Optimal Unit Commitment and Dispatch for Wind Farm Operations

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Optimal Unit Commitment and Dispatch for Wind Farm Operations

- Background and motivation
- Approach
- Example experimental result
- Conclusions and future work
Challenges for Wind Power

- Wind power intermittency creates significant barriers to expand utilization
  - Ramp events
  - Spinning reserve
- Better forecasting and smarter dispatch can reduce these barriers
  - Ensemble forecasts
  - Stochastic programming
  - Dynamic reserves
Examples of Weather + Optimization Coupling

- **Accurate timing of shut down due to severe weather**
  - Lead time required to take preventative measures (e.g., when a storm hits the turbines must be shut down, which takes several minutes).
  - The shut down causes a loss of energy generation.
  - The more precise (or less uncertain) the weather forecasting the more optimal can the time of shutdown be determined to minimize the loss.

- **Accurate reserve margins**
  - With improved power estimations and when losses occur, the need for alternative sources (e.g., fossil fuel plants) can be better determined.
  - More cost effective management of all generators as the need for high margins on power reserves and standby production will decrease.

- **Accurate area for shut down**
  - Improved weather forecasting will allow a more limited shut down of the facility since a subset of the affected areas could be determined.

- **Overall reduction in variability into the grid**
Unit Commitment and Dispatch

- Which power generators should be used, when and at what level in order to satisfy the demand for electricity?

- Conventional fossil-fueled or nuclear power generators require time and expense to power up and have limits on how quickly they can change their production levels.

- Unit commitment refers to deciding when to turn these generators on and off.

- Dispatch refers to deciding how much to produce from each generator.

- Because of the fixed costs and operating constraints on the generators, the power system has inflexibilities in dealing with unexpected load fluctuations and generator outages.

- To hedge against these uncertainties, system operators keep a certain amount of spinning reserve -- generators that are turned on but are producing at minimal levels so that they can increase production quickly.

- When the power system includes wind generators, the volatility of their output introduces additional uncertainty, requiring more spinning reserves, the cost of which detracts from the economics of using them.
Approach

- Coupling of a numerical weather prediction (NWP) code to optimization software
  - Output used to define a range of potential wind forecasts and create a scenario tree to estimate the uncertainty in the prediction

- Essentially a linear programming problem with uncertainty in both supply (i.e., wind) and demand

- Use stochastic optimization to hedge the unit commitment decisions
  - Reduce the amount of spinning reserves required
  - Improve the dependability of the wind resource
  - Wind generation is treated implicitly as a reduction in the net demand on the conventional generators

- Validate with a model-based forecast of a ramping event
Approach

- **Required data**
  - Set of electricity demands (loads) forecasted as a set of probabilistic scenarios for a ramping event
  - Set of generators (units) with several operating characteristics

- This leads to building recourse for each wind scenario and reduces the volume of spinning reserves as well as unmet demand and overall cost, regardless of the variance in the wind forecast.

- The optimization model is a mixed integer linear program
  - It determines when to start up the generators
  - It assigns generators a production level for each time period, which may depend on the load scenario.
Weather Model Configuration

- **WRF-ARW Community Model (v3.1.1)**
  - Focused on the region of a wind farm with appropriate physics and sufficient vertical resolution in the boundary layer to capture details in the regime swept out by turbine blades
  - 18/6/2 km nests (76x76x42)
  - 84 hour runs twice daily (initialized at 0 and 12 UTC) since April 2009
  - NAM for background and boundary conditions
  - WSM 6-class microphysics, YSU PBL, NOAH LSM, Grell-Devenyi ensemble, urban canopy model

- Select an off-shore location for “proposed” wind farm

- Identify simulation of ramping event from forecast archive
  - Interpolate wind data to 80m above sea level (assumed hub height of turbines for the “proposed” wind farm)
Example “Wind Farm” Forecast for a Ramping Event

Location of a hypothetical wind farm off the coast of New York City
Example “Wind Farm” Forecast for a Ramping Event

01/23/2010 - 19:00 EST

84-hour wind forecast showing speed and direction at a height of 10m and at the location of a hypothetical wind farm off the coast of New York City along the blade extent as well as wind trajectories.
Example “Wind Farm” Forecast for a Ramping Event

- 84-hour wind forecast showing speed and direction at a height of 80m (top, i.e., hub height for turbines at the location of a hypothetical wind farm off the coast of New York City) and at height of 10m (bottom)

- Peak wind speed before the ramp down is close to the cut-out speed of some turbines

- There is not lot of shearing from 10m to 80m because the off-shore flow is relatively laminar
Variability of Wind Velocity and Power Across the Blade Extent

- 84-hour wind forecast showing speed and direction at the maximum blade height of 120m (top) and minimum blade height of 40m (bottom)

- There is not lot of shearing from 40m to 120m because the off-shore flow is relatively laminar

- There is some variation in the wind speed along the full blade extent

- Three-dimensional, high-resolution wind modelling is required to determine power accurately, given the vertical variability
Variability of Wind Velocity and Power Across the Blade Extent

