_{\text{max}}} \leq F_s^k \leq F_s^{k_{\text{max}}}, k \in T_I \cup T_{II}, s \in S \cup \{s_0\}
\]

Branch Flow Constraints

\[
-P_{D_i}^R \leq \frac{(P_i^k - P_{i,s}^{k-1})}{\Delta T} \leq P_{U_i}^R, i \in G, s \in S \cup \{s_0\}, k \in T_I \cup T_{II}
\]

Generators’ Ramping Constraints

\[
P_{i,s}^k + P_{SU_{i,s}}^k \leq P_{i,s}^{\text{max}}, i \in G, s \in S \cup \{s_0\}, k \in T_I \cup T_{II}
\]

Generators’ Capacity Constraints

\[
P_{i,s}^k - P_{SD_{i,s}}^k \geq P_{i,s}^{\text{min}}, i \in G, s \in S \cup \{s_0\}, k \in T_I \cup T_{II}
\]

Generators’ Output Constraints

\[
P_{i,s}^{\text{min}} \leq P_{i,s}^k \leq P_{i,s}^{\text{max}}, s \in S \cup \{s_0\}, k \in T_I \cup T_{II}
\]

Upward/downward Generators’ STDC

\[
0 \leq P_{SU_{i,s}}^k \leq P_{U_i}^R \Delta T, s \in S \cup \{s_0\}, k \in T_I \cup T_{II}
\]

\[
0 \leq P_{SD_{i,s}}^k \leq P_{D_i}^R \Delta T, s \in S \cup \{s_0\}, k \in T_I \cup T_{II}
\]
Flowchart

初始化

随机优化？

地平线划分

场景生成

解决随机地平线调度

后处理

下一个间隔

确定性地平线调度
Progressive Hedging Algorithm

[Watson, Woodruff, et. al., 2011]

1. $k := 0$
2. For all $s \in S$, $x_s^{(k)} := \arg\min_{x,y_s} (c \cdot x + f_s \cdot y_s) : (x,y_s) \in Q_s$
3. $\bar{x}^{(k)} := \sum_{s \in S} Pr(s)x_s^{(k)}$
4. For all $s \in S$, $w_s^{(k)} := \rho (x_s^{(k)} - x_{s-1})$
5. $k := k + 1$
6. For all $s \in S$, $x_s^{(k)} := \arg\min_{x,y_s} \left( c \cdot x + w_s^{(k)} (x + \rho / 2 \| x - \bar{x}^{(k-1)} \|_2^2 + f_s \cdot y_s) : (x,y_s) \in Q_s \right)$
7. $\bar{x}^{(k)} := \sum_{s \in S} Pr(s)x_s^{(k)}$
8. For all $s \in S$, $w_s^{(k)} := w_s^{(k-1)} + \rho \left( x_s^{(k)} - x_{s-1} \right)$
9. $g^{(k)} := \sum_{s \in S} Pr(s) \| x_s^{(k)} - \bar{x}^{(k)} \|$
10. If $g^{(k)} < \epsilon$, then go to Step 5. Otherwise, terminate.
Variable Fixing

Percentage of Unchanged Periods for Decision Variables (Year)

Unchanged Rate (%) vs. Variables

Percentage of Unchanged Periods for Decision Variables (Month)

Unchanged Rate (%) vs. Variables
Constraints Removal

Percentage of Unbinding Periods for Constraints (Year)

Percentage of Unbinding Periods for Constraints (Month)
Variable Fixing and Constraints Removal

\[ \min : f_{TC} = \sum_i x_i T_{vi} + \sum_j y_j T_{cj} \]

Minimize the computation time

Subject to

\[ \sum_i x_i \log P_{vi} \geq \log(1 - C_v) \]

Probability Requirement for Variable Fixing

\[ \sum_j y_j \log P_{cj} \geq \log(1 - C_c) \]

Probability Requirement for Constraints Removal

\[ x_i \in \{0,1\}, y_i \in \{0,1\} \]

Decision Variables’ self-constraints

One extensive form with much reduced size.
We give the name *L-shaped linear programs* to linear programs of the form:

\[
\text{Minimize} \quad z = c^1 x + c^2 y
\]

subject to

\[
\begin{align*}
A^{11} x &= b^1, \\
A^{21} x + A^{22} y &= b^2,
\end{align*}
\]

\[
x \geq 0, \quad y \geq 0,
\]
Numerical Experiments

ERCOT System

5889 Buses;
7220 Branches;
523 Power Plants;
76 Aggregated Wind Farms;
9710.4 MW Installed Wind Capacity;
Represent 85% of Texas Demand.

Source: ERCOT.com
Numerical Experiments

Computation time for stochastic look-ahead scheduling simulation
(Unit: Seconds, 100 Scenarios, 96 Intervals)

- Deterministic Look-ahead
- Stochastic Extensive approach
- Our Stochastic Approach

Computation Time Reduction: 88%
## Numerical Experiments

### Problem Formulation Size for Look-ahead Scheduling

<table>
<thead>
<tr>
<th>Look-ahead Horizon</th>
<th>45 mins</th>
<th>90 mins</th>
<th>180 mins</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Deterministic Look-ahead Scheduling</strong></td>
<td>5028 X 25707</td>
<td>10056 X 51414</td>
<td>20169 X 102828</td>
</tr>
<tr>
<td><strong>Stochastic Look-ahead Scheduling (Extensive approach)</strong></td>
<td>36454 X 188468</td>
<td>72908 X 376936</td>
<td>177299 X 753872</td>
</tr>
<tr>
<td><strong>Stochastic Look-ahead Scheduling (Enhanced PH)</strong></td>
<td>3776 X 11472</td>
<td>6504 X 26376</td>
<td>8568 X 44776</td>
</tr>
<tr>
<td><strong>% of Original Problem Size (Row 2)</strong></td>
<td><strong>0.63%</strong></td>
<td><strong>0.62%</strong></td>
<td><strong>0.28%</strong></td>
</tr>
</tbody>
</table>

* For enhanced PH, the original formulation has the same size as extensive approach does. What is shown is the size of the final reduced form.
Summary

- We developed a stochastic look-ahead dispatch framework for (near)-real-time operation.
- We proposed a data driven criterion for stochastic programming applicability and horizontal partition.
- We designed enhanced hybrid computational framework of progressive hedging and L-shaped method for efficient & parallel computation.

**Future work:**
- LMP studies under stochastic economic dispatch.
References

References

Thank You!
Questions and Answers