Multi Area Stochastic Unit Commitment for High Wind Penetration in a Transmission Constrained Network

FERC 2011 Software Conference

Anthony Papavasiliou, Shmuel S. Oren

June 28th, 2011

Based on joint work with Richard P. O’Neill
Outline

1. Introduction

2. Model
   - Unit Commitment Model
   - Decomposition Algorithm
   - Scenario Selection
   - Wind Model

3. Results

4. Conclusions and Perspectives
Load Flexibility

2 fundamental approaches to deal with renewable energy variability via demand response

1 Centralized markets
   - Renewable producers bid in centralized real-time market (every 5’)
   - System operator procures sufficient operating reserve
   - Consumers can communicate with system through instantaneous response to price

2 Coupling load with renewables
   - Consumers communicate fixed amount of demand within fixed time window to renewable suppliers
   - Renewable resources appear behind the meter, system operator does not face variability
Research Objective

Want to quantify

- renewable energy utilization
- cost of unit commitment and economic dispatch
- capital investment in generation capacity

for the case of

- a system with renewables coupled to deferrable demand
- a system with renewables and with demand which responds to real-time prices

Stochastic unit commitment an appropriate model:

- Quantifies renewable energy utilization (decision variable)
- Quantifies operating costs (objective function)
- Quantifies capital investment on operating reserves (indirectly)
Validation Process

- **Introduction**
- **Model**
- **Results**
- **Conclusions and Perspectives**

**Validation Process**

1. **Scenario selection**
   - **Stochastic model** (renewable energy, demand, contingencies)
   - **Stochastic UC**
     - Representative outcomes
     - Outcomes
     - **Stoch < Det?**
     - Economic dispatch
     - Min load, startup, fuel cost
     - **Slow gen UC schedule**
     - Slow gen UC schedule
     - Deterministic UC
     - Outcomes

A. Papavasiliou, S. S. Oren  
FERC 2011
Unit commitment and economic dispatch: ramping, transmission, min/max capacity constraints, min up/down times

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

1. In the first stage we commit slow generators:
   \( u_{gst} = w_{gt}, \quad v_{gst} = z_{gt}, \quad g \in G_s, \quad s \in S, \quad t \in T \) (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: \( u_{gst}, \quad g \in G_f \) and \( p_{gst}, \quad g \in G_f \cup G_s \) (corresponds to real-time market)

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

Stochastic model (renewable energy, demand, contingencies) → Scenario selection → Representative outcomes → Stochastic UC → Economic dispatch

- Stoch < Det?
- Min load, startup, fuel cost
- Slow gen UC schedule
- Representative outcomes
- Outcomes

Deterministic UC
Lagrangian Decomposition Algorithm

Key idea: relax non-anticipativity constraints on both unit commitment and startup variables

1. Balance size of subproblems
2. Obtain lower and upper bounds at each iteration

Lagrangian:

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

- Second-stage subproblems, second-stage feasibility runs and economic dispatch simulations can be parallelized
- Implemented in PVM, CPLEX
Scenario Selection

- Stochastic model (renewable energy, demand, contingencies)
- Scenarios selection
  - Representative outcomes
  - Stochastic UC
    - Outcomes
      - Slow gen UC schedule
  - Deterministic UC
    - Economic dispatch
      - Outcomes
        - Slow gen UC schedule
      - Min load, startup, fuel cost

A. Papavasiliou, S. S. Oren  FERC 2011
Scenario Selection with Wind Uncertainty and Contingencies

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 $\omega_s \in \hat{\Omega}$. 
Example

Summer weekday, wind production uncertainty, 11 scenarios from 1000 samples:
Wind Model

Stochastic model (renewable energy, demand, contingencies)

Scenario selection

Representative outcomes

Stochastic UC

Stoch < Det?

