CERTS

CONSORTIUM FOR ELECTRIC RELIABILITY TECHNOLOGY SOLUTIONS

PSERC

Analyzing System Costs of Wind Power Uncertainty

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PSERC Seminar

Cornell University

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Overview

- <u>Project Motivation</u>: 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.
3. Model redispatch costs of wind power uncertainty using Monte Carlo simulation and the 39-bus test system.
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

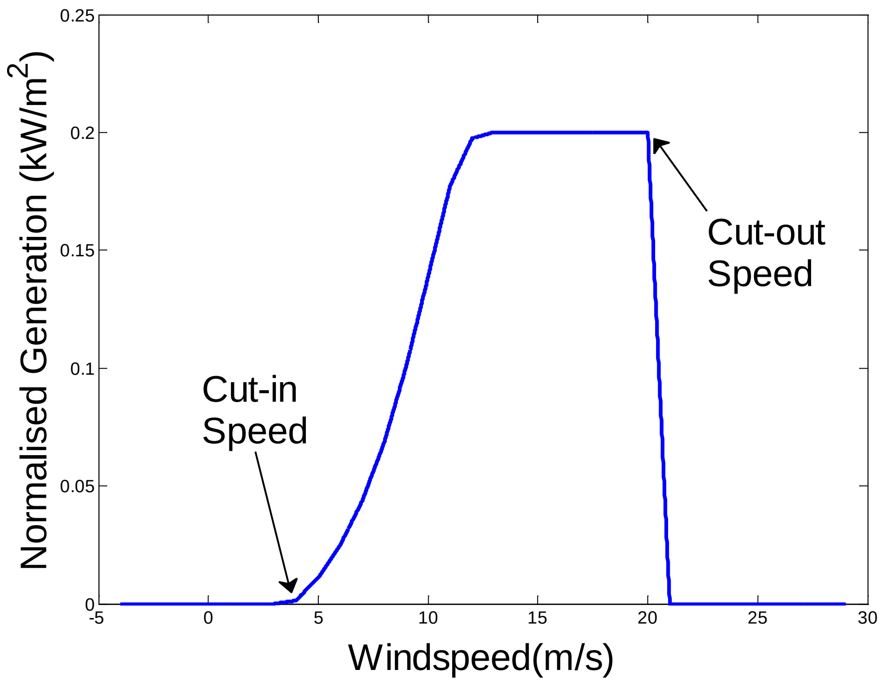
Step 2: Convert to Wind Farm Power Output

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 off-shore

- Characteristics: cut-in and cut-out speed



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

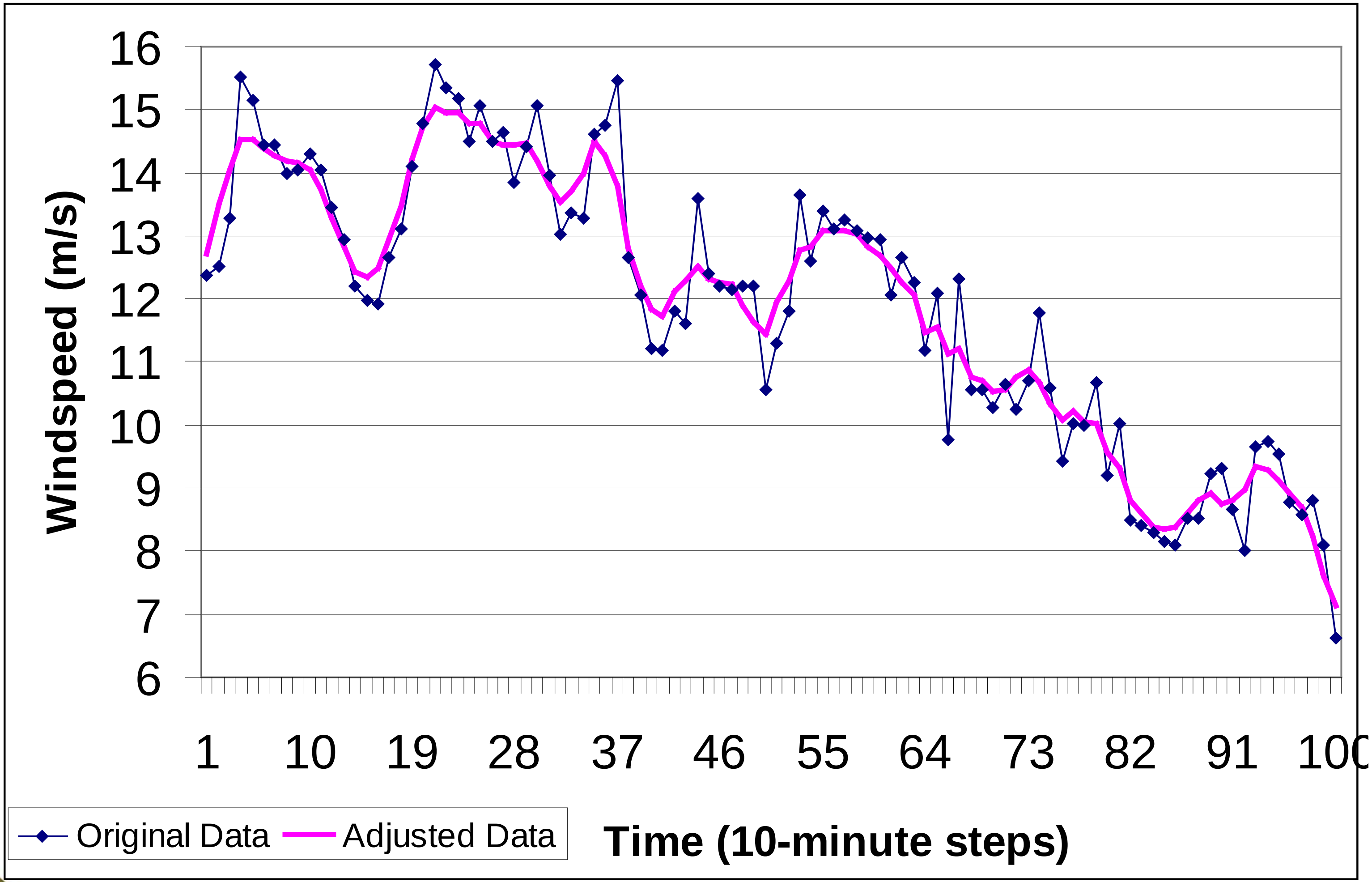
3. Geographic Diversity – Wind Speed

3a. Algorithm for wind speed data includes:

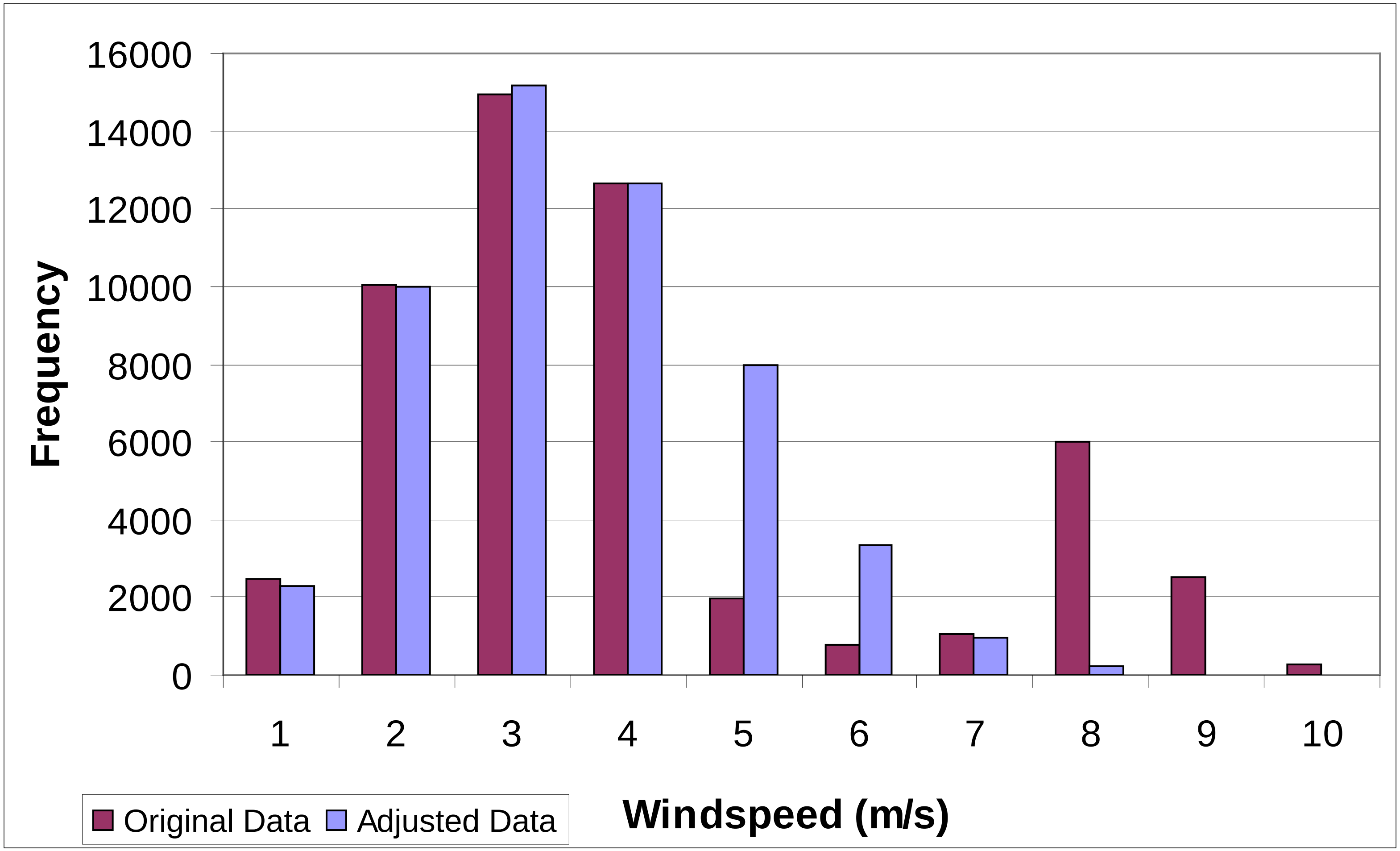
- Propagation time of wind through the wind farm – based on average windspeed and size of windfarm
- Normalized standard deviation of the wind resource, as a function of turbulence intensity of wind and dimensions of the windfarm
- Calculate a moving block average of original wind speed data and relate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

- "A Multi-Turbine Power Curve Approach," Norgaard, Holttinen
- Multiple articles for parameter values

Geographic Diversity – Nantucket Windspeed



Geographic Diversity – Distribution of Windspeed



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3. Geographic Diversity – Power Curve

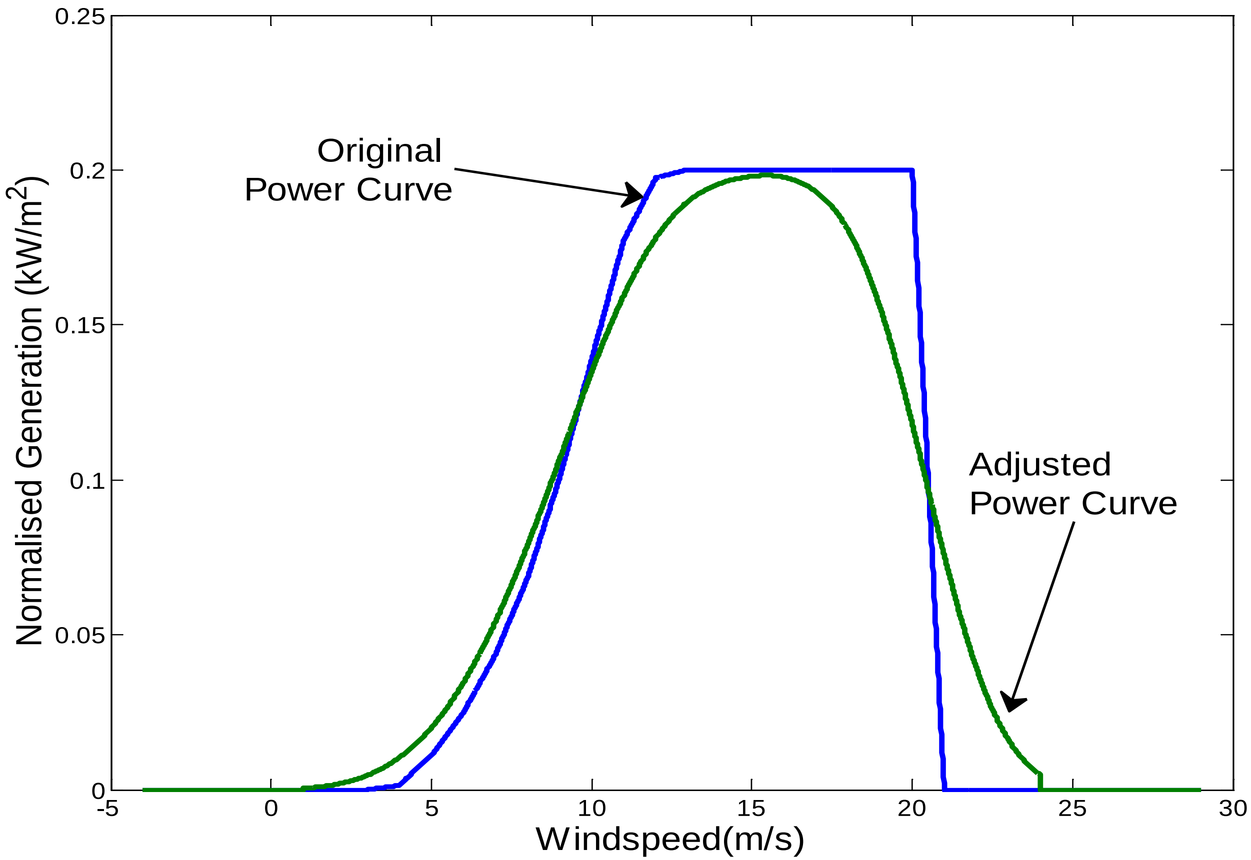
3b. Algorithm for power curve includes:

