A Stochastic Programming Framework for the Large-Scale Integration of Renewable Energy in Power Systems

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Catholic University of Louvain, Belgium

Joint work with
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December 11th, 2013
Renewables Making Headlines

Germany: Nuclear power plants to close by 2022

Denmark aims for 100 percent renewable energy in 2050

California to nearly double wind, solar energy output by 2020 -regulator
Uncertainty

Tehachapi Wind Generation in April – 2005

Could you predict the energy production for this wind park either day-ahead or 5 hours in advance?

Each Day is a different color.

Day 5

Day 26

Day 9

Day 29

Average

Megawatts

-100

0

100

200

300

400

500

600

700

1

2

3

4

5

6

7

8

9

10

11

12

13

14

15

16

17

18

19

20

21

22

23

24

Hour

California ISO
Variability of wind and solar resources - June 24, 2010
Stochastic unit commitment appropriate for quantifying:

- Renewable energy utilization
- Cost of unit commitment and economic dispatch
- Capital investment in generation capacity
A Ubiquitous Problem: Unit Commitment under Uncertainty

Appropriate for modeling various balancing options:
- Demand (deferrable, price responsive, wholesale)
- Storage (pumped / run-of-river hydro, batteries)
- Transmission control (FACTS, smart wires, switching)
A Ubiquitous Solution: Parallel Computing

- Optimization under uncertainty (stochastic / robust / probabilistically constrained) can be tackled by distributed algorithms: dual / primal-dual / proximal point / cutting plane methods
- Shift of computation towards parallelization (cloud, multi-core) is impending
- Competitive positioning due to access in LLNL HPC cluster (3rd largest supercomputer worldwide)
**Unit Commitment**

- **Objective:** \(\min \sum_{g,t} (K_g u_{gt} + S_g v_{gt} + C_g p_{gt})\)

- **Load balance:** \(\sum_{g \in G} p_{gt} = D_t, \forall t\)

- **Min / max capacity limits:** \(P^-_g u_{gt} \leq p_{gt} \leq P^+_g u_{gt}, \forall g, t\)

- **Ramping limits:** \(-R^-_g \leq p_{gst} - p_{gs,t-1} \leq R^+_g, \forall g, t\)

- **Min up times:** \(\sum_{q=t-UT_g+1}^t v_{gq} \leq u_{gt}, \forall g, t \geq UT_g\)

- **Min down times:** \(\sum_{q=t+DT_g}^{t+1} v_{gq} \leq 1 - u_{gt}, \forall g, t \leq N - DT_g\)

- **State transition:** \(v_{gt} \geq u_{gt} - u_{g,t-1}, \forall g, t\)

- **Integrality:** \(v_{gt}, u_{gt} \in \{0, 1\}, \forall g, t\)

- **Kirchhoff voltage/current laws**

- **Transmission line thermal constraints**

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The Real Thing

- 1,210 generators, 3 part offers (startup, no load, 10 segment incremental energy offer curve)
- 10,000 - Demand bids – fixed or price sensitive
- 50,000 - Virtual bids / offers
- 8,700 - eligible bid/offer nodes (pricing nodes)
- 6,125 - monitored transmission elements
- 10,000 - transmission contingencies modeled

Day-ahead Market – Average Daily Volumes
Relevant Literature

- Wind integration studies based on stochastic unit commitment: (Bouffard, 2008), (Wang, 2008), (Ruiz, 2009), (Tuohy, 2009), (Morales, 2009), (Constantinescu, 2011)
  - **Contribution:** coupling scenario selection inspired by importance sampling with dual decomposition algorithm

- Integrating demand response with unit commitment: (Sioshansi, 2009), (Sioshansi, 2011)
  - **Contribution:** simultaneous modeling of uncertainty and DR

- Parallel computing in power system operations: (Monticelli, 1987), (Pereira, 1990), (Falcao, 1997), (Kim, 1997), (Bakirtzis, 2003), (Biskas, 2005)
  - **Contribution:** application to sort-term scheduling
Validation Process

- Scenario selection
- Representative outcomes
- Stochastic UC
- Slow gen UC schedule
- Deterministic UC
- Economic dispatch
- Min load, startup, fuel cost

Stochastic model (renewable energy, demand, contingencies)