Min load, startup, fuel cost

Outcomes

Slow gen UC schedule

Economic dispatch

Deterministic UC

Outcomes

A. Papavasiliou, S. S. Oren

FERC 2011
Wind Model Data Source

- 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
Wind Sites
Calibration

1. Transform data to obtain a Gaussian distribution:

\[ y_{kt}^G = N^{-1}(\hat{F}_k(y_{kt})). \]

2. Remove systematic effects:

\[ y_{kt}^{GS} = \frac{y_{kt}^G - \hat{\mu}_{kmt}}{\hat{\sigma}_{kmt}}. \]

3. Estimate the autoregressive parameters \( \hat{\phi}_{kj} \) and covariance matrix \( \hat{\Sigma} \) using Yule-Walker equations.
Load duration curves for Altamont, Clark County, Imperial, Solano and Tehachapi, and power curve at the Tehachapi area.
Competing Reserve Rules

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

A. Papavasiliou, S. S. Oren  
FERC 2011
Model Summary

- 124 units (82 fast, 42 slow)
- 53665 MW power plant capacity
- 225 buses
- 375 transmission lines
- 42 scenarios
- Four studies
  - Without transmission constraints, contingencies
  - With transmission constraints, contingencies:
    - No wind
    - Moderate (7.1% energy integration, 2012)
    - Deep (14% energy integration, 2020)
Policy Comparison - No Wind Integration

No wind integration

Relative Cost

-0.03
-0.02
-0.01
0
0.01
0.02
0.03

Winter,ND
Spring,ND
Summer,ND
Fall,ND
Winter,WE
Spring,WE
Summer,WE
Fall,WE

Perfect Forecast
30% Peak Load
3+5 Rule
Policy Comparison - Moderate Integration

---

**Moderate integration**

![Graph depicting Relative Cost for different periods and strategies: Perfect Forecast, 30% Peak Load, 3+5 Rule.](image)
Policy Comparison - Deep Integration

The chart illustrates the relative cost of deep integration in different seasons (Winter (W), Spring (SP), Summer (SU), Fall (F)) and load conditions. The bars represent different scenarios:

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

The y-axis represents the relative cost, ranging from -0.06 to 0.06.
Policy Comparison - Deep Integration, No Transmission, No Contingencies
When deterministic policy reserve constraints are binding, deterministic policy overcommits.

When deterministic policy reserve constraints are not binding, deterministic policy underestimates value of protecting against adverse wind outcomes.
<table>
<thead>
<tr>
<th>Cost ($M)</th>
<th>No wind</th>
<th>Moderate</th>
<th>Deep</th>
<th>Deep nt-c</th>
</tr>
</thead>
<tbody>
<tr>
<td>RE waste (MWh)</td>
<td>0</td>
<td>890</td>
<td>2,186</td>
<td>105</td>
</tr>
<tr>
<td>Capacity (MW)</td>
<td>26,377</td>
<td>26,068</td>
<td>26,068</td>
<td>20,744</td>
</tr>
<tr>
<td>Daily savings ($)</td>
<td>104,321</td>
<td>198,199</td>
<td>188,735</td>
<td>29,461</td>
</tr>
<tr>
<td>Forecast gains (%)</td>
<td>35.4</td>
<td>41.9</td>
<td>46.7</td>
<td>23.0</td>
</tr>
</tbody>
</table>
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%
Conclusions

- **More wind not always better**: The optimal policy may waste excess wind power due to committing more slow resources.

- **Consistent performance of scenario selection**: Stochastic unit commitment policy yields 20.3% - 46.7% of potential benefits of perfect foresight over various types of uncertainty.

- **Transmission constraints influence capacity requirements**: overestimation of capacity credit from 1.2% of installed wind capacity to 39.8% for deep integration.
Perspectives

- Parallelization in Lawrence Livermore National Labs supercomputing cluster
- Price and market impacts of renewable energy and demand response integration

A. Papavasiliou, S. S. Oren, Integration of Contracted Renewable Energy and Spot Market Supply to Serve Flexible Loads, 18th World Congress of the International Federation of Automatic Control, 08/28-09/02, 2011, Milano, Italy


Thank you

Questions?

