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Assessment of Wind Power Scenario Generation Methods for Stochastic Unit Commitment

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A Word From Our Sponsors...

- Grid Modernization Laboratory Consortium (GMLC)
 - Project 1.4.26 – Multi-Scale Production Cost Modeling
- Bonneville Power Administration (BPA)
 - Funded work on high-accuracy probabilistic wind forecasting
 - Provide real-world data sets, publicly available

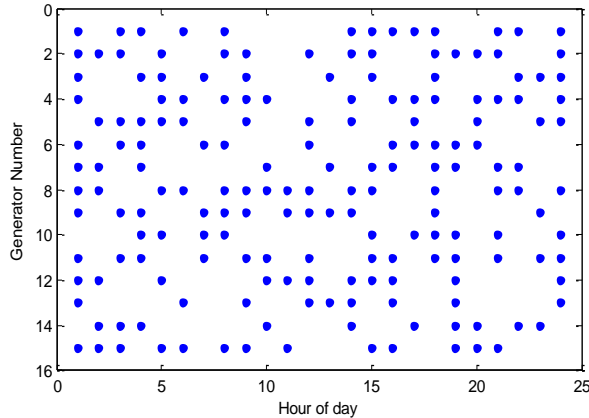
High-Level Talk Goals

- Somewhat surprising
 - This is *not* really about stochastic unit commitment / dispatch
 - Main lessons apply to deterministic variants as well

- Main theme
 - The nature of inputs to commitment / dispatch impacts costs and reliability
 - Duh! (?)
 - The nature of forecasts matters - a lot
 - Focus is overwhelmingly on optimization of operations, and not the inputs to these optimization models
 - Much work remains in understanding the relationship between forecasts and system cost / performance
 - Also key to understanding and communicating risk

The General Structure of a Stochastic Unit Commitment Optimization Model

Objective: Minimize expected cost



First stage variables:

- Unit On / Off



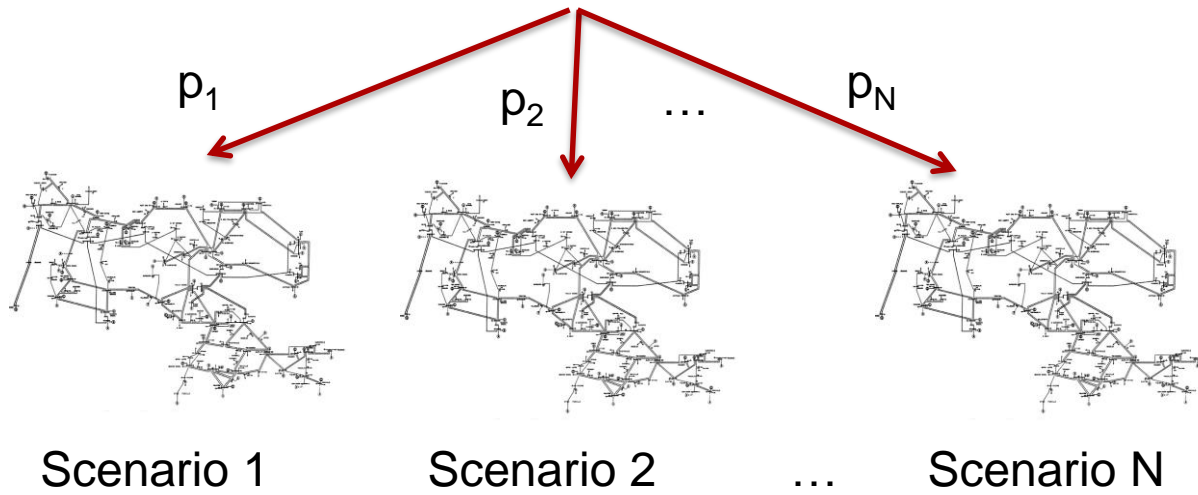
Nature resolves uncertainty

- Load
- Renewables output
- Forced outages



Second stage variables
(*per time period*):

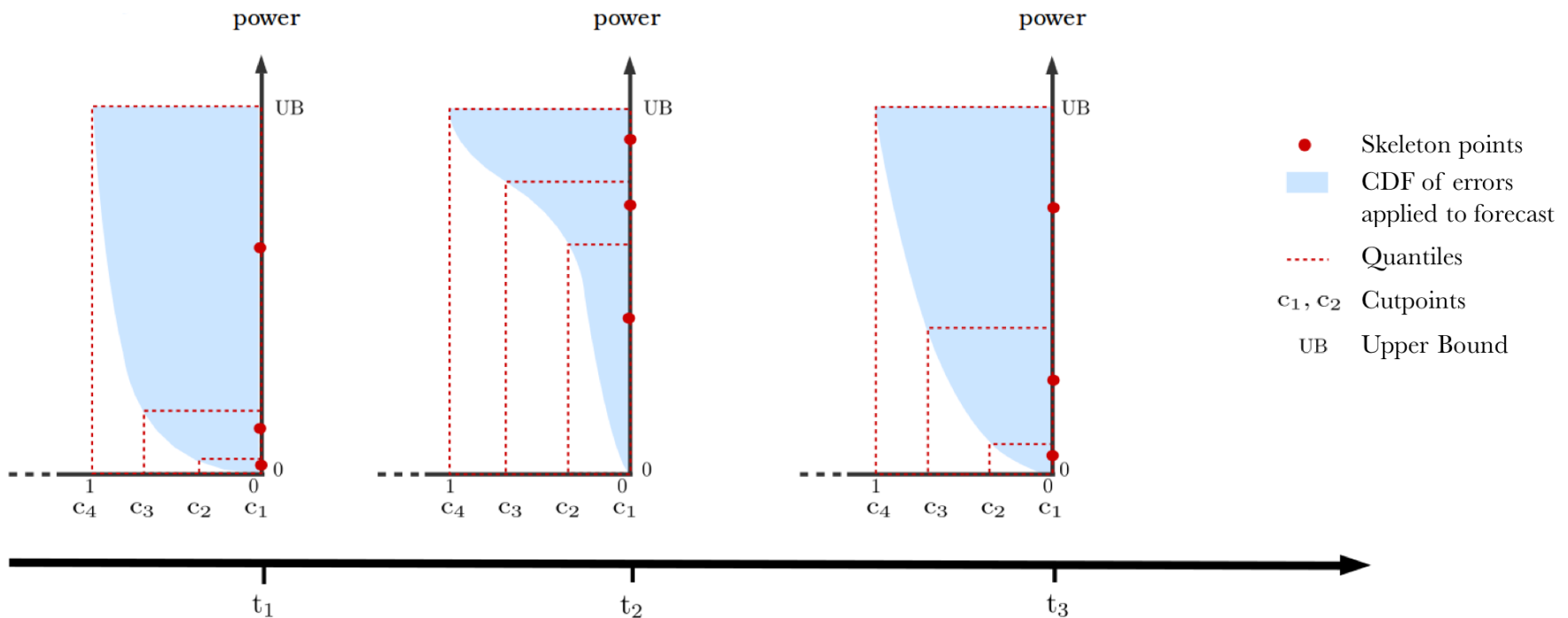
- Generation levels
- Power flows
- Voltage angles
- ...



Wind is **not** modeled as must-take, allowing for curtailment without penalty

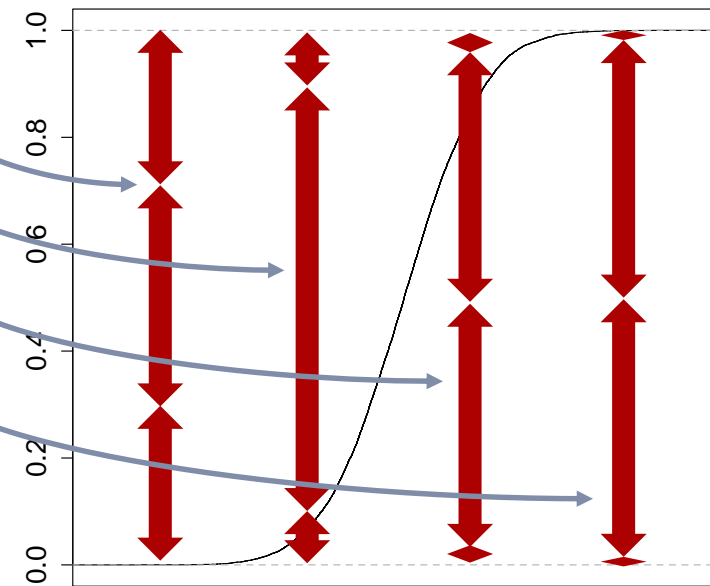
Epi-Spline Scenario Creation

- For a subset of hours in day (i.e., hours 1, 12, 24), calculate empirical **forecast error** CDF from relevant* historical forecast/actual pairs
 - Correlations in forecast error drop off quickly with time, allowing for independent calculations
- Divide distribution at cut points, and calculate the weighted average of the distribution between each cut point pair
- Apply error value to next-day forecast to obtain scenario value



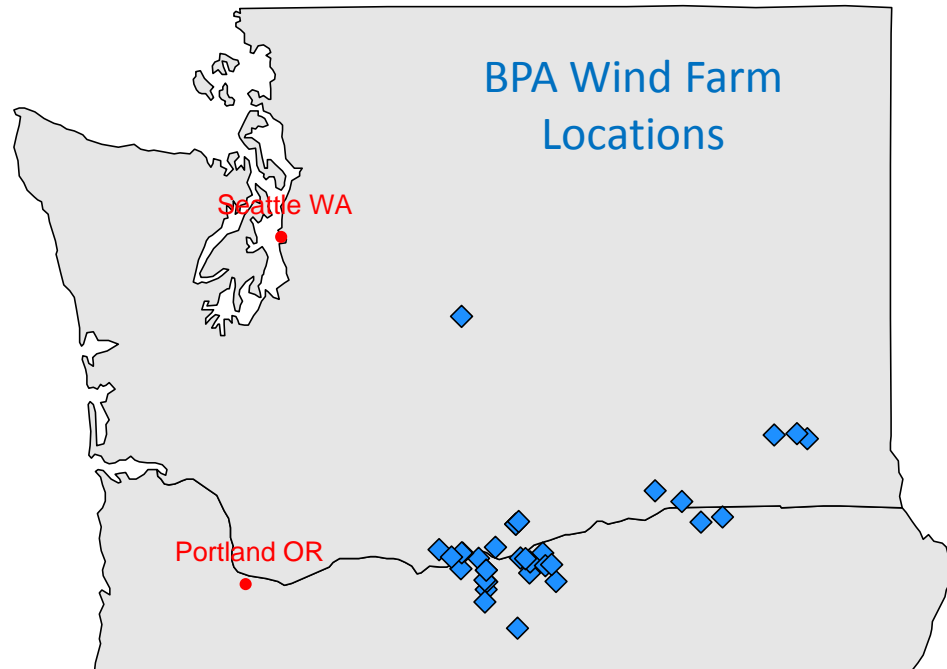
Scenario Set Comparison

- Current state-of-the-art method for scenario generation proposed by Pinson *et al.* uses quantile regression to produce a probabilistic forecast and samples from a Gaussian multivariate random variable
- We compare this to Epi-Spline scenarios using a range of cut point sets with increasing focus on 'tail' events
 - Cut points: 0 – 0.33 – 0.66 – 1
 - Cut points: 0 – 0.1 – 0.9 – 1
 - Cut points: 0 – 0.05 – 0.5 – 0.95 – 1
 - Cut points: 0 – 0.01 – 0.5 – 0.99 – 1



