Analyzing System Costs of Wind Power Uncertainty

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Project Motivation: Uncertainty in wind power forecasts raises concerns of integrating wind into power systems at acceptable costs.

Our analysis

- Estimates the *additional* cost of power system operations from uncertainty in wind and load forecasts.
- Determines the optimal amount of a paired resource (storage, demand response) to use to mitigate wind power uncertainty
Outline

- Wind power generation modeling
- Network modeling with MATPower, to simulate system performance
- Optimizing paired resource use
- Next steps
Project Stages

1. Model geographic diversity for wind power generation.
2. Model wind generation forecast error.
4. Determine amount of forecast error to mitigate (no network).
5. Integrate previous phases.
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Step 1: Obtain Wind Speed Data

- 10 minute historical wind speed data available from UMass for sites around New England
- Many sites have multiples years of data
- A number of sites appropriate for wind turbines
- Anemometers from 30m to 80m height
Step 2: Convert to Wind Farm Power Output

1. Select wind turbine
   - On-shore vs. off-shore turbines
2. Adjust wind speed data for hub height
   - Includes adjustment for surface roughness and wind shear
3. Account for geographic diversity → decreased variability
   - Within a single wind farm
   - Across multiple wind farms
1. Wind Turbine Selection

- **Turbines**
  - GE 2.5 MW becoming most common in US
  - GE 3.0 to 3.5 MW for offshore

- **Characteristics: cut-in and cut-out speed**

![Graph showing normalised generation vs. windspeed](image)
2 - 3. Geographic Diversity

2 - 3a. Adjust wind speed data to represent aggregated wind speed for entire wind farm area

3b. Adjust the power curve to represent multiple, aggregated turbines

➢ Our study – single windfarm per bus
  ▪ Wind turbines spread across 5 to 10 km
  ▪ Probability of simultaneous changes in wind speed across entire wind farm area is essentially zero
    • Probability of dropping to below cut-in
    • Probability of spiking to above cut-out
3. Geographic Diversity – Wind Speed

3a. Algorithm for wind speed data includes:

- Propagation time of wind through the wind farm – based on average windspeed and size of windfarm
- Normalized standard deviation of the wind resource, as a function of turbulence intensity of wind and dimensions of the windfarm
- Calculate a moving block average of original wind speed data and relate to Weibull parameters of original wind speed dataset

- Multiple articles for parameter values
Geographic Diversity – Nantucket Windspeed

- Original Data
- Adjusted Data

Windspeed (m/s)

Time (10-minute steps)
Geographic Diversity – Distribution of Windspeed

![Graph showing the distribution of windspeed with frequency on the y-axis and windspeed (m/s) on the x-axis, comparing original data and adjusted data.](image-url)
3b. Algorithm for power curve includes:

- Adjust power curve to represent multiple wind turbines (~convolution with Normal distribution)
- Adjust resulting power curve for total energy capture to equal original power curve

**Final Calculation:** Determine wind farm power generation by using adjusted wind speed data with adjusted turbine power curve
3. Geographic Diversity – Power Curve

- Power curve adjusted for a large windfarm
  - \(~200\) MW, 200 km long windfarm(s)
3. Geographic Diversity – Power Curve

- Power curve adjusted for a small windfarm
  - ~50MW, 5 to 10 km long single windfarm
Geographic Diversity – Nantucket Generation

![Graph showing power generation over time with original and adjusted data]

- **Power Generation (MW)**
- **Time (10-minute step)**

Original Data

Adjusted Data

1 11 21 31 41 51 61 71 81 91
Geographic Diversity – Multiple Windfarms

- Most research on geographic diversity discusses effects of multiple windfarms
  - Hundreds of kilometer distribution of turbines
- PSERC / CERTS project
  - Geographic diversity modeled explicitly for individual, small windfarms
  - Geographic diversity of multiple windfarms modeled implicitly through locating each windfarm at a specific bus, allowing for transmission constraints
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Wind Speed Forecasting

- Linear regression model used for day-ahead and hour-ahead forecasts
- Persistence model used for 10-minute forecasts.
- (For load modeling, a neural network forecasting model was used.)
Wind Speed Forecasting