- 84-hour wind forecast showing speed and direction at the hub height of 80m (top)
- Given traditional wind turbine power curve, evaluate potential variation in power across the blade extent

\[ P = 0.5A \cdot Cp \cdot Ng \cdot Nb \cdot \rho \cdot v^3 \]

- where \( \rho \) is the air density, \( v \) is the wind speed, \( A \) is the swept out area, \( Cp \) = Coefficient of performance, \( Ng \) = generator efficiency, \( Nb \) = gearbox/bearings efficiency

- 84-hour wind power forecast across the blade extent (maximum [red] vs. minimum height [blue]) relative to hub height (bottom)
- Significant variability in operating range (i.e., > 20mph), especially during and after the ramp down
- Associated uncertainty needs to be incorporated into power forecasts
Sample Model Domain to Capture Variations in Ramp

Location of a hypothetical wind farm off the coast of New York City and 8x8 samples at hub height (80m) to capture uncertainty due to phase errors.
Example Use Case: System Operator Perspective

- System operator has to adjust dispatch to account for variations in wind energy for a ramping event.

- Consider the response to an unanticipated “ramp down” event (unanticipated at the 24 hours ahead unit commitment time) that will be predicted in the hour to two hour ahead time frame, allowing for recourse dispatch of other units to be accomplished.
  - Will mitigate the effects of the large loss of supply, and be attributable to both the weather model forecasting ability and the optimization software’s ability to quickly re-run the dispatch case without that wind power.

- Can use 24 hour unit commitment as normally done, then hourly dispatch for 4-8 hours ahead (instead of a full 24 hours to limit computation).
  - Choose generators with the proper ramp up times to fit this scenario.

- A key financial aspect of this case is the ability to, over time, reduce spinning reserve on the system, based on growing confidence in both the accuracy of the day ahead forecast and, more importantly, confidence in the “day of” time frame, allowing a longer window for bringing up additional supply.
Example Use Case: System Operator Perspective

- Unit commitment with multiple net load scenarios
- 10 generating units with various characteristics
  - initial production level (the level at which it is operating when our schedule begins)
  - minimum (lowest amount of power the generator can produce on an on-going basis) and maximum generation level
  - minimum up and down times, the minimum number of hours a generator must be on (or off) once turned on (or off)
  - maximum ramp up and ramp down rates (the maximum amount that a generator can increase or decrease production in an hour)
  - start-up cost, from fuel consumption during that time
  - fixed cost incurred in each hour when the unit is running, regardless of the amount of power it produces
  - linear fuel consumption cost
### 10-Unit Problem

- **Deterministic model uses mean demand, explicit spinning reserve requirement**
- **Stochastic model builds recourse for each scenario, implicit (system) spinning reserve**

<table>
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Example Use Case: System Operator Perspective

- 85 time periods from the hourly weather model output from 20 of the sample points are used to represent the wind generation uncertainty
  - 1045 states reflecting temporal and spatial phase errors for the ramp event

- The load levels represent the net load after subtracting the output of the wind generators
  - Because of its near zero operating costs, it nearly always makes sense to use all of the available wind power

- The uncertainty in the load (due entirely to the volatility of the wind) is represented probabilistically by a scenario tree
Example Use Case: System Operator Perspective

- A state represents the amount of net load at a point in time
- Multiple states at the same point in time represent alternative realizations of the load in different scenarios
- Solution identifies the best set of units to commit and the optimal production level for all units for all scenarios
- Eventually, spinning reserve could be scheduled as a function of wind power probability
Modelling Wind Intermittency

- Demand is uncertain, i.e., $d_t$ is a random variable
- Wind energy is forecast using weather models
  - Wind speed and direction can be forecast but with uncertainty currently based upon spatial and temporal phase errors
  - For each farm, generation $g_{i,t}$ is a random variable
- Assume that wind energy (subject to cut-in constraints) has to be used (regulatory)
  - A must-take constraint
- Therefore, the total demand can be written as
  - $D_t = d_t - S_i g_{i,t}$ (a new random variable)
  - High-demand scenario is a ramp event
Wind Intermittency and Ensemble Forecasting

- Transitions represent the uncertainty in the net load resulting from wind power volatility.
- In a given state at a given hour, there may be multiple possibilities for the net load in the next hour.
- Each possibility represents a transition.