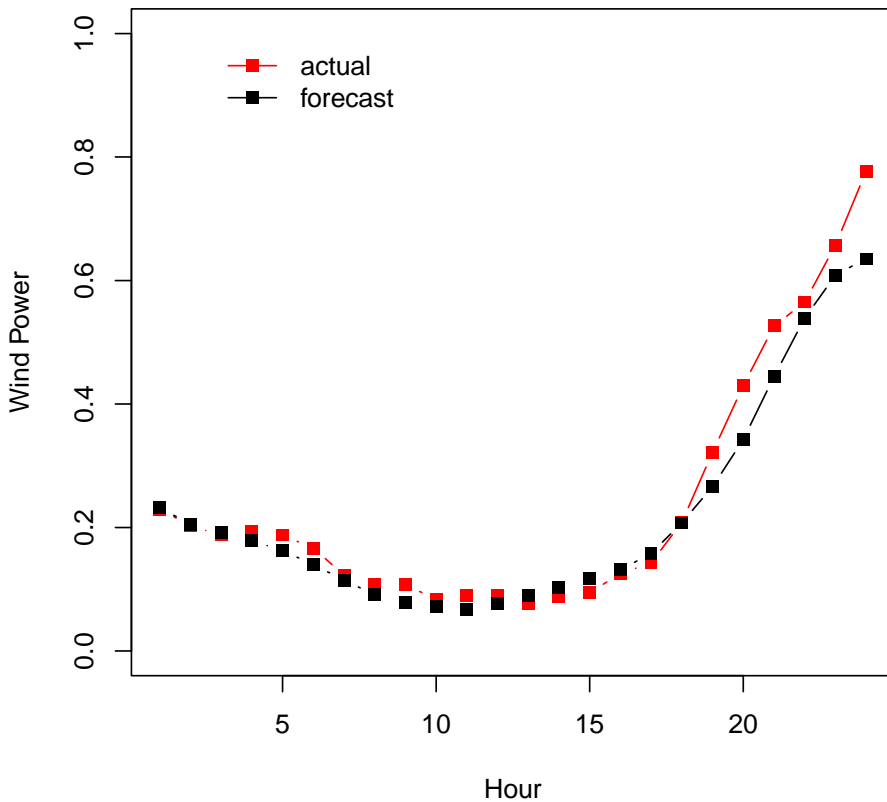
Application and Data

- Generate wind power scenarios using data from Bonneville Power Administration (BPA)
 - BPA has 33 wind farms, with a total capacity of 4782 MW
 - Using vendor-issued forecast data and actual power measurements from November 2015 through May 2017
 - Create day-ahead scenarios of aggregated wind power for balancing area using forecasts issued at 11am on previous day
 - Rolling horizon scenario creation, starting February 1, 2017 (with previous data used for training)

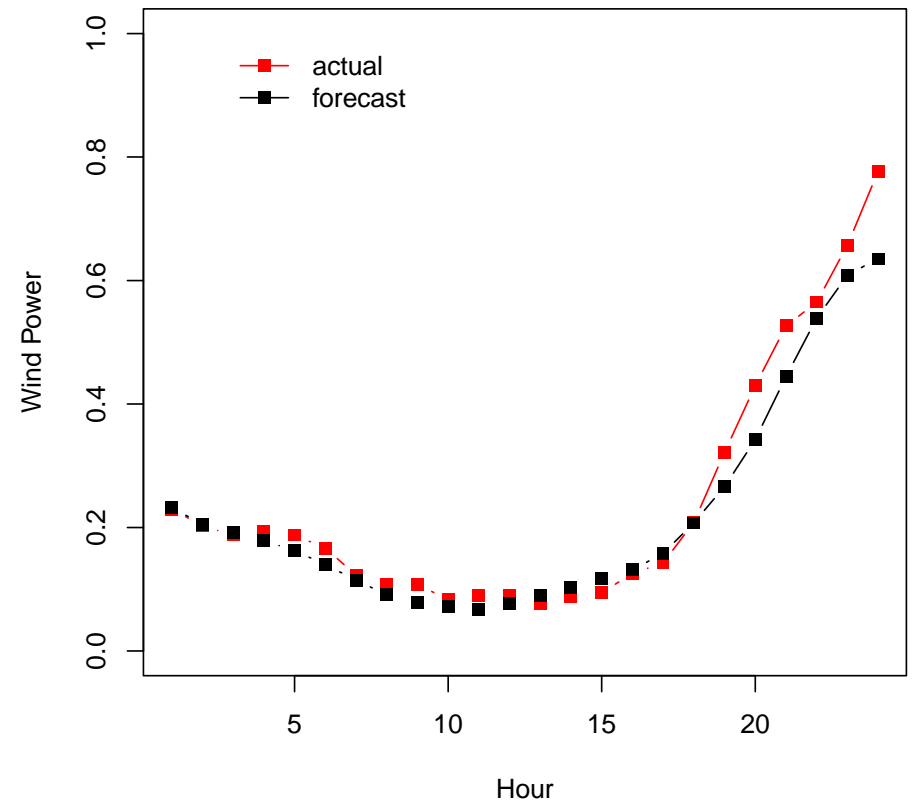


Scenario Comparison: On a 'Good' Forecast Day...

Quantile Regression
March 7, 2017

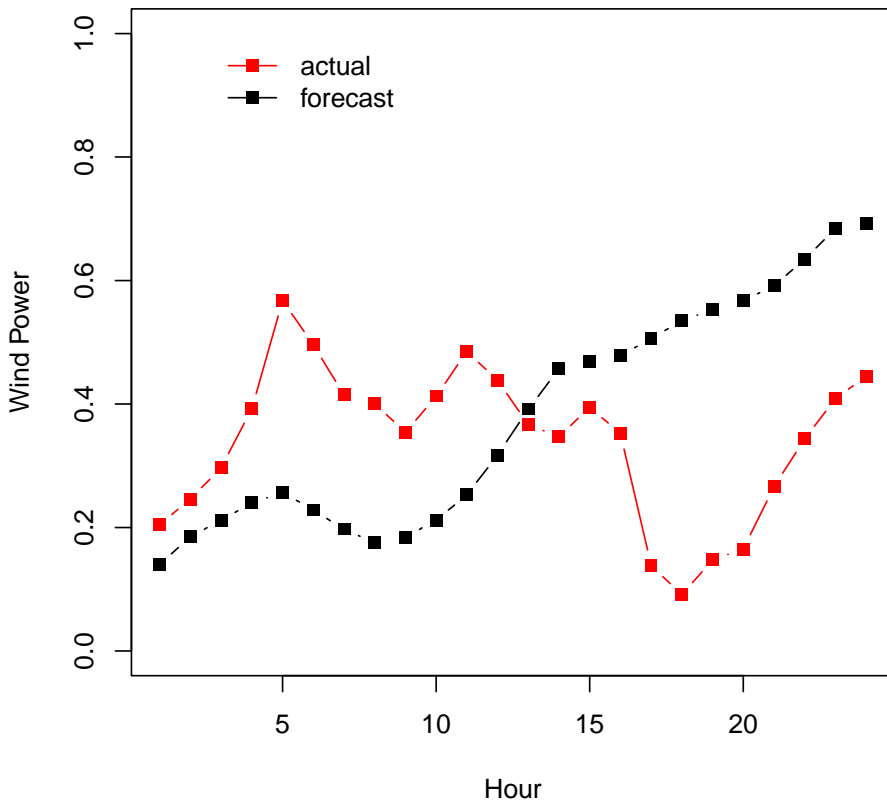


Epi-Spline, CP: 0-0.33-0.66-1
March 7, 2017

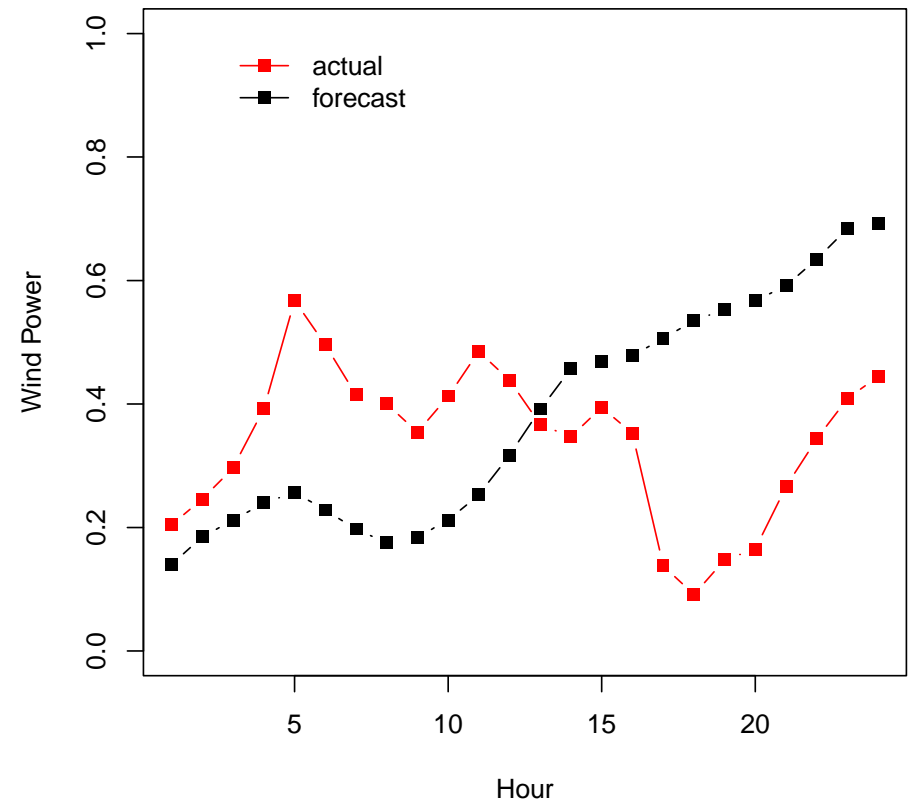


Scenario Comparison: And on a 'Bad' Forecast Day...