Contact: tonypap@berkeley.edu

http://www2.decf.berkeley.edu/~tonypap/publications.html
Demand Bids

- Traditional economists’ approach to modeling demand response: decreasing ask bids that are incorporated in a social welfare maximization unit commitment model
- Not suitable for deferrable demand due to intertemporal dependency of consumption
The Optimal Control Problem

Real-time price

- RT market payments and load-shedding penalty
- Decision algorithm: how much to buy from RT market
- Charge rate constraint
- RT market purchase constraint
- State which tells us how far we are
Problem Formulation

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

- **State vector**: \( x_t = (\lambda_t, r_t) \)
  - \( \lambda_t \): spot market price of the resource
  - \( r_t \): remaining energy to be satisfied in \((r_1 = R)\)
- **Control**: \( \mu_t(x) \leq C_p 1 \{ \lambda_t \leq \lambda^{th} \} \). Amount of power which is supplied to customer
- **Dynamics**: \( r_{t+1} = r_t - u_t \Delta t \)
Integrating Demand Bids to Stochastic Unit Commitment

Wind and firm load outcomes

Price outcomes

Wind, firm load and price models

Flexible Demand
Model Details
Conclusions Details

Flexible load outcomes

Price response outcomes

Price response algorithm

Economic dispatch

Min load, startup, fuel cost, renewables utilization

Stochastic UC

Reserve requirements

Firm load minus wind representative outcomes

Scenario Selection

Coupling vs Demand bids?

A. Papavasiliou, S. S. Oren

FERC 2011
Coupling Contracts

We consider the following arrangement:

- Match large groups of renewable power suppliers to aggregations of flexible consumers
- Consumers specify deadlines for flexible consumption tasks (EV charging, water pumping, refrigeration etc.)
- Aggregators serve deferrable loads primarily from renewable generation assets, possibly resorting to real-time market purchases
- System operator reserves the right to interrupt service when marginal price exceeds a strike level
- Aggregators co-optimize charging patterns and real time market participation
The Optimal Control Problem

Available wind

Real-time price

RT market payments and load-shedding penalty

Decision algorithm: how much to buy from RT market

Charge rate constraint

RT market purchase constraint

State which tells us how far we are
Problem Formulation

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

- State vector: \( x_t = (\lambda_t, s_t, r_t) \)
  - \( \lambda_t \): spot market price of the resource
  - \( s_t \): amount of resource which is freely available
  - \( r_t \): remaining energy to be satisfied in \((r_1 = R)\)
- Control: \( \mu_t(x) \leq C_p 1 \{ \lambda_t \leq \lambda^{th} \} \). Amount of power which is supplied to customer
- Dynamics: \( r_{t+1} = r_t - u_t \Delta t \)
Integrating Coupling to Stochastic Unit Commitment

- Wind and price outcomes
- Firm load outcomes
- Wind, firm load and price models
- Wind and price outcomes
- Flexible load outcomes
- Coupling algorithm
- Stochastic UC
- Reserve requirements, UC schedule
- Economic dispatch
- Total load representative outcomes
- Scenario selection
- Coupling
- vs
- Demand bids?

A. Papavasiliou, S. S. Oren
FERC 2011
Uncertainty and Reserves

Two types of uncertainty:

- Continuous disturbances (load and renewable supply forecast error)
- Discrete disturbances (generator and transmission line failures)

Reserve requirements

- Operating reserves for continuous disturbances
- Contingency reserves for discrete disturbances
Continuous Disturbances

Wind Production Uncertainty

Load Uncertainty
Discrete Disturbances
**Stochastic Unit Commitment Formulation**

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

s.t.