- 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

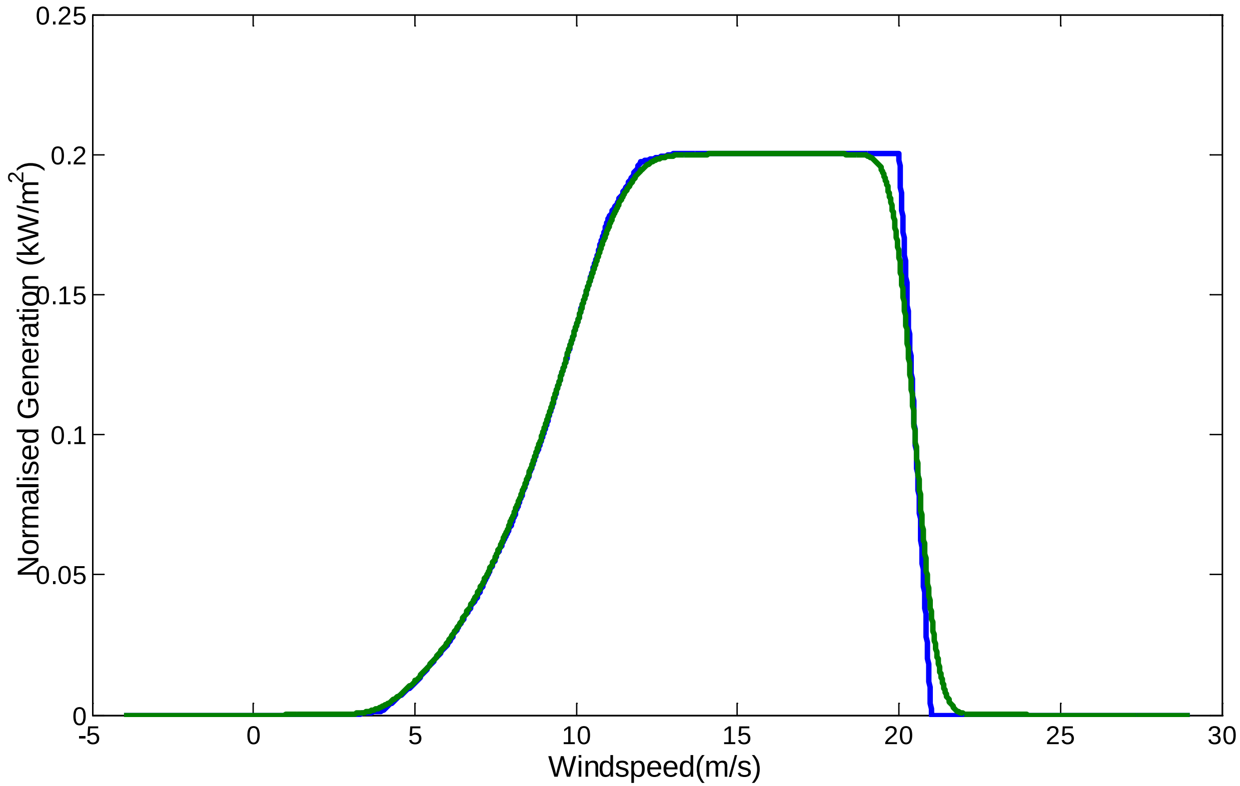
3. Geographic Diversity – Power Curve

- Power curve adjusted for a large windfarm
  - ~200 MW, 200 km long windfarm(s)

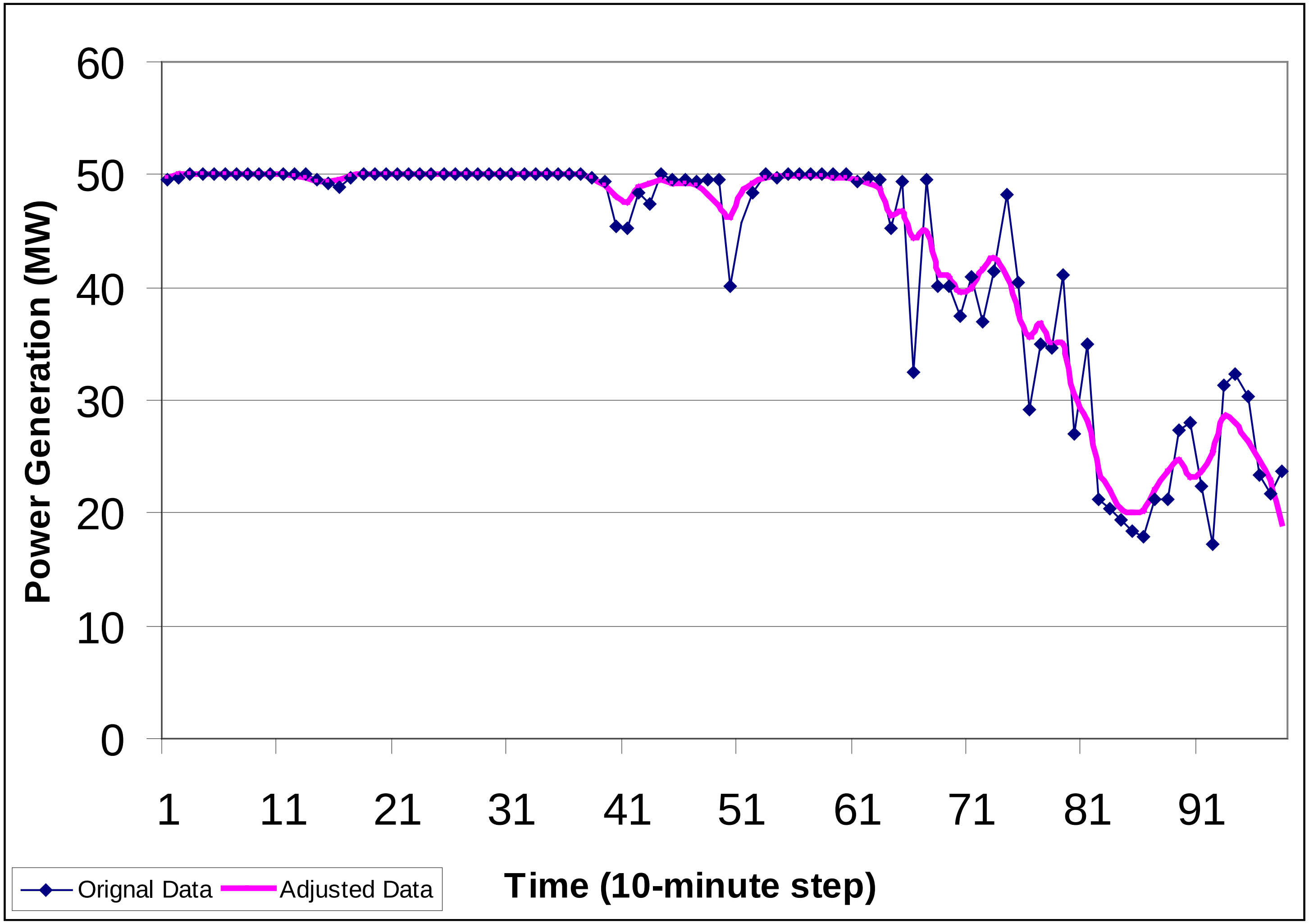


3. Geographic Diversity – Power Curve

- Power curve adjusted for a small windfarm
  - ~50MW, 5 to 10 km long single windfarm



Geographic Diversity – Nantucket Generation



Geographic Diversity – Multiple Windfarms

- Most research on geographic diversity discusses effects of multiple wind farms
  - 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

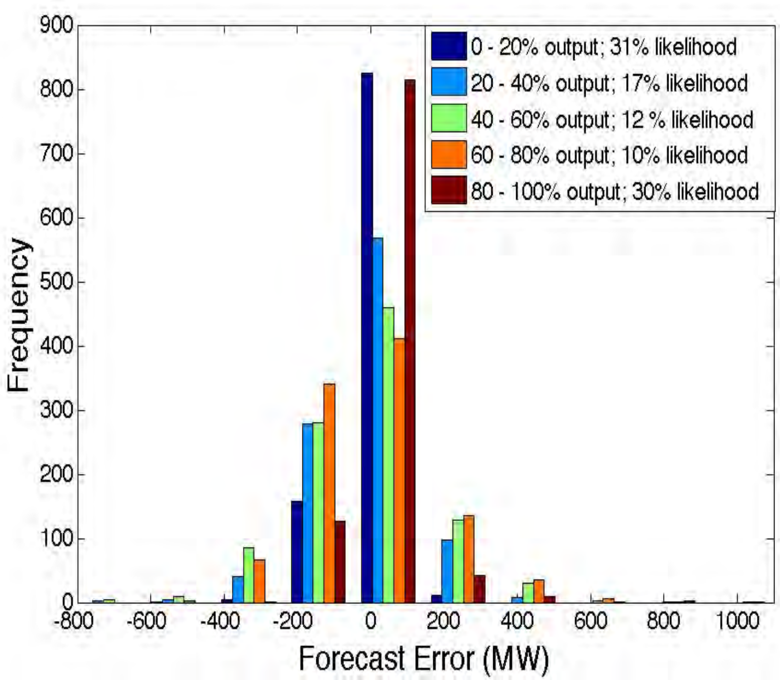
- Linear regression model used for day-ahead and hour-ahead forecasts
- Persistence model used for 10-minute forecasts.
- (For load modeling, a neural network forecasting model was used.)