Quantile Regression
March 5, 2017

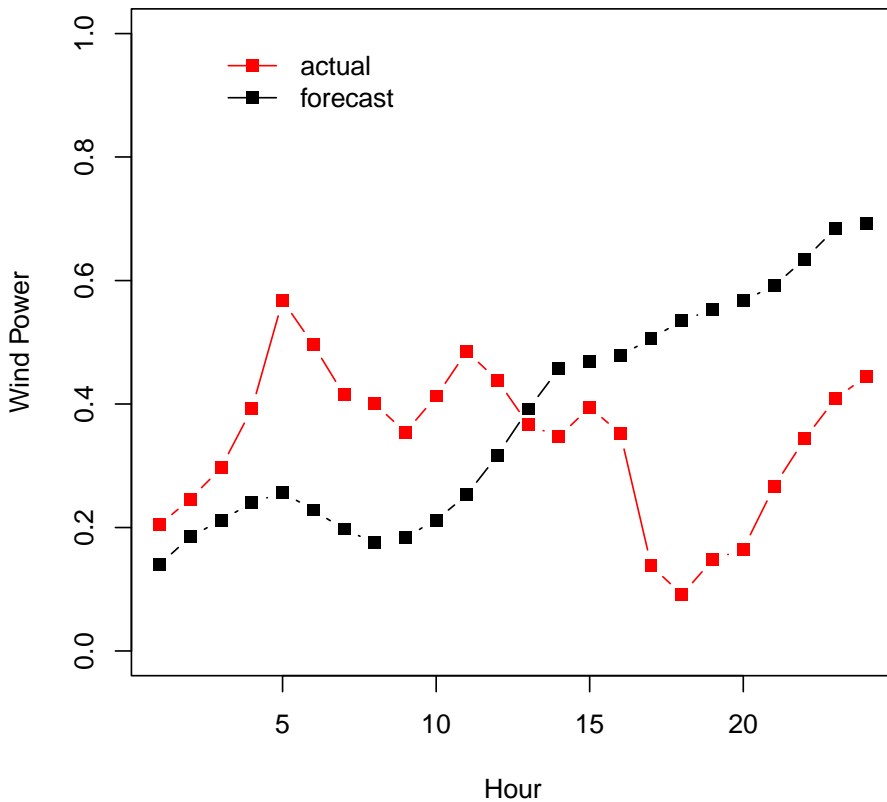


Epi-Spline, CP: 0-0.33-0.66-1
March 5, 2017

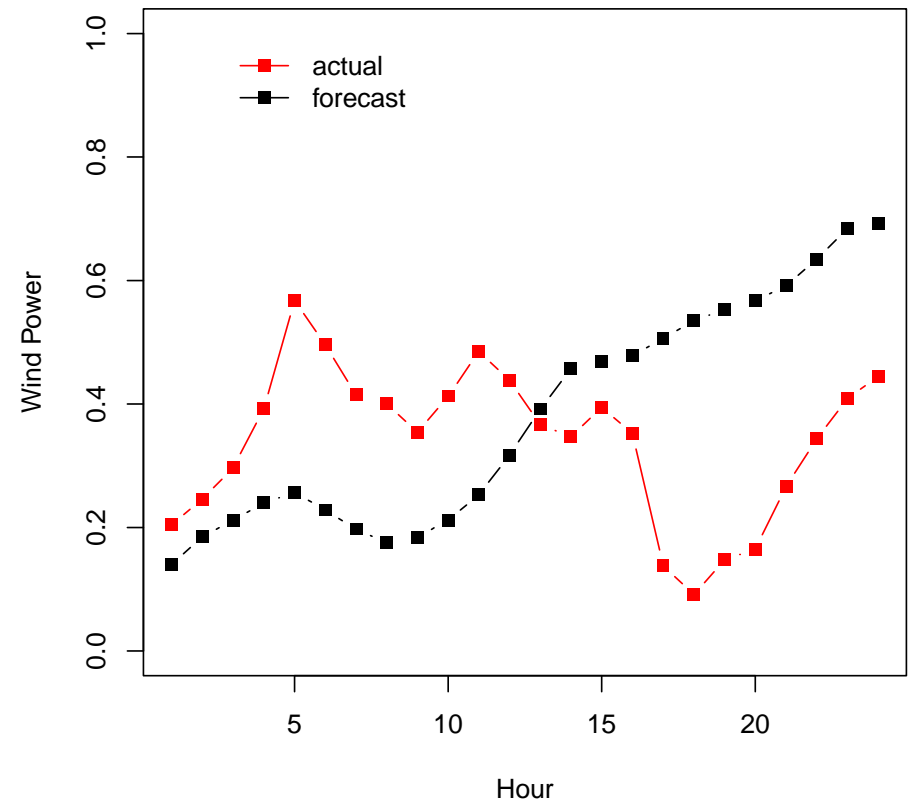


Scenario Comparison: And on a 'Bad' Forecast Day...

Quantile Regression
March 5, 2017

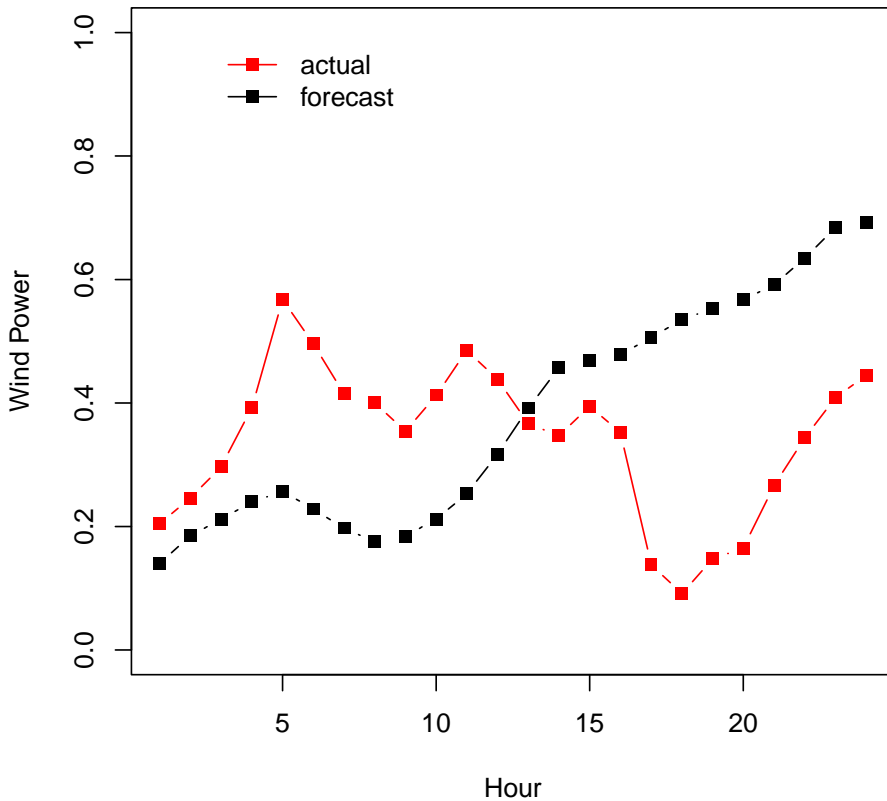


Epi-Spline, CP: 0-0.1-0.9-1
March 5, 2017

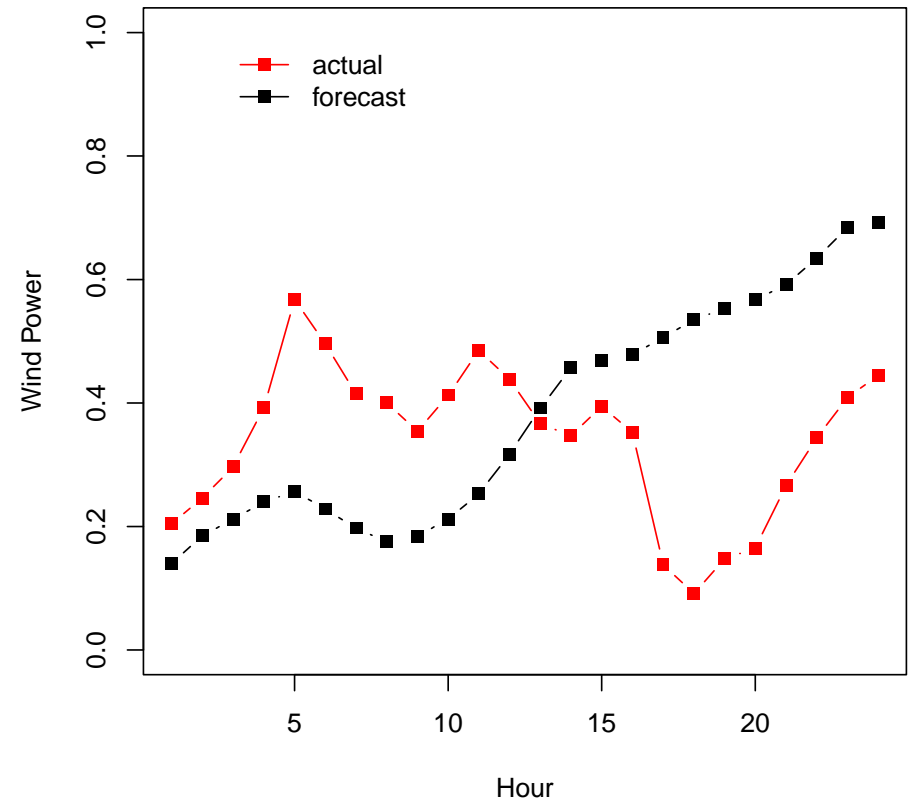


Scenario Comparison: And on a 'Bad' Forecast Day...