\[
\sum_{l \in LI_n} e_{lst} + \sum_{g \in G_n} p_{gst} = D_{nst} + \sum_{l \in LO_n} e_{lst}, n \in N, s \in S, t \in T
\]

\[
e_{lst} = B_{ls} (\theta_{nst} - \theta_{mst}), l = (m, n) \in L, s \in S, t \in T
\]

\[
e_{lst} \leq TC_l, l \in L, s \in S, t \in T
\]

\[- TC_l \leq e_{lst}, l \in L, s \in S, t \in T
\]

\[
p_{gst} \leq P_{gs}^+ u_{gst}, g \in G, s \in S, t \in T
\]

\[
P_{gs}^- u_{gst} \leq p_{gst}, g \in G, s \in S, t \in T
\]
Stochastic Unit Commitment Formulation (II)

\[ p_{gst} - p_{gs,t-1} \leq R_g^+, g \in G, s \in S, t \in T \] (8)

\[ p_{gs,t-1} - p_{gst} \leq R_g^-, g \in G, s \in S, t \in T \] (9)

\[ \sum_{q=t-UT_g+1}^{t} v_{gsq} \leq u_{gst}, g \in G_f, s \in S, t \geq UT_g \] (10)

\[ \sum_{q=t+1}^{t+DT_g} v_{gsq} \leq 1 - u_{gst}, g \in G_f, s \in S, t \leq N - DT_g \] (11)

\[ \sum_{q=t-UT_g+1}^{t} z_{gq} \leq w_{gt}, g \in G_s, t \geq UT_g \] (12)
Stochastic Unit Commitment Formulation (III)

\[
\sum_{q=t+1}^{t+DT_g} z_{gq} \leq 1 - w_{gt}, \ g \in G_s, \ t \leq N - DT_g \quad (13)
\]

\[
z_{gt} \leq 1, \ g \in G_s, \ t \in T \quad (14)
\]

\[
v_{gst} \leq 1, \ g \in G, \ s \in S, \ t \in T \quad (15)
\]

\[
z_{gt} \geq w_{gt} - w_{g,t-1}, \ g \in G_s, \ t \in T \quad (16)
\]

\[
v_{gst} \geq u_{gst} - u_{gs,t-1}, \ g \in G_f, \ s \in S, \ t \in T \quad (17)
\]

\[
\pi_s u_{gst} = \pi_s w_{gt}, \ g \in G_s, \ s \in S, \ t \in T \quad (18)
\]

\[
\pi_s v_{gst} = \pi_s z_{gt}, \ g \in G_s, \ s \in S, \ t \in T \quad (19)
\]

\[
p_{gst}, \ v_{gst} \geq 0, \ u_{gst} \in \{0, 1\}, \ g \in G, \ s \in S, \ t \in T \quad (20)
\]

\[
z_{gt} \geq 0, \ w_{gt} \in \{0, 1\}, \ g \in G_s, \ t \in T \quad (21)
\]
Second-Stage Decision Subproblem (Per Scenario)

\[(P2_s) : \min \sum_{g \in G} \sum_{t \in T} \pi_s(k_g u_{gst} + s_g v_{gst} + c_g p_{gst}) \]
\[+ \sum_{g \in G_s} \sum_{t \in T} \pi_s(\mu_{gst} u_{gst} + \nu_{gst} v_{gst}) \]
\[s.t.
\]
\[(2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (15), (17) \]
\[p_{gst} \geq 0, v_{gst} \geq 0, u_{gst} \in \{0, 1\}, g \in G, t \in T \]
First-Stage Decision Subproblem and Multiplier Update

First-stage decision subproblem

\[(P1) : \min - \sum_{g \in G_s} \sum_{s \in S} \sum_{t \in T} \pi_s (\mu_{gst} w_{gt} + \nu_{gst} z_{gt})\]

s.t.

\[(12), (13), (14), (16)\]

\[w_{gt} \in \{0, 1\}, z_{gt} \geq 0, g \in G_s, t \in T\]

Multiplier update

\[\mu_{gst}^{k+1} = \mu_{gst}^k + \alpha_k \pi_s (w_{gt}^k - u_{gst}^k), g \in G_s, s \in S, t \in T\]

\[\nu_{gst}^{k+1} = \nu_{gst}^k + \alpha_k \pi_s (z_{gt}^k - v_{gst}^k), g \in G_s, s \in S, t \in T.\]
Scenario Selection Literature

- J. M. Morales, S. Pineda, A. J. Conejo and M. Carrion, *Scenario reduction for futures trading in electricity markets*
Scenario Selection without Contingencies

1. Generate a sample set $\Omega_S \subset \Omega$ that is adequately large. The appropriate sample size can be chosen such that
   $$\sum_{\omega \in \Omega_S} \frac{C_D(\omega)}{|\Omega_S|}$$
   converges.