Outcomes

Stoch < Det?
Unit Commitment and Economic Dispatch

- Deterministic model (Sioshansi, 2009)
  1. Reserve requirements
     \[ \sum_{g \in G} s_{gt} + \sum_{g \in G_f} f_{gt} \geq T_{t}^{\text{req}}, \sum_{g \in G_f} f_{gt} \geq F_{t}^{\text{req}}, t \in T \]
  2. Import constraints
     \[ \sum_{l \in IG_j} \gamma_{jl} e_{lt} \leq IC_j, j \in IG, t \in T \]
  - Slow generator schedules are fixed in economic dispatch model: \[ w_{gt} = w^*_{gt}, g \in G_s \]
Two-Stage Stochastic Unit Commitment

1. In the first stage we commit slow generators:
   \[ u_{gst} = w_{gt}, v_{gst} = z_{gt}, g \in G_s, s \in S, t \in T \] (corresponds to day-ahead market)

2. Uncertainty is revealed: net demand \( D_{nst} \), line availability \( B_{ls} \), generator availability \( P^+_{gs}, P^-_{gs} \)

3. Fast generator commitment and production schedules are second stage decisions: \( u_{gst}, g \in G_f \) and \( p_{gst}, g \in G_f \cup G_s \) (corresponds to real-time market)

4. Objective:
   \[
   \min \sum_{g \in G} \sum_{s \in S} \sum_{t \in T} \pi_s (K_g u_{gst} + S_g v_{gst} + C_g p_{gst})
   \]
Introduction

Methodology

Results

Conclusions and Perspectives

Unit Commitment Model

Decomposition and Scenario Selection

Wind Model

Lagrangian Decomposition Algorithm

- Decomposition methods: (Nowak, 2000), (Takriti, 1996), (Carpentier, 1996), (Redondo, 1999), (Bertsimas, 2013)

- **Contribution:** relax non-anticipativity constraints on both unit commitment and startup variables

  1. Feasible solution at each iteration
  2. Optimality gap at each iteration

Lagrangian:

\[
\mathcal{L} = \sum_{g \in G} \sum_{s \in S} \sum_{t \in T} \pi_s (K_g u_{gst} + S_g v_{gst} + C_g p_{gst}) \\
+ \sum_{g \in G_s} \sum_{s \in S} \sum_{t \in T} \pi_s (\mu_{gst}(u_{gst} - w_{gt}) + \nu_{gst}(v_{gst} - z_{gt}))
\]
Parallelization

- Lawrence Livermore National Laboratory Hera cluster: 13,824 cores on 864 nodes, 2.3 Ghz, 32 GB/node
- MPI calling on CPLEX Java callable library
Scenario Selection for Wind Uncertainty and Contingencies

- **Past work:** (Gröwe-Kuska, 2002), (Dupacova, 2003), (Heitsch, 2003), (Morales, 2009)
- **Contribution:** Scenario selection algorithm inspired by importance sampling

1. Generate a sample set \( \Omega_S \subset \Omega \), where \( M = |\Omega_S| \) is adequately large. Calculate the cost \( C_D(\omega) \) of each sample \( \omega \in \Omega_S \) against the best deterministic unit commitment policy and the average cost \( \bar{C} = \frac{1}{M} \sum_{i=1}^{M} C_D(\omega_i) \).

2. Choose \( N \) scenarios from \( \Omega_S \), where the probability of picking a scenario \( \omega \) is \( C_D(\omega)/\bar{C} \).

3. Set \( \pi_S = C_D(\omega)^{-1} \) for all \( \omega^s \in \hat{\Omega} \).

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2 wind integration cases: moderate (7.1% energy integration, 2012), deep (14% energy integration, 2020)

California ISO interconnection queue lists locations of planned wind power installations

NREL Western Wind and Solar Interconnection Study archives wind speed - wind power for Western US
Calibration

- Relevant literature: (Brown, 1984), (Torres, 2005), (Morales, 2010)
- Calibration steps
  1. Remove systematic effects:
     \[ y_{kt}^S = y_{kt} - \hat{\mu}_{kmt} \frac{\hat{\sigma}_{kmt}}{\hat{\sigma}_{kmt}}. \]
  2. Transform data to obtain a Gaussian distribution:
     \[ y_{kt}^{GS} = N^{-1}(\hat{F}_k(y_{kt}^S)). \]
  3. Estimate the autoregressive parameters \( \hat{\phi}_{kj} \) and covariance matrix \( \hat{\Sigma} \) using Yule-Walker equations.
Data Fit