Quantile Regression
March 5, 2017

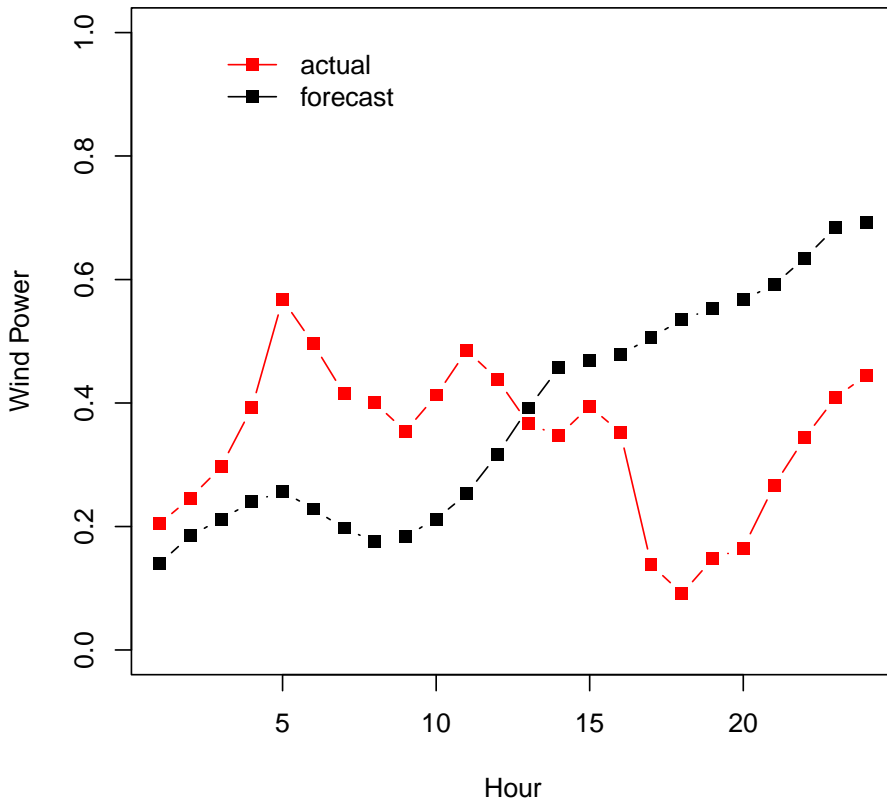


Epi-Spline, CP: 0-0.05-0.5-0.95-1
March 5, 2017

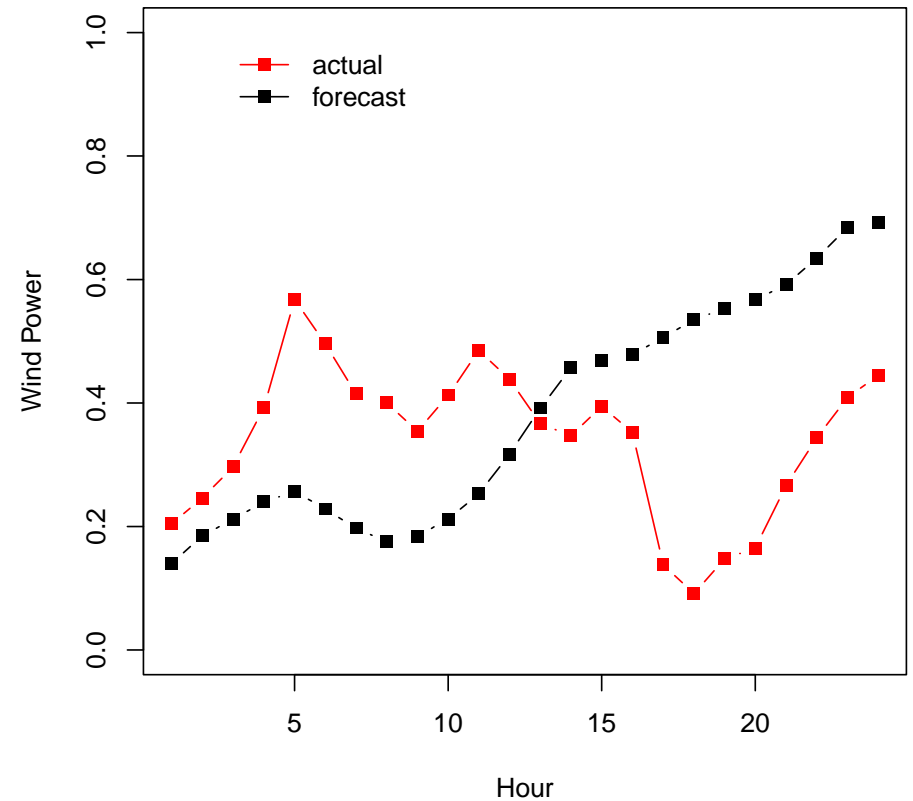


Scenario Comparison: And on a 'Bad' Forecast Day...

Quantile Regression
March 5, 2017



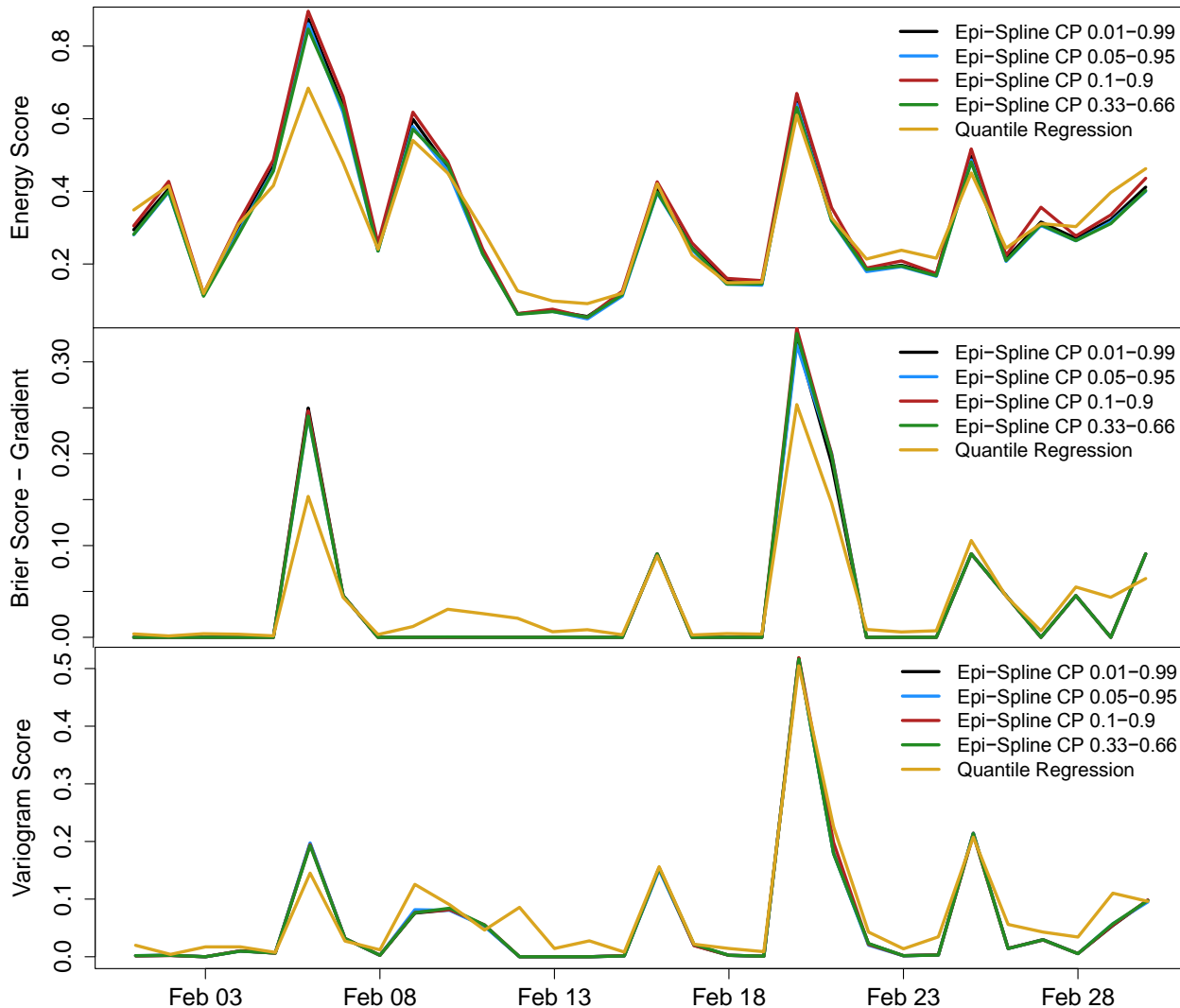
Epi-Spline, CP: 0-0.01-0.5-0.99-1
March 5, 2017



Assessing Scenario Quality

- Visual comparisons only get you so far...
- There are a number of proper scoring rules used to evaluate probabilistic forecasts and scenarios
 - Energy Score (has known discrimination issues)
 - Brier Score (event-based, need to know what you care about upfront)
 - Variogram Score (improved discrimination using pairwise differences)
- However, ultimate test of quality is performance in a real-world system
 - We simulate 'real-world' using unit-commitment optimization
 - Scenarios should represent a wide enough range of plausible wind power realizations to ensure a feasible solution as the future unfolds
 - However, too wide of a range will drive costs up unnecessarily

Plots/Results of Metrics



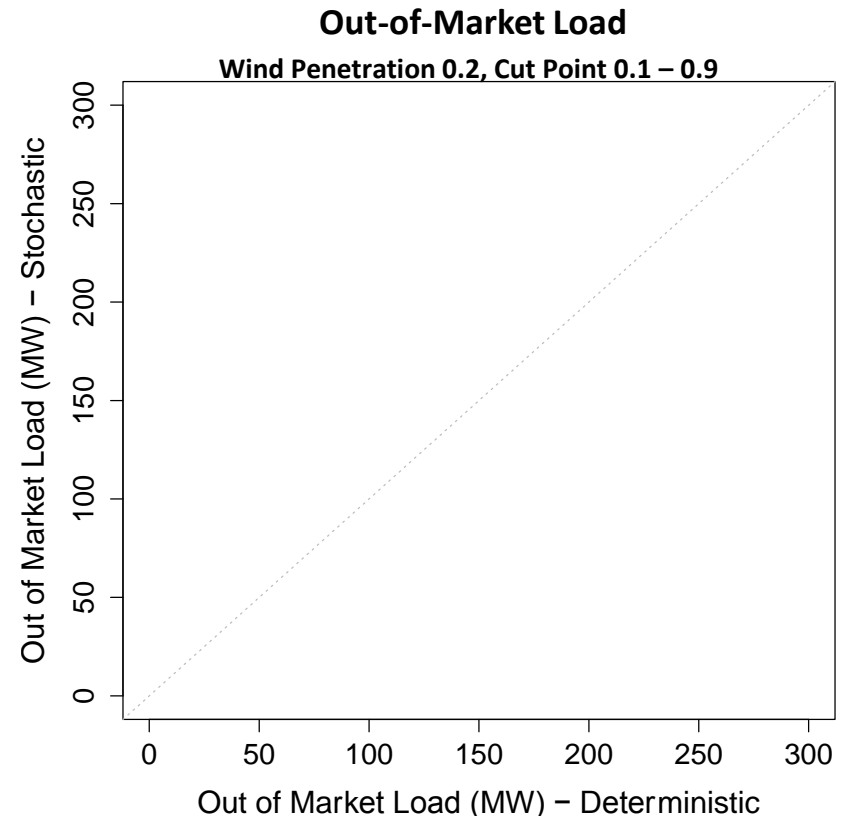
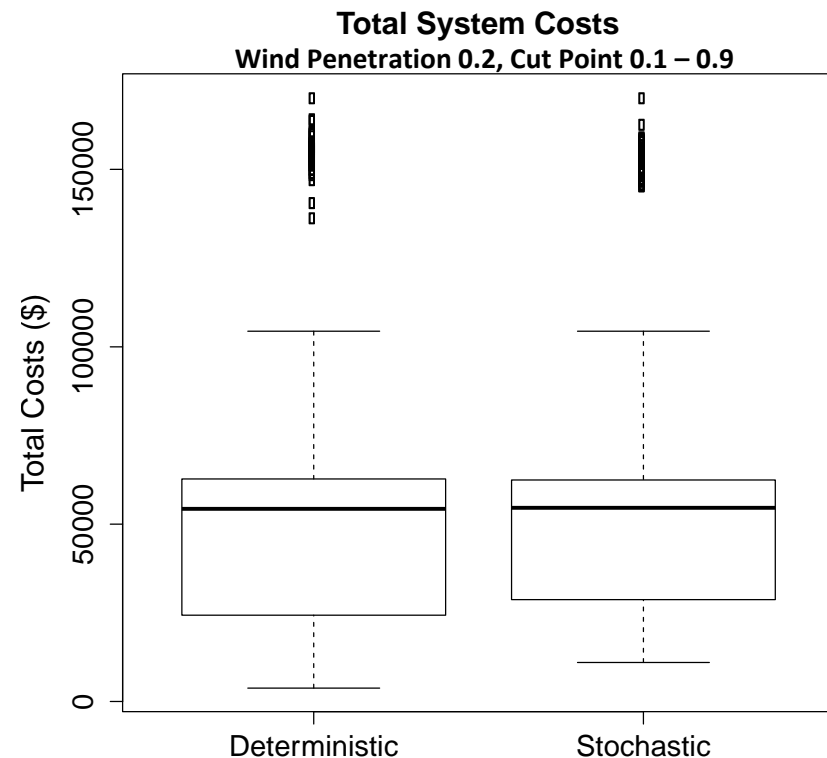
- Slight, but inconsistent differences between Epi-Spline and Quantile Regression scenarios
- Virtually *no discrimination* among cut point sets of Epi-Spline scenarios
- The best metrics cannot tell us much about scenario quality