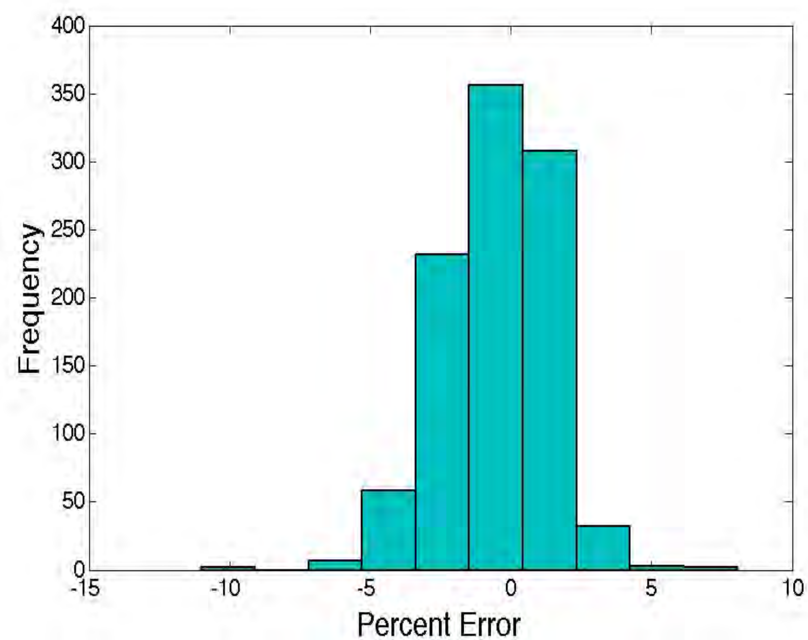
Wind Speed Forecasting

- 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

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

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

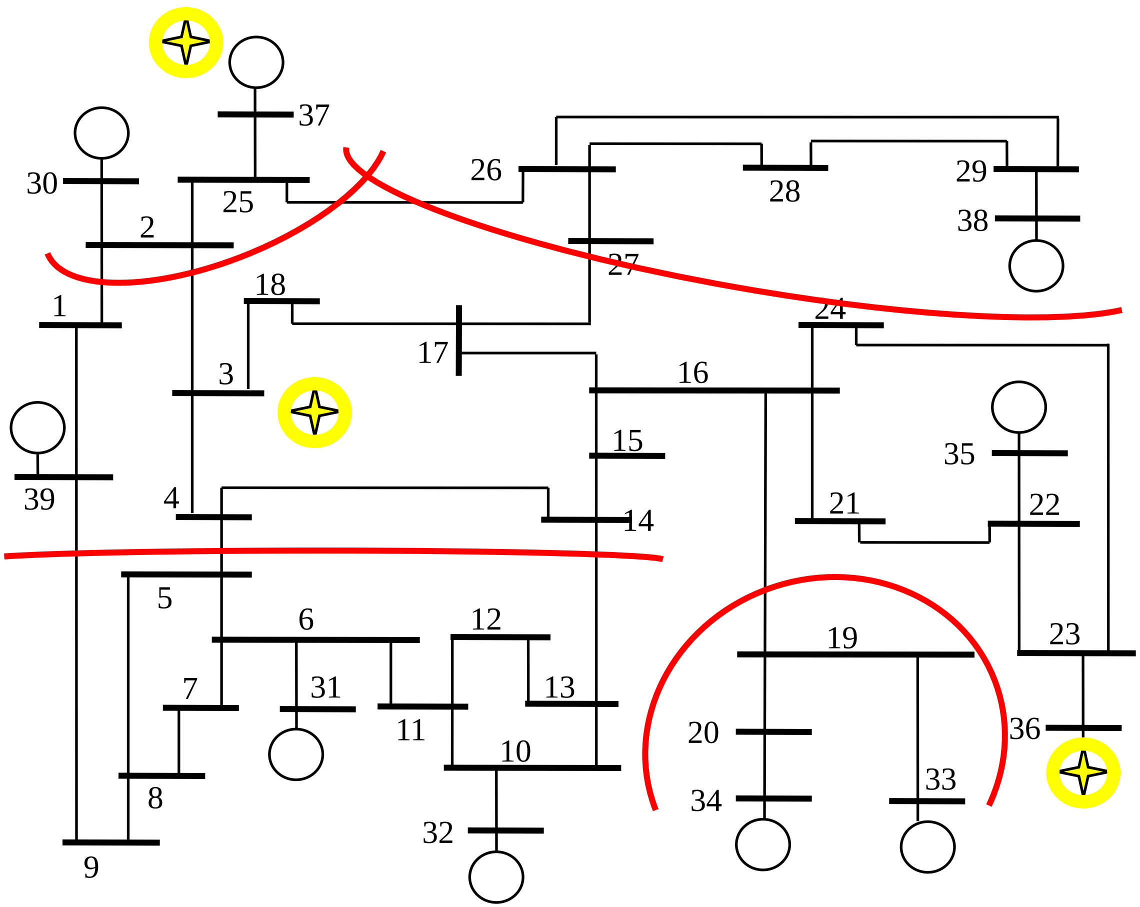
Re-run OPF with actual wind generation and demand, observing ramping constraints

(>20,000 OPF runs)