<table>
<thead>
<tr>
<th>From State ID</th>
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<th>Probability</th>
<th>To State ID</th>
<th>Load</th>
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In state 0 above (representing the start of the planning period) there are 5 possible transitions, shown above with their probabilities.
Scenario Tree

- A scenario is a sequence of states in chronological order, linked together by transitions.
- All scenarios start at the same state and branches occur when there are multiple possibilities for the net load in the next period.
- The boxes in the tree to the right represent states (e.g., period 22, load 1257 MW).
- The branches represent transitions (e.g., from state period 22, load 1257 MW):
  - 25% of the time a transition occurs to state period 23, load 1226 MW.
  - 75% of the time a transition occurs to state period 23, load 1242 MW.
Power Production

- Total (conventional) power generation for each scenario
- Since the dispatch satisfies all the demand in each scenario, the total power generation equals the load
Power Production During Ramping Event

The stochastic optimization model will adjust to the changing demand profiles for all scenarios.
Deterministic Cases

- In the deterministic cases, the load in each period equals the expected value, or (ensemble) mean, over all the forecast scenarios in that period.
- Hence, the forecast would typically represent the expected load.
- However, in using an expected load forecast, system operators know that there are risks resulting from deviations from the forecast, such as ramp events.
- To hedge against these risks, system operators keep a certain amount of spinning reserve, generators that are turned on but producing at minimal levels that can increase production quickly.
  - The margin of spinning reserve required is usually defined as a percentage of the load.
  - Usually, the reserve margin is specified in operating policies and is a fixed parameter, although operators may deviate from policy (sometimes requiring additional reserves) based on their judgment of these risks.
## Deterministic vs. Stochastic Unit Commitment

### Lower-variance tree

<table>
<thead>
<tr>
<th>Explicit Reserves (%)</th>
<th>Implicit (System) Reserves (%)</th>
<th>Unmet Demand (MWH)</th>
<th>Cost ($)</th>
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### Higher-variance tree

<table>
<thead>
<tr>
<th>Explicit Reserves (%)</th>
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- Both trees have the same mean, but higher variance in the lower tree makes a difference
- We would expect that more explicit/implicit reserves mean less unmet demand
- More explicit/implicit reserves in the lower tree result in more unmet demand
- Stochastic model has always less spinning reserves, less unmet demand and less cost, regardless of the variance
Conclusions and Future Work

- Using a stochastic load forecast derived from NWP output, together with stochastic optimization substitutes analytic risk assessment for ad hoc adjustments to spinning reserves made based on operator judgment.

- Stochastic unit commitment can achieve lower cost and comparable (or better) reliability to deterministic dispatch methods.

- Predictive optimization with sufficient lead time can improve both dispatch and commitment.

- Future work will include:
  - Use of true NWP ensemble to represent uncertainty in weather forecast.
  - Including full three-dimensional representation of wind to determine power.
Backup

Slides
Physical & Digital Intelligence Applied to Smart Grids

IT Intermittency Solution

Coordinated control of centralized and distributed energy generation, transmission and storage with advance warning via forecasting and prediction from generation to user.

Physical & Digital Intelligence to Enable Forecasting & Prediction of Distributed Energy Generation

High Quality Public + Private Data

Weather Model
- Solar Radiation
- Wind Velocity Field
- Wave Intensity

Input Sensor Array → $X_n$ → Energy Conversion Model

Energy Conversion Model
- $P_n = f(\eta_n, P_{n-m}, X_{n-m})$

Output Sensor Array → $\eta_n$ → Forecast Model

Forecast Model
- $P_{n+q} = F(\eta_n, P_{n+/-s}, X_{n+/-r})$

Computer Models for Primary Energy Conversion Technologies

Grid Energy Forecast

溪程計中 for Real-Time Model Parameter Estimators

Modeling of Physical Systems

NWP

Solar Energy (W/m²)

Wind Speed (m/s)

*WARNING: The diagram includes a data chart showing solar radiation and wind speed with corresponding energy output and input sensor arrays. The model parameter estimation is depicted through equations and visual representations.*

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Unit Commitment Problem (Distributed Generation)

- Integer programming problem with uncertain demand & supply
  - -> Stochastic optimization
- The heat rate of a unit is a (nonlinear) function of load -> nonlinear optimization
  - maintenance improves heat rate and hence CO2 emissions
Approach

**Mixed Integer Linear Programming (MILP)**
- Binary variables represent start-up and shut-down decisions
- Continuous variables represent production level decisions
- Variable production costs are piecewise linear
- Cutting planes generated to strengthen linear representation of discreteness constraints

**Stochastic Programming with Recourse**
- Stage 1 (e.g., once per day): commit units with probabilistic scenarios for wind generation
- Stage 2,...,n (e.g. 24 hours per day): dispatch committed units to serve load net of wind generation in each scenario (commitment does not change)
- Replicated over 3-7 days
- Bundle constraints represent non-anticipatory decision policies (i.e., current decisions cannot depend on foreknowledge of future)
Modeling the Uncertainty – Scenario Tree

A 24 to 72 hour weather forecast horizon is assumed
Dynamic Decision Making Using Stochastic Programming

Demand scenario trees

- Values in the boxes show demand values for two scenario trees.
- Red line shows mean demand.
- Values on the arcs represent probabilities.
- Both trees have equal means at each time period.
- Lower demand values have higher variability.

- Risks change dynamically
  - Forecast updates
  - Information sets

- Hedging risks
  - Recourse decisions

- Deterministic vs. stochastic decisions
  - Average case leaves unserved demand in extreme cases
  - Extreme cases overcompensate on reserves