Re-enactment Methodology

- Stochastic day-ahead unit commitment optimization model applied to small, five-generator network (Max demand ~1400 MW)
 - Copper plate model, ignoring network flows
 - Hourly, rolling-horizon simulation with economic dispatch on the hour
 - Not carrying additional reserves, as scenarios should capture required flexibility
- Stochastic wind power scenarios use real data from BPA
 - Scale wind power to assess different wind penetration levels
 - Create day-ahead scenarios based on vendor-issued forecast, determine generator commitments, simulate system performance on realized actual wind power values
- Evaluate different scenario sets and wind penetration levels
 - Comparing cost (fixed and variable), renewables used and curtailed, over-generation, and out-of-market load
- Have started work on larger test systems, but full results are pending

Unit Commitment Performance

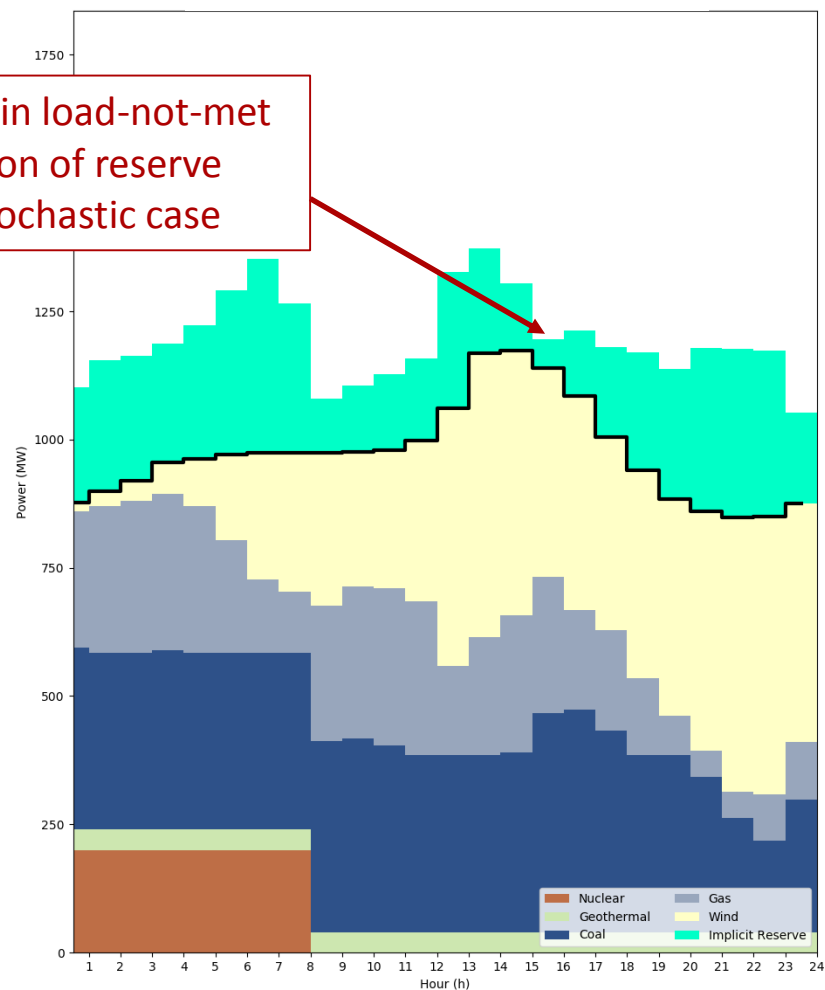
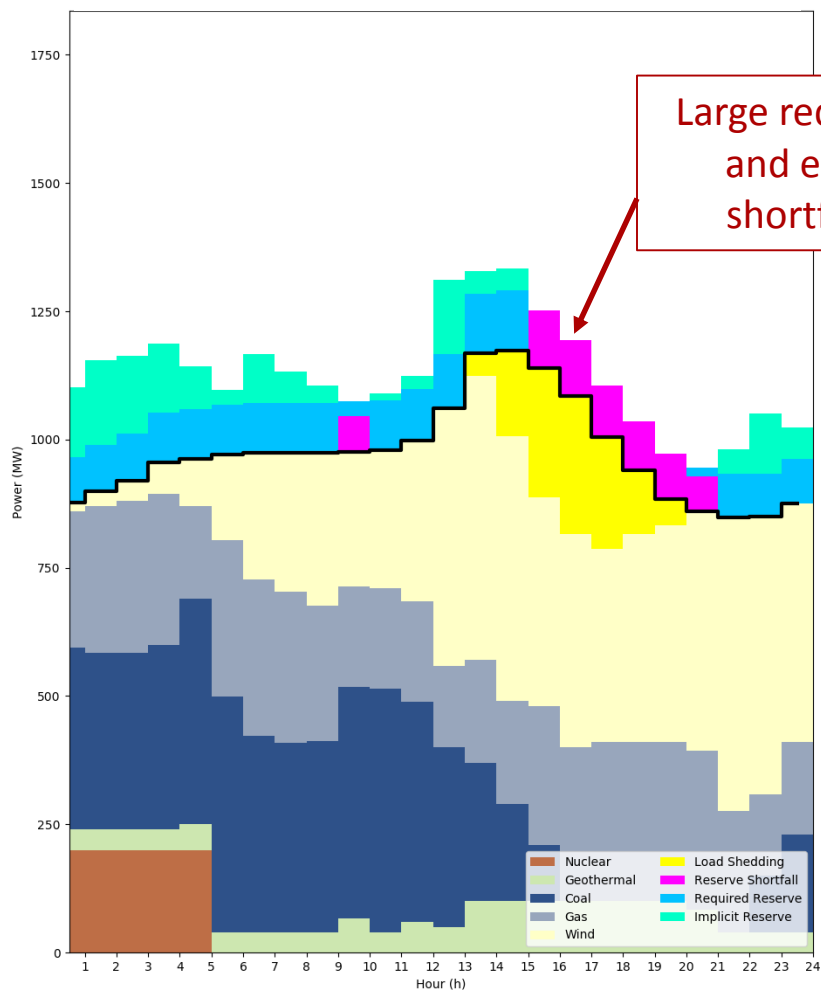
- Costs are comparable in deterministic and stochastic solutions
- However, we do not account for the cost of procuring additional generation in real-time to serve the out-of-market load (not met in day-ahead market)