2. Define a set of criteria that are deemed important for the scenario set. Select the set of scenarios $\hat{\Omega} \subset \Omega_S$ that best satisfy these criteria.

3. \[
\min_{\pi_S \in R} \sum_{t \in T} \left( \sum_{s \in S} \pi_s \omega_t^s - \mu_t \right)^2
\]
   s.t.
   $$\sum_{s \in S} \pi_s = 1, \pi_s \geq 0.01$$
## Wind Sites

<table>
<thead>
<tr>
<th>County</th>
<th>Existing</th>
<th>Moderate</th>
<th>Deep</th>
</tr>
</thead>
<tbody>
<tr>
<td>Altamont</td>
<td>954</td>
<td>954</td>
<td>1,086</td>
</tr>
<tr>
<td>Clark</td>
<td>-</td>
<td>-</td>
<td>1,500</td>
</tr>
<tr>
<td>Imperial</td>
<td>-</td>
<td>-</td>
<td>2,075</td>
</tr>
<tr>
<td>Solano</td>
<td>348</td>
<td>848</td>
<td>1,149</td>
</tr>
<tr>
<td>Tehachapi</td>
<td>1,346</td>
<td>4,886</td>
<td>8,333</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>2,766</strong></td>
<td><strong>6,688</strong></td>
<td><strong>14,143</strong></td>
</tr>
</tbody>
</table>
Simulation

1. Generate autoregressive noise of order $p$:

$$Y_{GS}^{k,t+1} = \sum_{j=0}^{p} \hat{\phi}_{kj} Y_{GS}^{t-j} + \omega_{kt}.$$ 

2. Add seasonal and hourly mean and variance:

$$Y_{G}^{k,t} = \hat{\sigma}_{kmt} Y_{GS}^{k,t} + \hat{\mu}_{kmt}.$$ 

3. Transform series to non-Gaussian:

$$Y_{kt} = \hat{F}_{k}^{-1}(N(Y_{G}^{k,t})).$$ 

4. Use an approximation $\hat{P}_{k}(\cdot)$ of the aggregate power curve for each location to simulate wind power production:

$$P_{kt} = \hat{P}_{k}(Y_{kt}).$$
Policy Comparison - Moderate Integration

$26,732 daily savings, 41.5% of perfect forecast savings realized
Policy Comparison - Deep Integration

$56,795 daily savings, 34.4% of perfect forecast savings realized
Running Times

- CPLEX 11.0.0
- DELL Poweredge 1850 servers (Intel Xeon 3.4 GHz, 1GB RAM)
- \((P_1), (P_{2s})\) run for 200 iterations, \((ED_s)\) run for last 100 iterations
- Average running time of 5685 seconds on single machine
- Average MIP gap of 0.8%
Conclusions: Case Study 1

- **Benefits of stochastic unit commitment:** Stochastic unit commitment policy yields 34.4% - 41.5% of potential benefits of perfect foresight.

- **More wind power is not always better:** The optimal policy may waste excess wind power due to committing more slow resources.
Conclusions: Case Study 2

- Influence of increased wind integration on:
  - renewable energy waste: negligible
  - capacity requirement savings: negligible
  - operating cost savings: substantial
  - benefits of stochastic unit commitment: substantial
More Perspectives

- **Enhancements**
  - Solar power modeling
  - Improved time series models for renewable power production
  - Integration of demand response in a transmission constrained network
  - Stochastic Dual Dynamic Programming algorithms for solving smart charging problem

- **Contracts for deferrable consumers**