Altamont

Clark County

Imperial

Solano

Tehachapi

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Model Summary

- **System characteristics**
  - 124 units (82 fast, 42 slow)
  - 53665 MW power plant capacity
  - 225 buses
  - 375 transmission lines

- **Four studies**
  - Deep (14% energy integration) without transmission constraints, contingencies
  - With transmission constraints, contingencies:
    - No wind
    - Moderate (7.1% energy integration, 2012)
    - Deep (14% energy integration, 2020)
Competing Reserve Rules

- Perfect foresight: anticipates outcomes in advance
- Percent-Of-Peak-Load rule: commit total reserve $T_{\text{req}}$ at least $x\%$ of peak load, $F_{\text{req}} = 0.5 T_{\text{req}}$
- 3+5 rule: commit fast reserve $F_{\text{req}}$ at least 3% of hourly forecast load plus 5% of hourly forecast wind, $T_{\text{req}} = 2 F_{\text{req}}$
Day Types

- 8 day types considered, one for each season, one for weekdays/weekends
- Day types weighted according to frequency of occurrence

![Graph showing net load (MW) by day type and hour]
Policy Comparison - Deep Integration, No Transmission, No Contingencies

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Explanation of SUC Superior Performance

- When reserve constraints are binding, deterministic policy overcommits.
- When reserve constraints are not binding, deterministic policy underestimates value of protecting against adverse wind outcomes.
Policy Comparison - No Wind Integration

No wind

Relative Cost

-3% -1% 0% 1% 2% 3%

Winter WD Spring WD Summer WD Fall WD Winter WE Spring WE Summer WE Fall WE

- Perfect Forecast
- 30% Peak Load
- 3+5 Rule

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Policy Comparison - Moderate Integration

The graph shows the relative cost for different seasons and years for Perfect Forecast and 30% Peak Load, as well as the 3+5 Rule. The moderate integration policy is compared across various scenarios.
Policy Comparison - Deep Integration

- Relative Cost
- Perfect Forecast
- 30% Peak Load
- 3+5 Rule
### Summary

<table>
<thead>
<tr>
<th></th>
<th>Deep-S</th>
<th>No Wind</th>
<th>Moderate</th>
<th>Deep</th>
</tr>
</thead>
<tbody>
<tr>
<td>RE daily waste (MWh)</td>
<td>100</td>
<td>0</td>
<td>890</td>
<td>2,186</td>
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<tr>
<td>Cost ($M)</td>
<td>5.012</td>
<td>11.508</td>
<td>9.363</td>
<td>7.481</td>
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<tr>
<td>Capacity (MW)</td>
<td>20,744</td>
<td>26,377</td>
<td>26,068</td>
<td>26,068</td>
</tr>
<tr>
<td>Daily savings ($)</td>
<td>38,628</td>
<td>104,321</td>
<td>198,199</td>
<td>188,735</td>
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<tr>
<td>Forecast gains (%)</td>
<td>32.4</td>
<td>35.4</td>
<td>41.9</td>
<td>46.7</td>
</tr>
</tbody>
</table>

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How Many Scenarios? Do we want to solve a more representative problem less accurately or a less representative problem more accurately?

<table>
<thead>
<tr>
<th>Model</th>
<th>Gens</th>
<th>Buses</th>
<th>Lines</th>
<th>Hours</th>
<th>Scens.</th>
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<tbody>
<tr>
<td>CAISO1000</td>
<td>130</td>
<td>225</td>
<td>375</td>
<td>24</td>
<td>1000</td>
</tr>
<tr>
<td>WILMAR</td>
<td>45</td>
<td>N/A</td>
<td>N/A</td>
<td>36</td>
<td>6</td>
</tr>
<tr>
<td>PJM</td>
<td>1011</td>
<td>13867</td>
<td>18824</td>
<td>24</td>
<td>1</td>
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</table>