Stochastic vs Deterministic

Deterministic: 2017-03-18
CP: 0 – 0.01 – 0.5 – 0.99 – 1

Stochastic: 2017-03-18
CP: 0 – 0.01 – 0.5 – 0.99 – 1



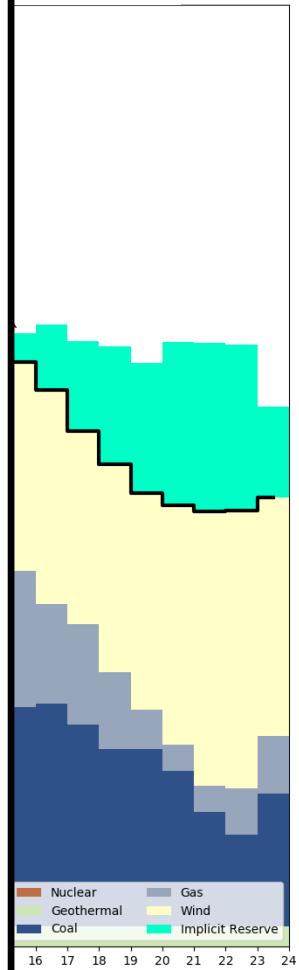
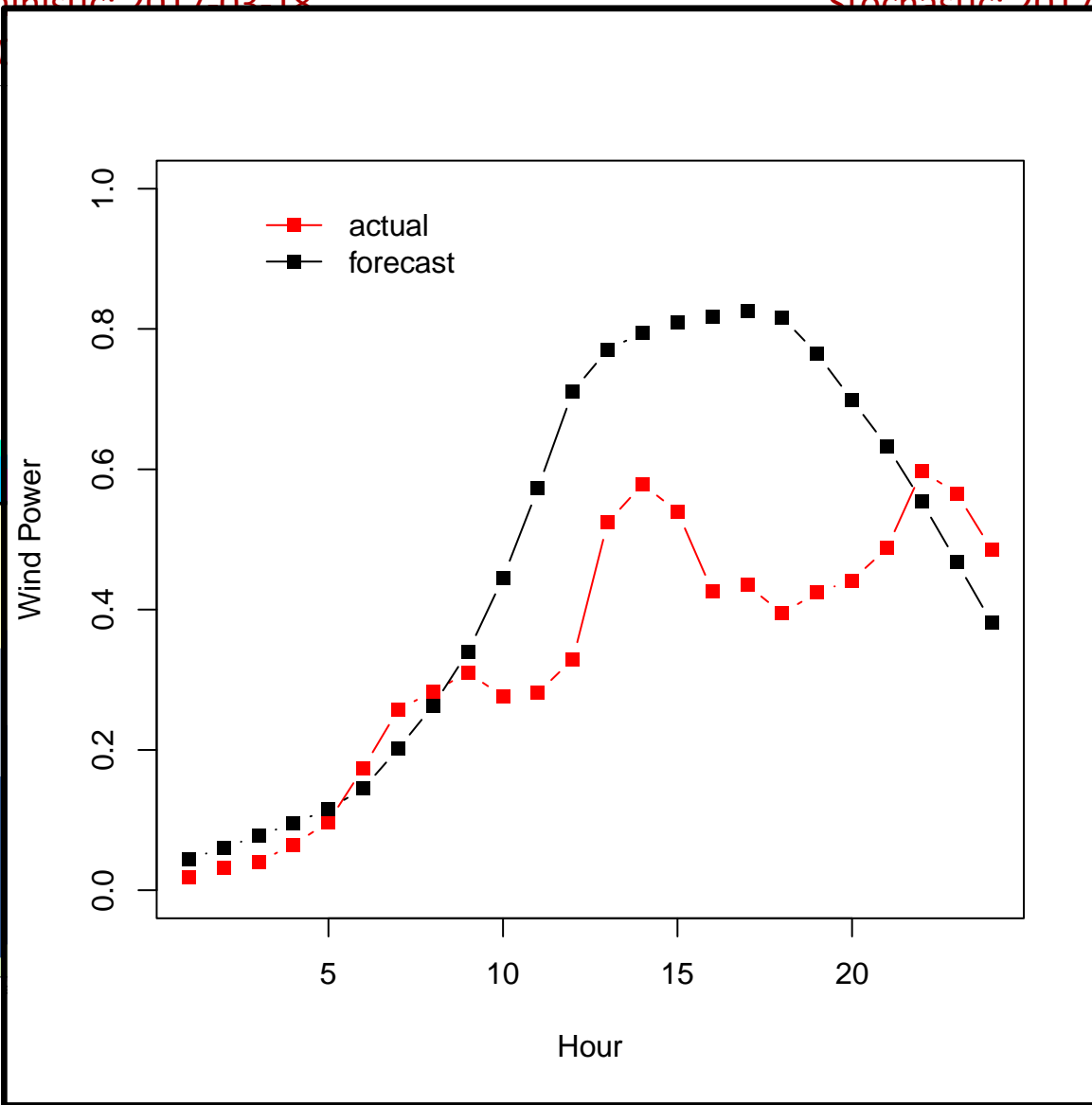
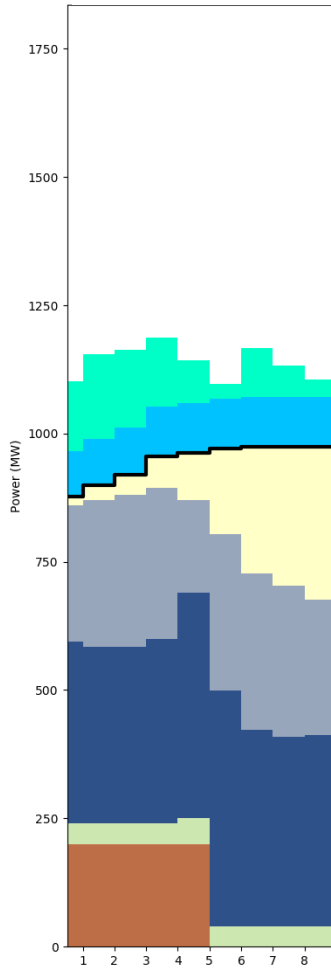
Variable costs: 227111.27
Fixed costs: 445983.41
Renewables penetration rate: 33.03%

Variable costs: 181086.81
Fixed costs: 571981.60
Renewables penetration rate: 32.88%

Stochastic vs Deterministic

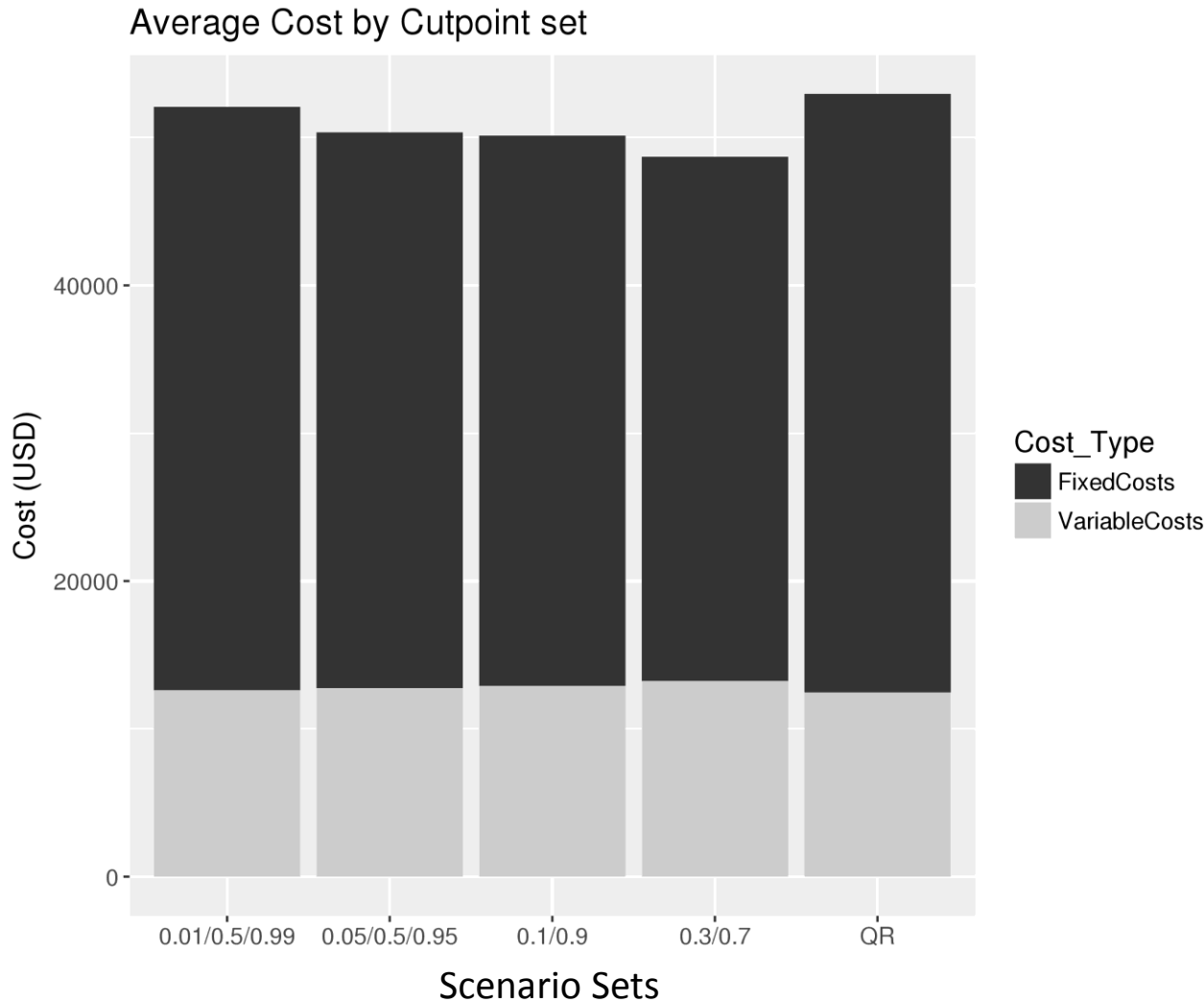
Deterministic: 2017-03-18
CP: 0 - 0

Stochastic: 2017-03-18
0.99 - 1



Variable costs: 227111.27
Fixed costs: 445983.41
Renewables penetration rate: 33.03%

Compare Scenario Sets: Cost

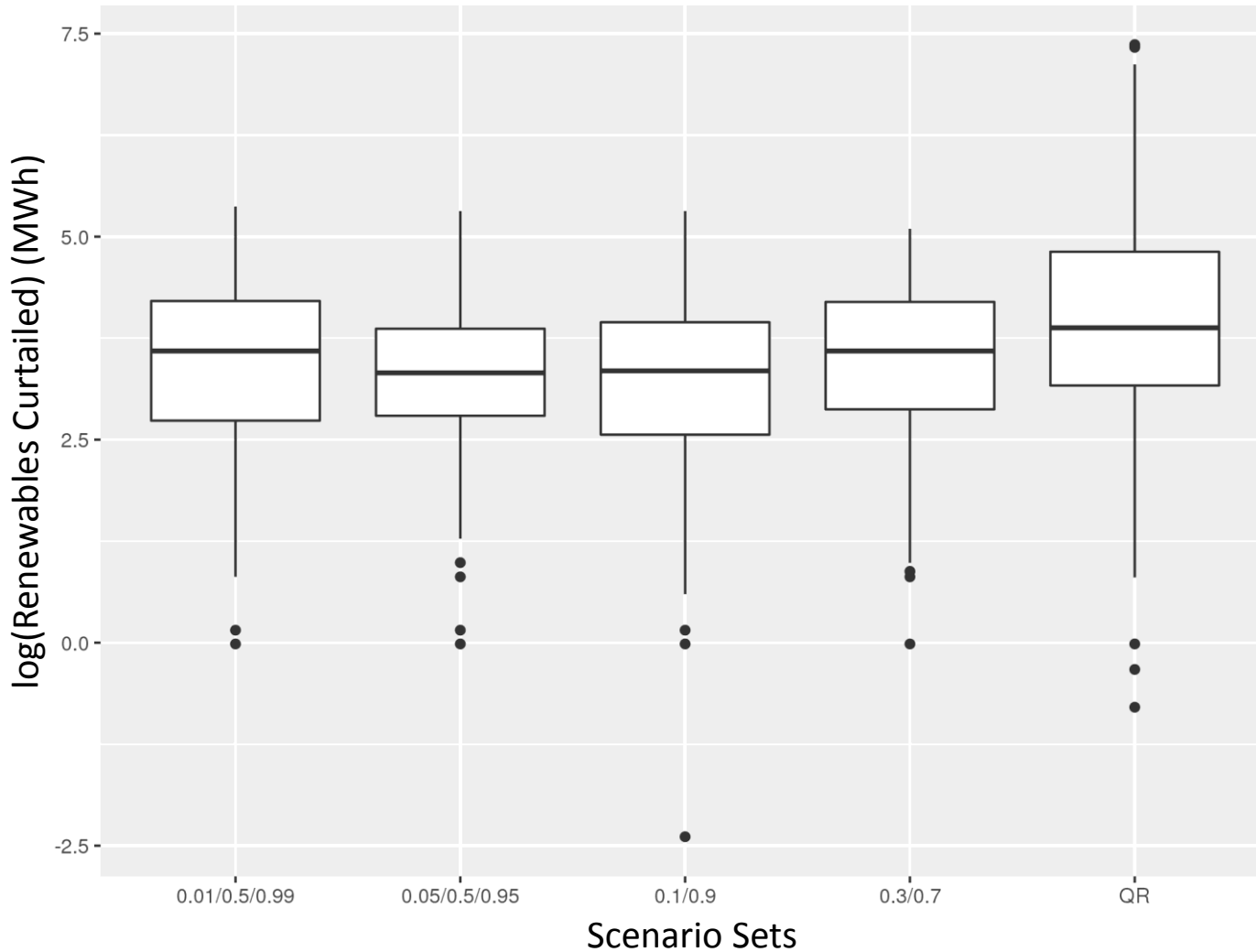


- Slight generation cost variation among scenario sets
- Wider sets have higher costs, to deal with the increased variability
- However, this doesn't account for the cost of procuring additional generation that isn't met in day-ahead scheduling