- For 10-minute forecasts
  - Wind speed partitioned into 5 equal sized cohorts
  - Wind speeds range from 0m/s to ~ 20m/s
  - 20% of range of wind speeds in each cohort
- A forecast was created for the wind speed dataset, and a probability distribution of the forecast error in each cohort was created.
Forecast Uncertainties

- **Wind generation**: 5 bins to create 5 forecast-error probability distributions
- **Demand**: Single bin (ANN forecast, NAPS paper by Chin Yen Tee)
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Determining Redispatch Costs

- Use MATPower OPF with a Monte Carlo Simulation (MCS) framework to estimate the additional cost of power system operation with uncertainty in wind and load forecasts.

- Base case scenarios are defined and then MCS is used to identify redispatch costs from wind and load uncertainty.

- Quantifying the cost of the uncertainty in wind power forecasts is defined in terms of changes in production cost and system lambda.
**MCS Framework**

- **Generate wind forecast**
  - Time = t – 1

- **MCS**: Sample forecast error distribution for wind & demand, and then...
  - Time = t

- **OPF**: Run MATPower for base case dispatch with exact wind forecast
  - Time = t – 1

- **Re-run OPF** with actual wind generation and demand, observing ramping constraints
  - (>20,000 OPF runs)
46 base cases defined based on wind power forecast, load level and non-wind ramp-rate:

- Wind Output Forecast: 5%, 20%, 40%, 60%, 80%
- Reserves Margin: 7.5%, 10%, 15%, 20%, 25%
- Non-Wind Ramp Rate: 17.5%, 35%
- Allowed to spill wind? Yes / No
Simulating Wind Power in 39-Bus System
Initial Assumptions

- Wind speed smoothed geographically for 25 mi² wind farm
- Identical generator cost curve at each bus
- Ramping costs are 10% higher than energy alone
- Demand forecast uncertainty distributed proportionally across system
- No transmission constraints
Wind-Load Extremes, $
Production Costs

Production Cost with Wind & Load Uncertainty, 35% Ramping

- Base Case
- No Spilling
- Allow Spilling
- Spill & Load Unc.

Production Cost with Wind & Load Uncertainty, 17.5% Ramping
System Lambda

System Lambda with Wind & Load Uncertainty, 35% Ramping

System Lambda with Wind & Load Uncertainty, 17.5% Ramping
Voltage Profile & Line Flows

Note, the bars show one standard deviation, implying symmetry. This will be investigated further to determine if + or − deviations predominate.
Voltage Profile & Line Flow Results
Wind-Load Extremes, Loss

Real Power Loss

- Hi Wind-Low Load
- Mid Wind & Load
- Low Wind-Hi Load

Reactive Power Loss

- Hi Wind-Low Load
- Mid Wind & Load
- Low Wind-Hi Load
Interim Results

- Wind power forecast uncertainty does not significantly increase the range of production cost ... across all scenarios
  - Flexibility in using available wind power while spilling excess wind decreases costs.
  - Low-wind – High-load increases costs and system lambda volatility.

- **System lambda** volatility is greater at low ramp rates and when excess wind cannot be spilled.

- **The voltage profile** shows that 20% of the buses may vary beyond +/- 0.06pu.
  - The voltage at buses 28, 29 & 38 is seen to vary the most (upper right branch).

- **Power flows** from buses 2-30, 16-21 & 21-22 are most effected by the wind and load uncertainty.
Next: Improve Assumptions & Input Data

- Add cost of interruptible load
  - To achieve 100% OPF convergence (assume $10,000/MWh urban; $5,000/MWh rural)

- Develop better generator cost curves
  - Use actual generation technology mix (RDI PowerDat)
  - Using heat rates, differentiate cost curves for each technology

- Improve ramping cost assumptions
  - Flat 10% cost premium currently used
Next: Expand Reporting & System Elements

➢ System elements

  ▪ Include transmission expansion and transmission constraints
    • Important to capture distinctions in location for DR and wind
  ▪ Model three wind farms
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Determining Forecast Error Mitigation