Base Cases Simulations

- 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

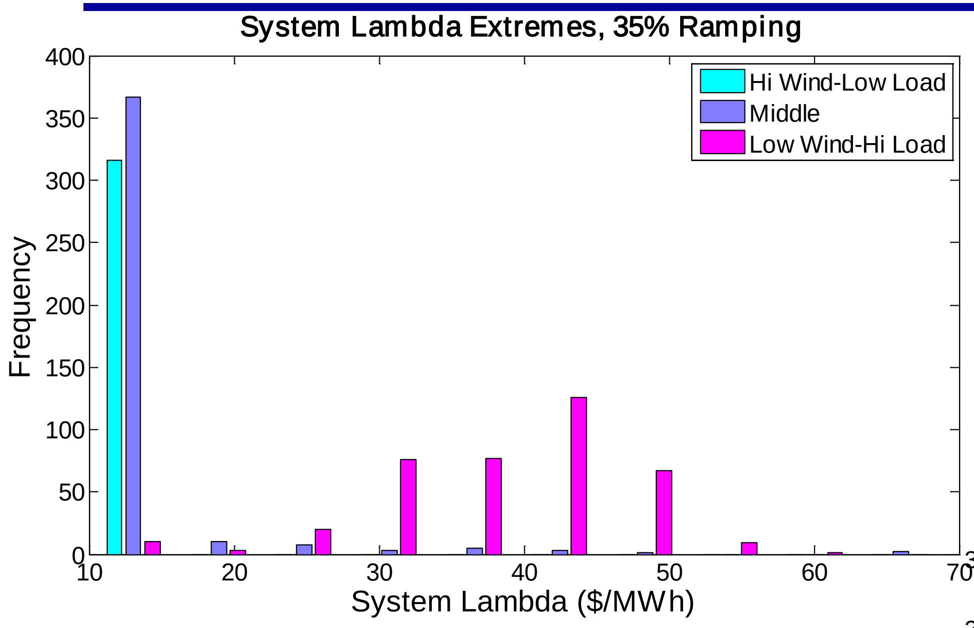
Simulating Wind Power in 39-Bus System

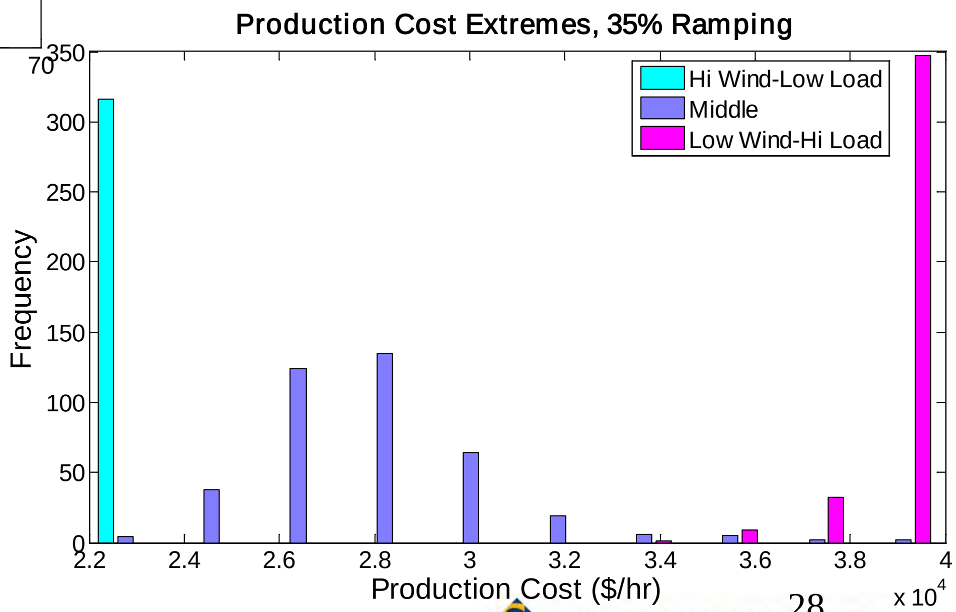


Initial Assumptions

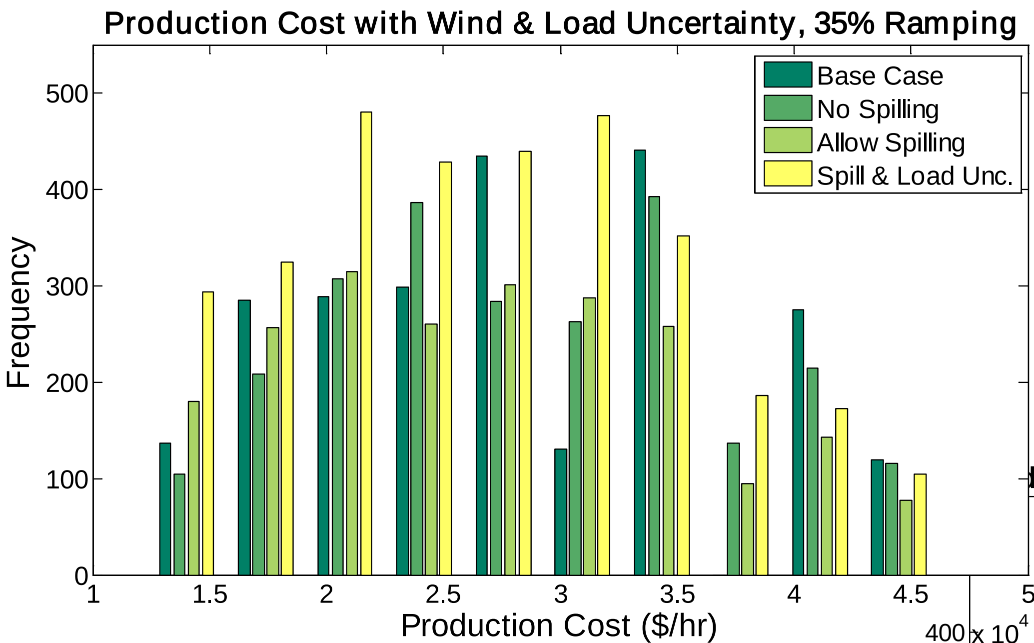
- Wind speed smoothed geographically for 25 mi^2 wind farm
- Identical generator cost curve at each bus
- Ramping costs are 10% higher than energy alone
- Demand forecast uncertainty distributed proportionally across system
- No transmission constraints