Compare Scenario Sets: Curtailment

Renewable curtailment by cutpoint set

note log scaling on y-axis



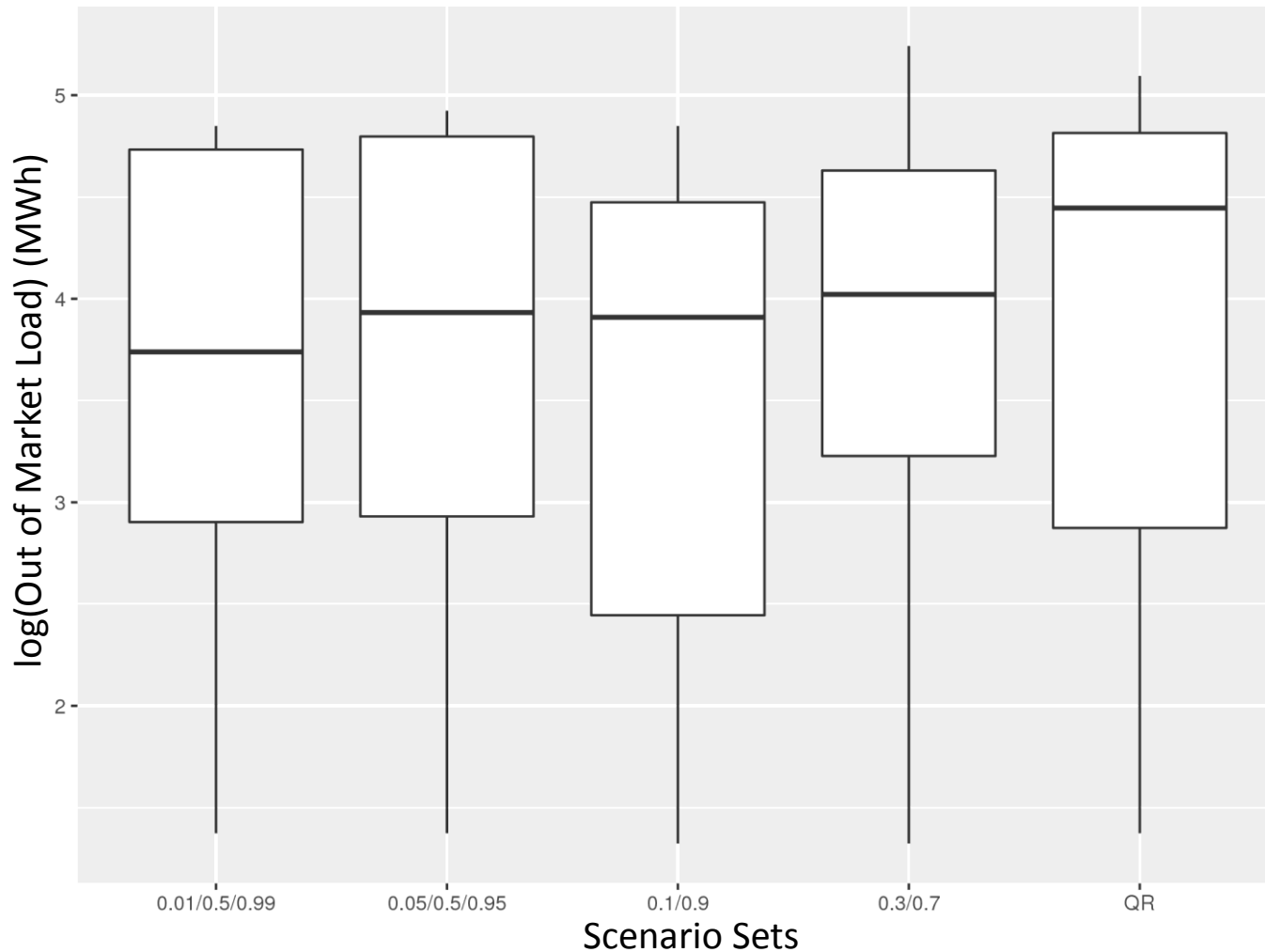
- More curtailment with quantile regression scenarios
- Thermal generation often cannot respond fast enough for extreme ramps in wind

Compare Scenario Sets:

Out-of-Market Load – All Penetration Levels

Out of Market Load by Scenario Set

note log scaling on y-axis

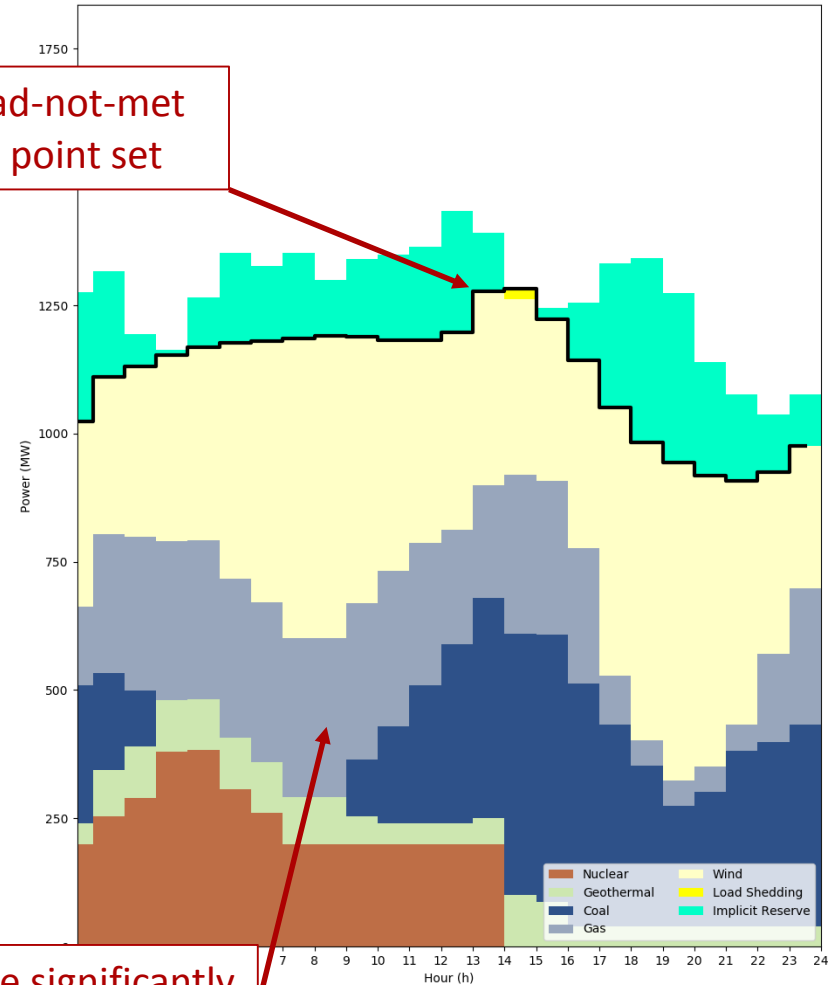
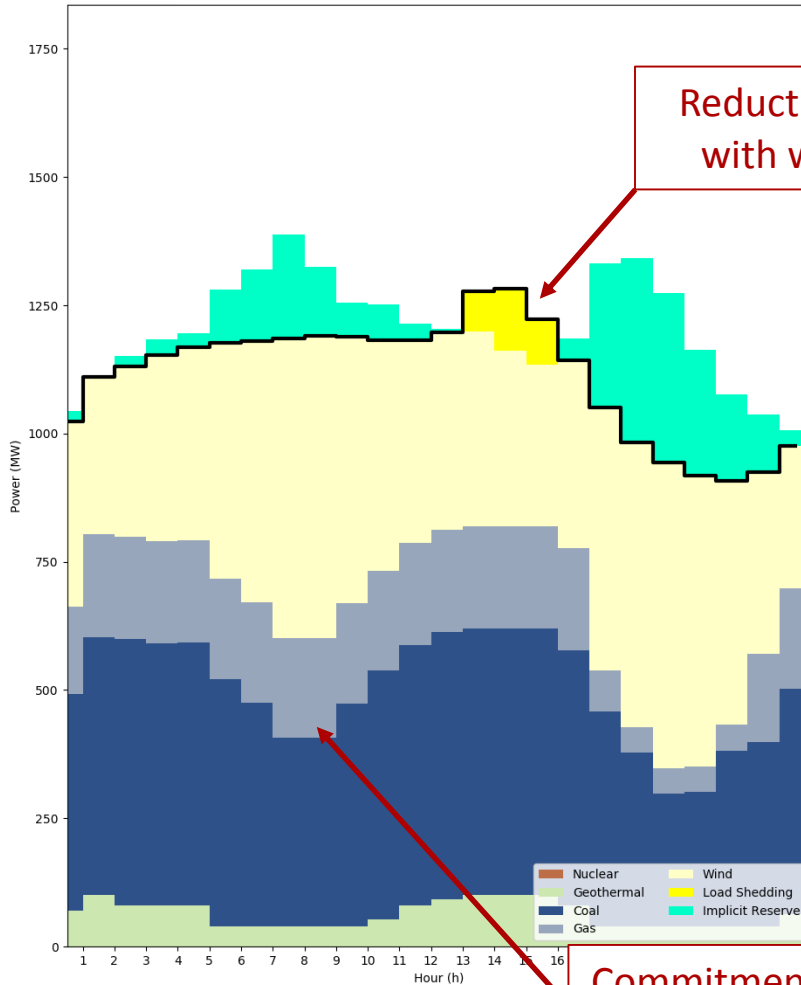


- More out-of-market load with quantile regression scenarios
- Mean value is lowest for the widest cut point set, as the scenarios are able to capture more potential variability