- Develop a framework to reduce net wind power variability
  - Through the use of paired, dedicated resources
  - Through diversification of sites
- Forecast errors are mitigated by
  - Demand response resources (DRR)
  - Gas turbine, storage, …
- Decision framework uses updated forecasts, to assess the need for alternative resources
Day Ahead Forecast Uncertainty

![Graph showing wind generation (MW) over time with day ahead forecast and actual values compared. The graph indicates fluctuations in wind generation throughout the day, highlighting the uncertainty in forecasting.]
10-Minute Ahead Forecast Uncertainty

- **Wind Generation (MW)**
- **Time**

- **10 min Ahead Forecast**
- **Actual**
The Framework

1) Day ahead  
2) Hour ahead  
3) 10 min ahead

Day ahead Hourly Generation Schedule

Hour ahead Forecast

Hour ahead discrepancy

Activation of slower DRR

10 minute Forecast

10-min ahead discrepancy

Activation of faster DRR

Adjusted generation schedule for next hour
The Framework

1) Generation Schedule (Day Ahead) \( \equiv G_1 \)

2) Hour Ahead Correction:
\[
\Delta_{1h} = G_1 - (\alpha_{1h} + \beta_{1h}P_{1h}), \text{ and }
\]
\[
DR_{1h} = \begin{cases} 
\Delta_{1h} \gamma_{1h} & \text{if } \Delta_{1h} > 0 \\
0 & \text{otherwise}
\end{cases}
\]
where, otherwise \( 0 \) if \( DR \) and \((1h,1,1h)\)

\( DR_t \) is quantity of DR \( t \) ahead
\( \gamma_t \) is the fraction of shortfall to cover, \( t \) ahead

3) 10 Minute Ahead Correction:
\[
\Delta_{10M} = G_1 - DR_{1h} - (\alpha_{10M} + \beta_{10M}P_{10M}), \text{ and }
\]
\[
DR_{10M} = \begin{cases} 
\Delta_{10M} \gamma_{10M} & \text{if } \Delta_{10M} > 0 \\
0 & \text{otherwise}
\end{cases}
\]
What are the best $\gamma$s to use?

- Selection of the fraction of the forecast error to mitigate at each step, $\gamma$, depends on the relative costs:

$$C_T = \Delta_{1h}\gamma_{1h}C_{1h} + \Delta_{10M}\gamma_{10M}C_{10M} + \Delta_{RT}C_{RT}$$

- We can assume

$$C_{1h} \leq C_{10M} \leq C_{RT}$$
Cost to Mitigate Wind Uncertainty

Given that the cost associated with mitigating wind variability with this strategy is given by

\[ C_T = \Delta_{1h} \gamma_{1h} C_{1h} + \Delta_{10M} \gamma_{10M} C_{10M} + \Delta_{RT} C_{RT} \]

Develop a framework to identify the best fraction of the forecast error to mitigate at each market stage (determine the \( \gamma \)s)
The fraction of shortfall that is mitigated at each time scale, $\gamma$, is not constant across time scales.

Using the appropriate $\gamma$ values has a significant impact on costs.

- For relative costs of 1, 1.5 & 3 (RT, 10min, HA), the total cost of DR usage is reduced by 25% under the optimal gamma values.

Specific $\gamma$ values are location and market specific.
Project Stages: Integrate framework

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Next Step: Integrate all elements of project

1. Geographic smoothing of wind power output, \textit{plus}

2. MCS framework using the 39-bus model to simulate costs of redispatch, \textit{plus}
   - (With transmission constraints)

3. ‘\(\gamma\)’ decision framework to decide the capacity of the paired resource to use (specifically demand response)

\begin{itemize}
\item In order to find the most cost-effective locations and quantities of various demand response programs, to mitigate wind variability on the network.
\end{itemize}
Summary

- Geographic diversity of wind power generation modeling shows decreased variability as expected.
- Framework to analyze costs of redispatch to mitigate wind variability:
  - To be updated with consistent set of input assumptions.
  - To be expanded to include transmission constraints.
- Framework to determine percentage of forecast error to mitigate, ‘\(\gamma\),’ to be combined with network modeling.

Questions?