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<thead>
<tr>
<th>Model</th>
<th>Integer var.</th>
<th>Cont. var.</th>
<th>Constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAISO1000</td>
<td>3,121,800</td>
<td>20,643,120</td>
<td>66,936,000</td>
</tr>
<tr>
<td>WILMAR</td>
<td>16,000</td>
<td>151,000</td>
<td>179,000</td>
</tr>
<tr>
<td>PJM</td>
<td>24,264</td>
<td>833,112</td>
<td>1,930,776</td>
</tr>
</tbody>
</table>
Gaps Versus Number of Scenarios

A large number of scenarios:
- results in a more accurate representation of uncertainty
- increases the amount of time required in each iteration of the subgradient algorithm
Consistent performance of scenario selection:
- Stochastic unit commitment yields 32.4%-46.7% of benefits of perfect foresight over various types of uncertainty
- Favorable performance relative to Sample Average Approximation with 1000 scenarios.

Insights from parallel computing³:
- Reducing the duality gap seems to yield comparable benefits relative to adding more scenarios
- All problems solved within 24 hours (operationally acceptable), given enough processors.

Transmission constraints and contingencies strongly influence results - need for advanced optimization

- Overestimation of capacity credit from 1.2% of installed wind capacity to 39.8% for deep integration
- Underestimation of daily operating costs from 7.481 $M to 5.102 $M for deep integration

First steps towards integrating deferrable demand models with renewable supply uncertainty\(^4\): Deferrable demand imposes no additional capacity requirements, coupling results in 3.06% - 8.38% operating cost increase

Perspectives

- **Modeling resources**
  - Transmission networks (FACTS, switching, smart wires)
  - Demand response
  - Storage (hydro, batteries)
  - Solar power

- **Computational extensions: industrial-scale systems**
  - Larger systems: PJM, Germany
  - Better algorithms: proximal point, bundle, cutting plane algorithms

- **Model extensions**
  - Capacity expansion planning, incentivizing capacity investment
  - European balancing market rules
References


A. Papavasiliou, S. S. Oren, *Stochastic Modeling of Multi-Area Wind Production*, under review in Resources special section on Spatial and Temporal Variation of the Wind Resource.

Questions?

Contact: anthony.papavasiliou@uclouvain.be

### Demand Response Results

<table>
<thead>
<tr>
<th>No wind</th>
<th>Daily Cost ($)</th>
<th>Daily Load Shed (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>9,012,031</td>
<td>17.301</td>
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</table>

<table>
<thead>
<tr>
<th>Centralized Moderate Bids Moderate Coupled Moderate</th>
<th>8,677,857</th>
<th>1.705</th>
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<tbody>
<tr>
<td>211,010</td>
<td>609.914</td>
<td>2.217</td>
</tr>
<tr>
<td>265,128</td>
<td></td>
<td></td>
</tr>
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<tr>
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<th>8,419,322</th>
<th>10.231</th>
</tr>
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<tbody>
<tr>
<td>578,909</td>
<td>1221.492</td>
<td>112.452</td>
</tr>
<tr>
<td>705,497</td>
<td></td>
<td></td>
</tr>
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</table>
Load Flexibility

System operator control

Coupling renewables with deferrable demand

Price-responsive demand

Centralized

Decentralized

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## Demand Response Study

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<th></th>
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<th>Moderate</th>
<th>Deep</th>
</tr>
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<tbody>
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<td>Wind capacity (MW)</td>
<td>0</td>
<td>6,688</td>
<td>14,143</td>
</tr>
<tr>
<td>DR capacity (MW)</td>
<td>0</td>
<td>5,000</td>
<td>10,000</td>
</tr>
<tr>
<td>Daily wind energy (MWh)</td>
<td>0</td>
<td>46,485</td>
<td>95,414</td>
</tr>
<tr>
<td>Daily DR energy (MWh)</td>
<td>0</td>
<td>40,000</td>
<td>80,000</td>
</tr>
<tr>
<td>DR/firm energy (%)</td>
<td>0</td>
<td>6.1</td>
<td>12.2</td>
</tr>
</tbody>
</table>
Centralized Load Dispatch

- Stochastic unit commitment with additional constraint:
  \[ \sum_{t=1}^{N} p_{gst} = R \]

- Assumptions of centralized load control:
  - Central co-optimization of generation and demand (computationally prohibitive)
  - Perfect monitoring and control of demand

- Centralized load control represents an idealization that can be used for:
  - Quantifying the cost of decentralizing demand response
  - Estimating the capacity savings of deferrable demand
Demand Bids