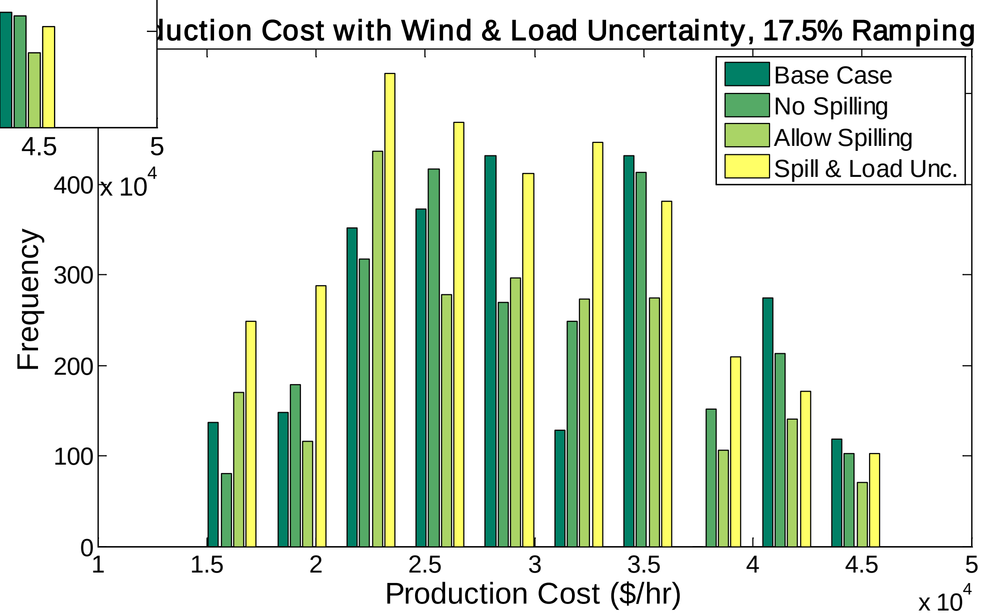
Wind-Load Extremes, $



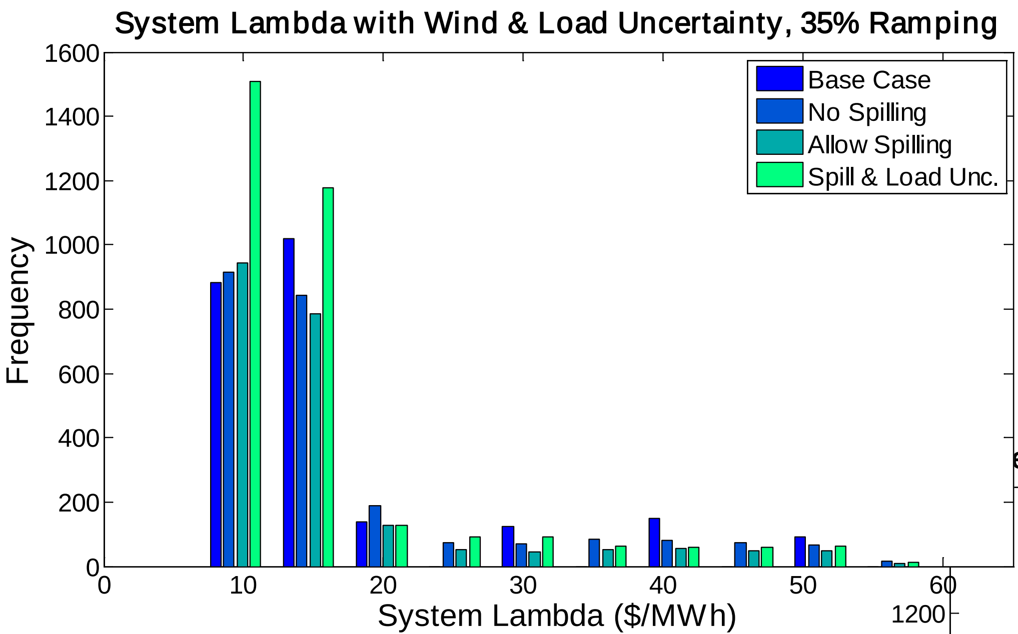


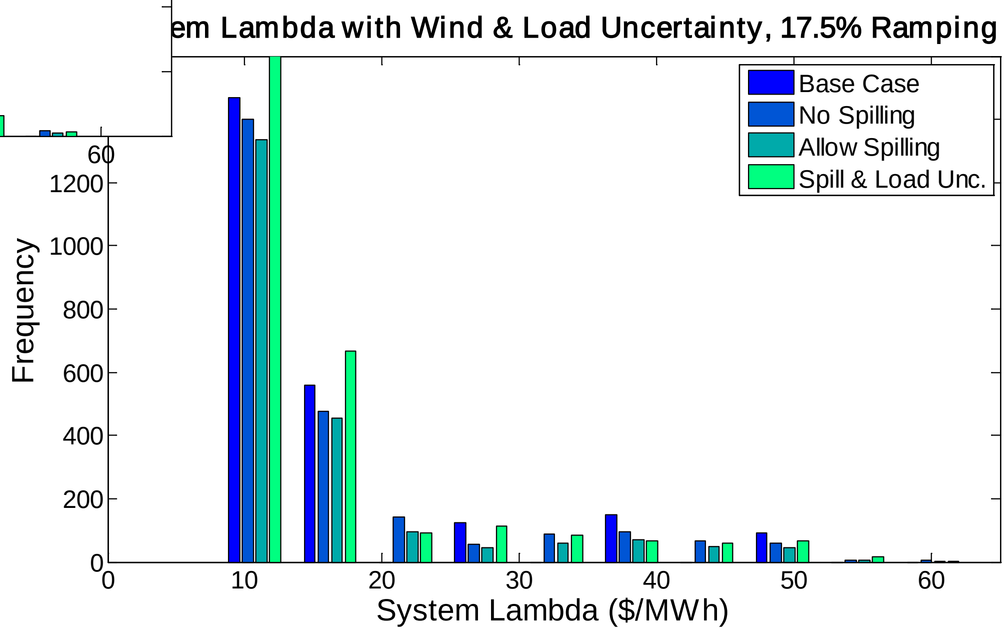
Production Costs



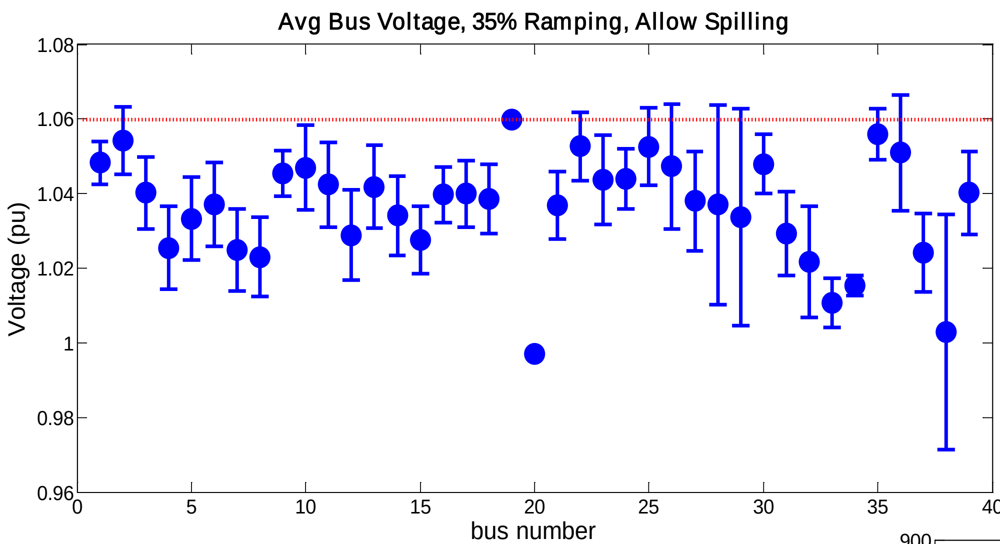


System Lambda

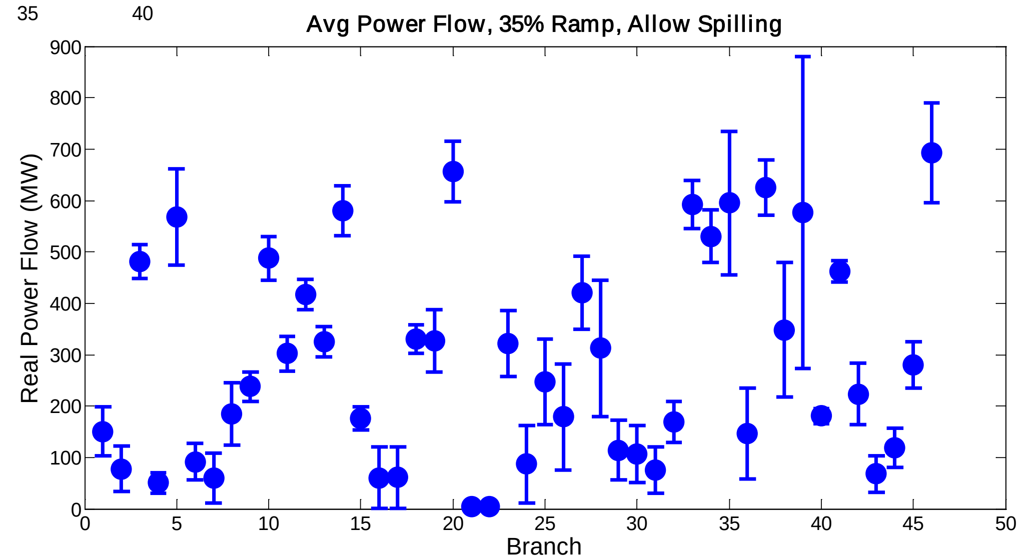




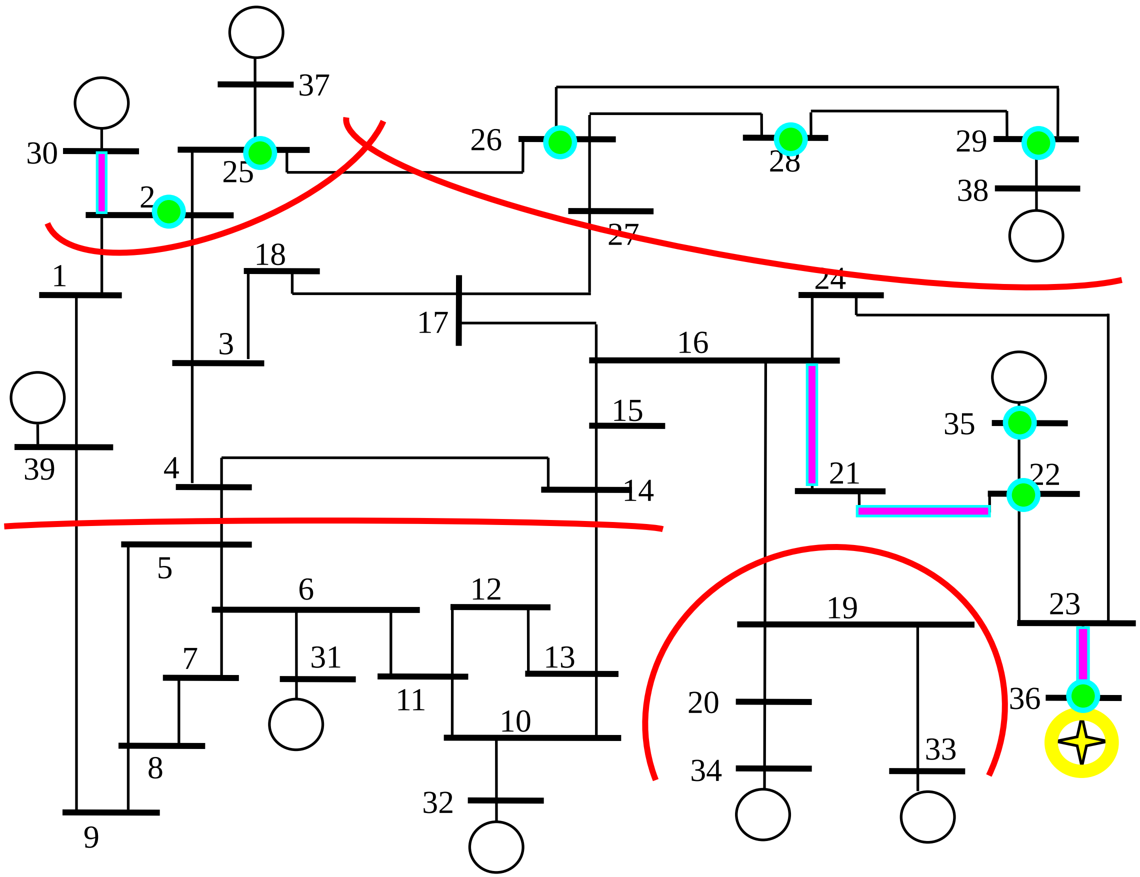
Voltage Profile & Line Flows



Note, the bars show one standard deviation, implying symmetry. This will be investigated further to determine if + or – deviations predominate.