- Based on retail consumer model of (Borenstein and Holland, 2005), (Joskow and Tirole, 2005), (Joskow and Tirole, 2006)

- State contingent demand functions used in economic dispatch $D_t(\lambda_t; \omega) = a_t(\omega) - \alpha b\lambda^R - (1 - \alpha)b\lambda_t$

- Note that the demand function model has to:
  - Be comparable to the deferrable demand model in terms of total demand $R$
  - Be consistent with the observed inflexible demand in the system
Coupling

\[ \min_{\mu_t(x_t)} \mathbb{E} \left[ \sum_{t=1}^{N-1} \lambda_t (\mu_t(x_t) - s_t)^+ \right] \Delta t + \rho r_N \]

\[ \mu_t(x) \leq C, \ (\mu_t(x) - s_t)^+ \leq M_t, \ r_{t+1} = r_t - u_t \]
Integrating Demand Response in Stochastic Unit Commitment

**Decision support**

- Wind and firm load outcomes → Scenario selection → Net load representative outcomes → Centralized stochastic UC → UC schedule → Reserve requirements,
- Wind, firm load and price models → Scenario selection → Flexible load outcomes → Centralized economic dispatch → Decision support
- Wind outcomes → Coupling algorithm → Coupling-based economic dispatch
- Firm load outcomes → Bid-based economic dispatch
- Wind outcomes → Centralized economic dispatch
- Centralized vs Coupling vs Demand bids?

**Evaluation**

- Wind outcomes
- Firm load outcomes
- Price outcomes
- Coupling outcomes
- Flexible load outcomes
- Coupling-based economic dispatch
- Bid-based economic dispatch
- Centralized economic dispatch
- Centralized vs Coupling vs Demand bids?

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Running Times

- CPLEX 11.0.0
- DELL Poweredge 1850 servers (Intel Xeon 3.4 GHz, 1GB RAM)
- \((P1)\), \((P2_s)\) run for 120 iterations, \((ED_s)\) run for last 40 iterations
- Average running time of 43776 seconds on single machine
- Average MIP gap of 1.39%
Cost Ranking: Winter Weekdays

- $S = 1000$ corresponds to Shapiro’s SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes
Cost Ranking: Spring Weekdays

- $S = 1000$ corresponds to Shapiro’s SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes
**Cost Ranking: Summer Weekdays**

- $S = 1000$ corresponds to Shapiro’s SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes
Cost Ranking: Fall Weekdays

- $S = 1000$ corresponds to Shapiro’s SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes
Among three worse policies in summer, \( S = 1000 \) with \( G = 2\%, \ 2.5\% \)

Best policy for all day types has a 1\% optimality gap
(\( S = 1000 \) only for spring)

For all but one day type the worst policy has \( G = 2.5\% \)

For spring, best policy is \( G = 1, \ S = 1000 \)

For spring, summer and fall the worst policy is the one with the fewest scenarios and the greatest gap, namely
\( G = 2.5, \ S = 10 \)
Top performance for winter, summer and fall is attained by proposed scenario selection algorithm based on importance sampling.

For all day types, the importance sampling algorithm results in a policy that is within the top 2 performers.

Satisfactory performance (within top 3) can be attained by models of moderate scale (S50), provided an appropriate scenario selection policy is utilized.
Run Time Ranking: Winter Weekdays

Best-case running times ($S = P$)
Run Time Ranking: Spring Weekdays

Best-case running times \((S = P)\)
Run Time Ranking: Summer Weekdays

- Best-case running times ($S = P$)
Best-case running times ($S = P$)
Running Times: Winter Weekdays

Graphs showing running times for different gaps and parameters:
- Gap = 1%, WinterWD
- Gap = 1.5%, WinterWD
- Gap = 2%, WinterWD
- Gap = 2.5%, WinterWD

Each graph plots running time in hours against different scales for various parameters (P = 10, 50, 100, 1000).
Running Times: Summer Weekdays

Gap=1%, SummerWD

Gap=1.5%, SummerWD

Gap=2%, SummerWD

Gap=2.5%, SummerWD
Running Times: Fall Weekdays

Gap=1%, FallWD

Gap=1.5%, FallWD

Gap=2%, FallWD

Gap=2.5%, FallWD