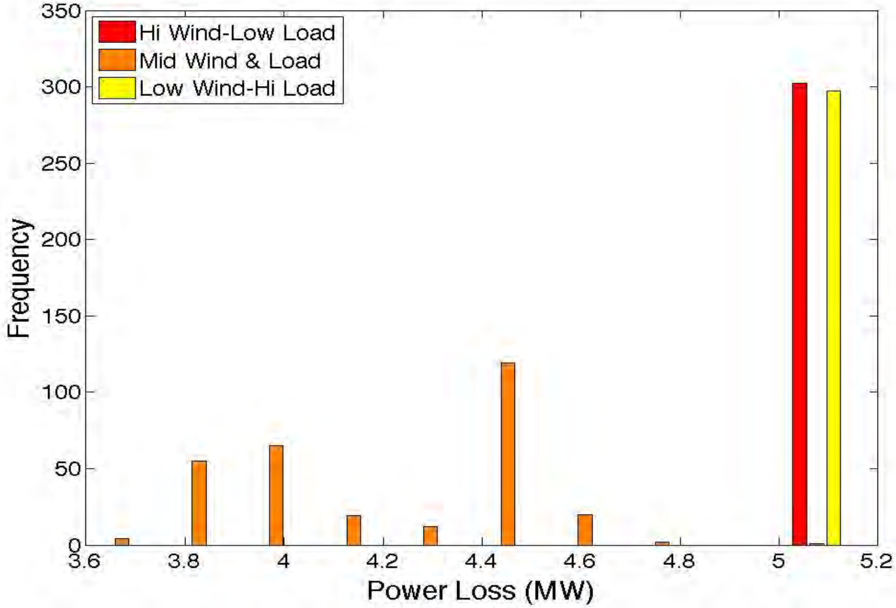


Voltage Profile & Line Flow Results

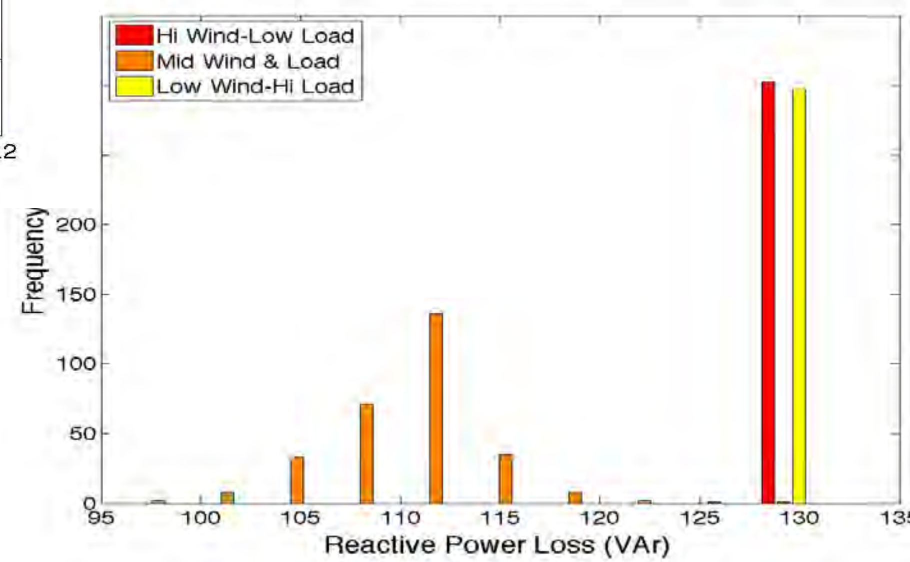


Wind-Load Extremes, Loss

Real Power Loss



Reactive Power Loss



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

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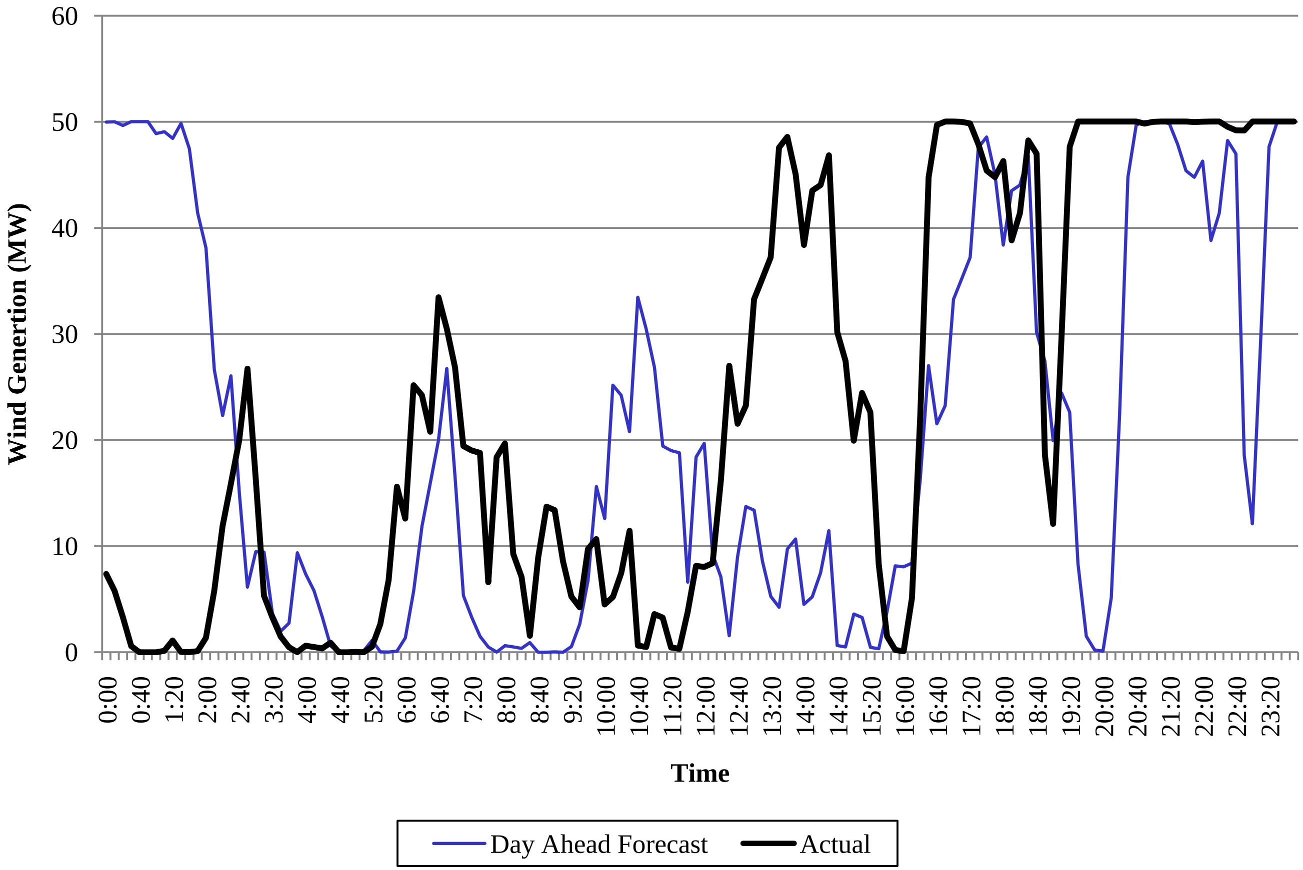
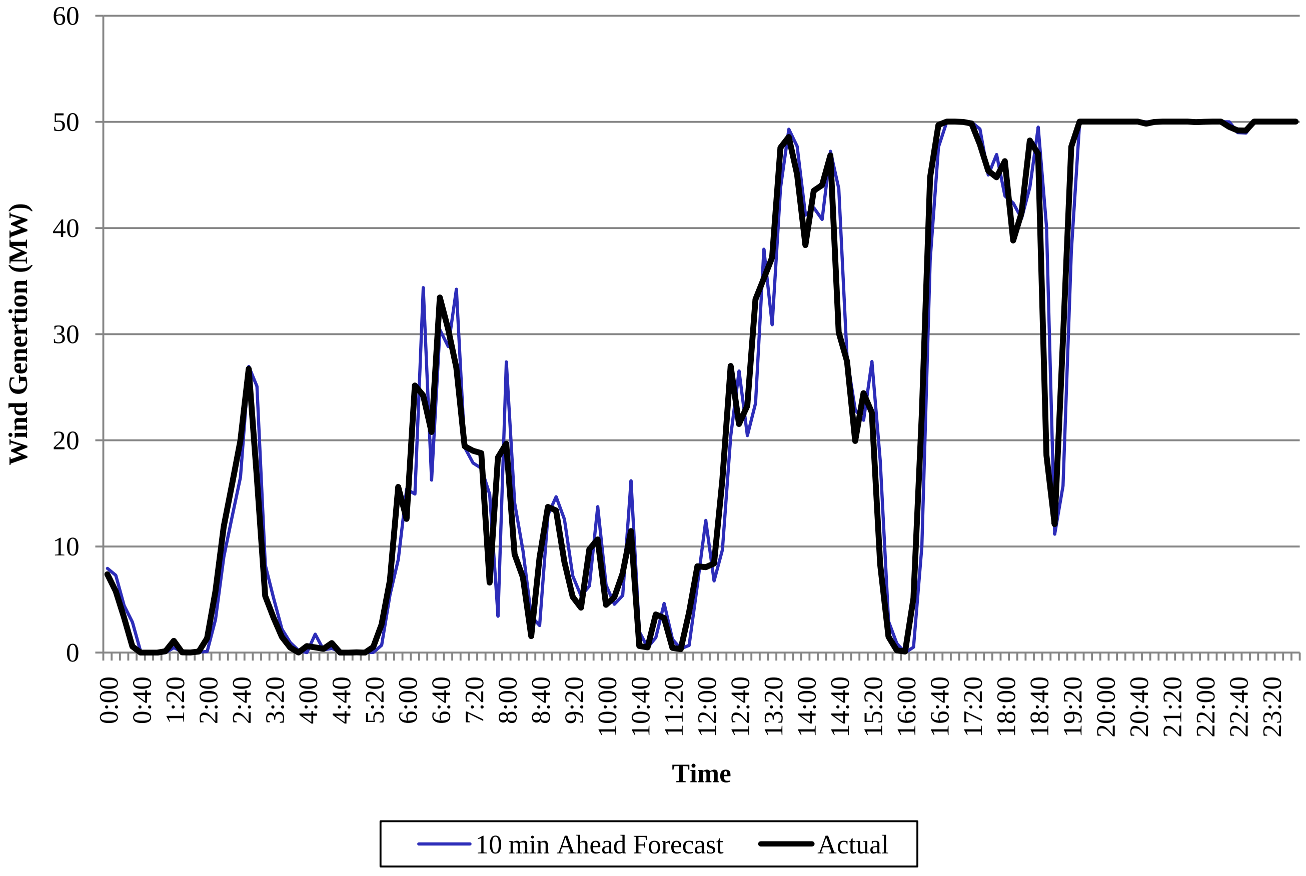
Day Ahead Forecast Uncertainty

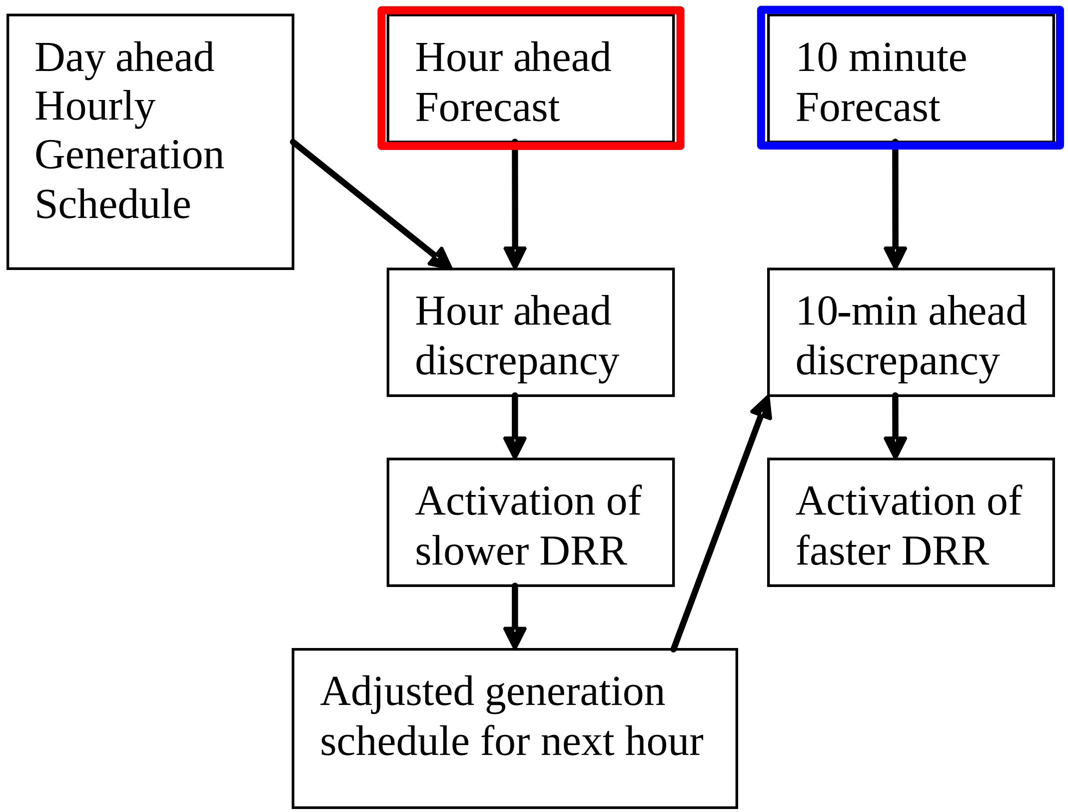


10-Minute Ahead Forecast Uncertainty



The Framework

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



The Framework

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

2) Hour Ahead Correction:

$$\Delta_{1h} = G_1 - \boxed{(\alpha_{1h} + \beta_{1h} P_{1h})}, \text{ and}$$

$$\mathrm{DR}_{1h} = \begin{cases} \Delta_{1h}\gamma_{1h} & \text{if } \Delta_{1h} > 0 \\ 0 & \text{otherwise} \end{cases}, \text{ where}$$

DR_t is quantity of DR t ahead

γ_t is the fraction of shortfall to cover, t ahead

3) 10 Minute Ahead Correction:

$$\Delta_{10M} = G_1 - DR_{1h} - \boxed{(\alpha_{10M} + \beta_{10M} P_{10M})}, \text{ and}$$

$$\mathrm{DR}_{10M} = \begin{cases} \Delta_{10M}\gamma_{10M} & \text{if } \Delta_{10M} > 0 \\ 0 & \text{otherwise} \end{cases}$$

What are the best γs to use?

- Selection of the fraction of the forecast error to mitigate at each step, γ, 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 γs)

The Bottom Line

- The fraction of shortfall that is mitigated at each time scale, γ, is not constant across time scales
- Using the appropriate γ 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 γ 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, *plus*
2. MCS framework using the 39-bus model to simulate costs of redispatch, *plus*
   - (With transmission constraints)
3. ‘γ’ decision framework to decide the capacity of the paired resource to use (specifically demand response)

➢ In order to find the most cost-effective locations and quantities of various demand response programs, to mitigate wind variability on the network.

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, ‘γ,’ to be combined with network modeling

- QUESTIONS?