Single Day Commitments

2017-04-02
 CP: 0 – 0.33 – 0.66 – 1

2017-04-02
 CP: 0 – 0.01 – 0.5 – 0.99 – 1



Reduction in load-not-met
 with wider cut point set

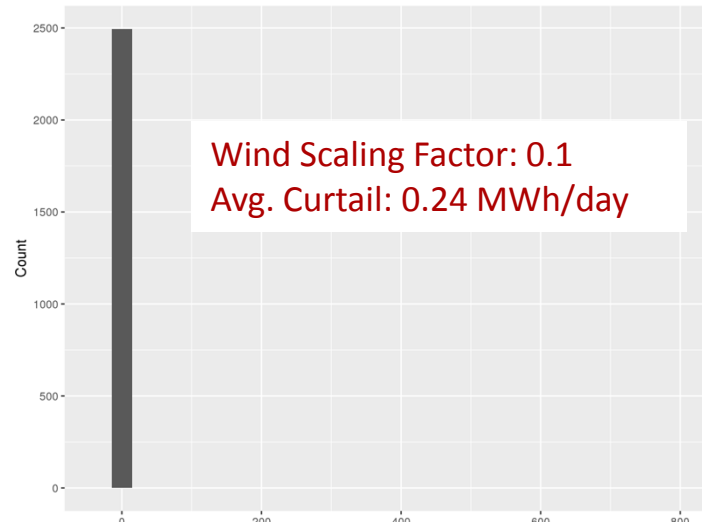
Commitments change significantly
 between cut point sets

Variable costs: 298129.21
 Fixed costs: 307123.20
 Renewables penetration rate: 38.83%

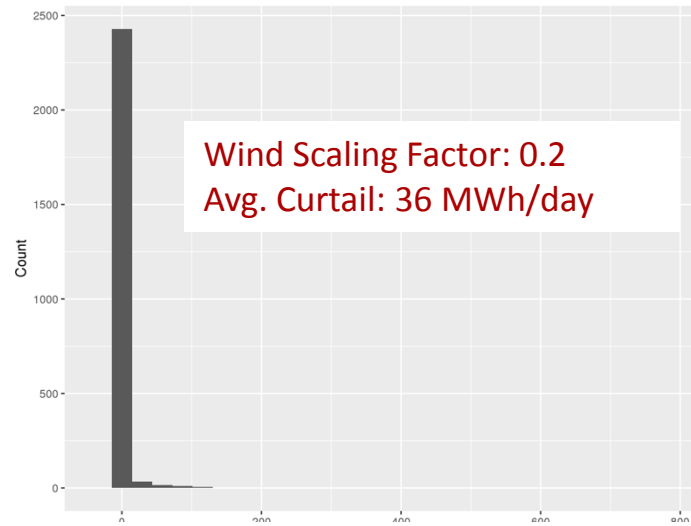
39.05%

Wind Penetration Level: Curtailment

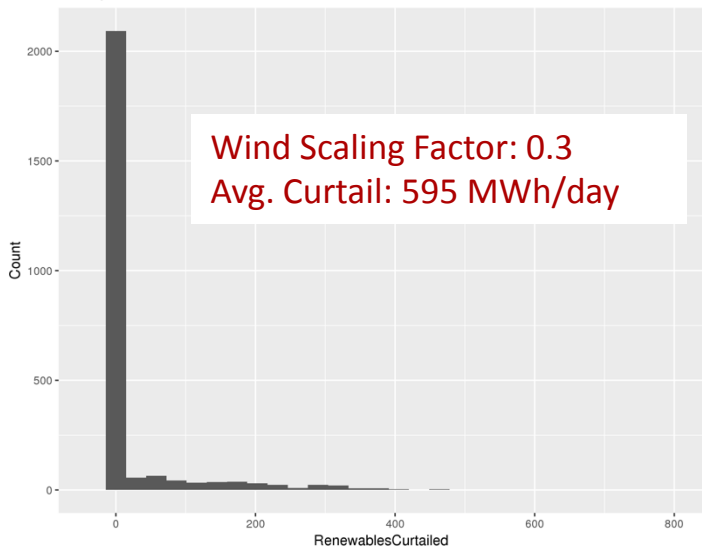
Hourly Wind Curtailment: Scale 0.1



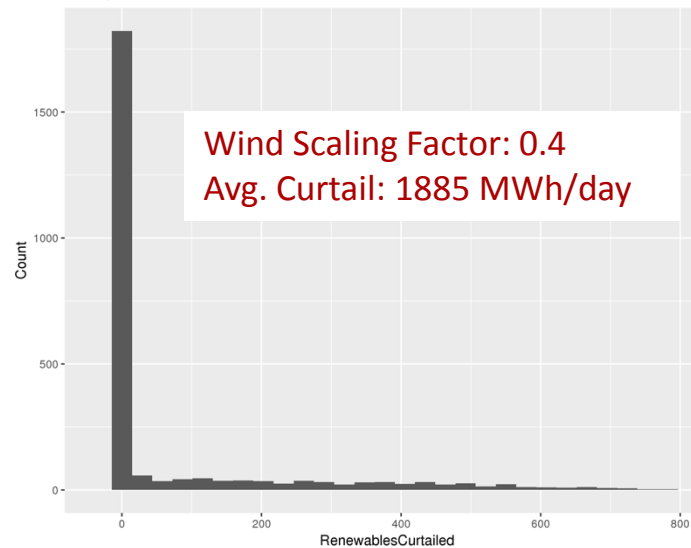
Hourly Wind Curtailment: Scale 0.2



Hourly Wind Curtailment: Scale 0.3



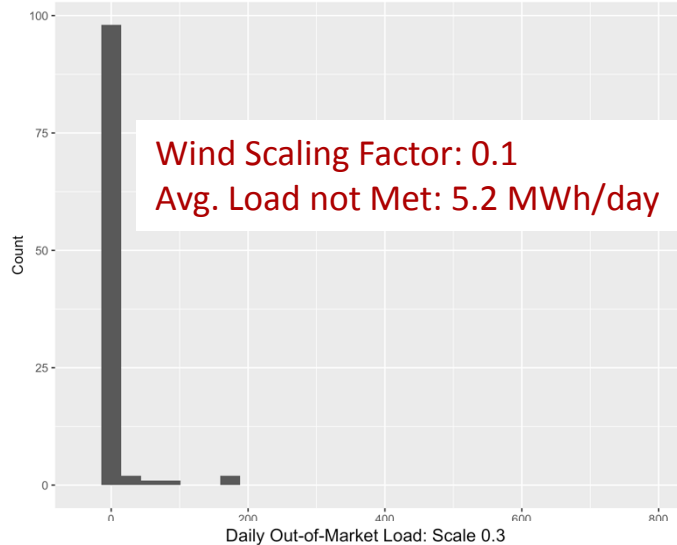
Hourly Wind Curtailment: Scale 0.4



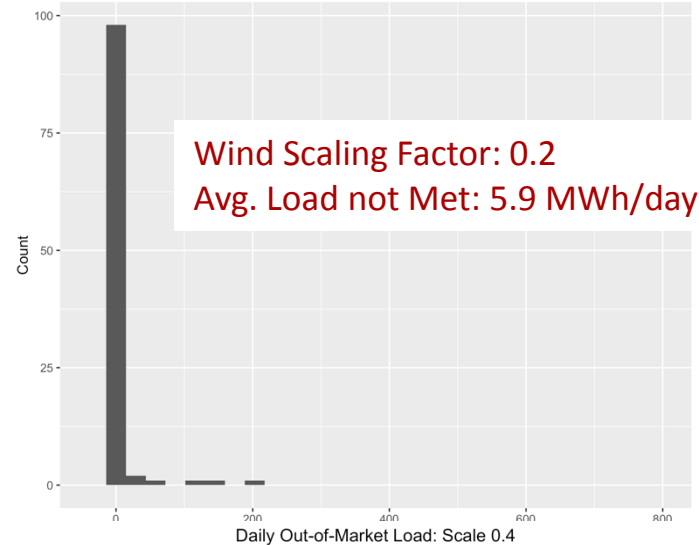
- Scaling factor is in relation to total capacity of BPA system
- Renewable penetration is 11, 22, 31, and 38%, respectively
- Curtailment increases sharply with increased renewable penetration

Wind Penetration Level: Out-of-Market Load

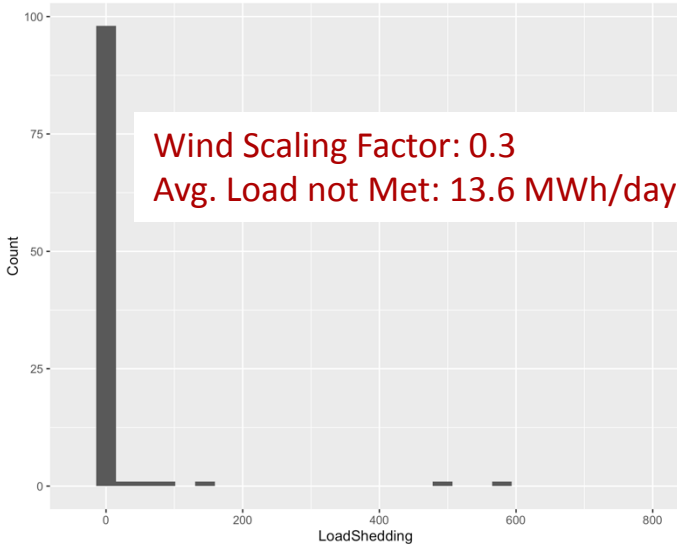
Daily Out-of-Market Load: Scale 0.1



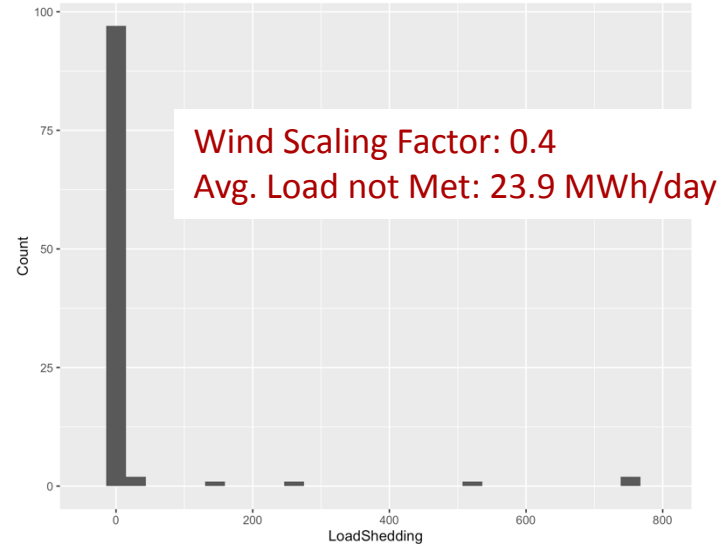
Daily Out-of-Market Load: Scale 0.2



Daily Out-of-Market Load: Scale 0.3



Daily Out-of-Market Load: Scale 0.4

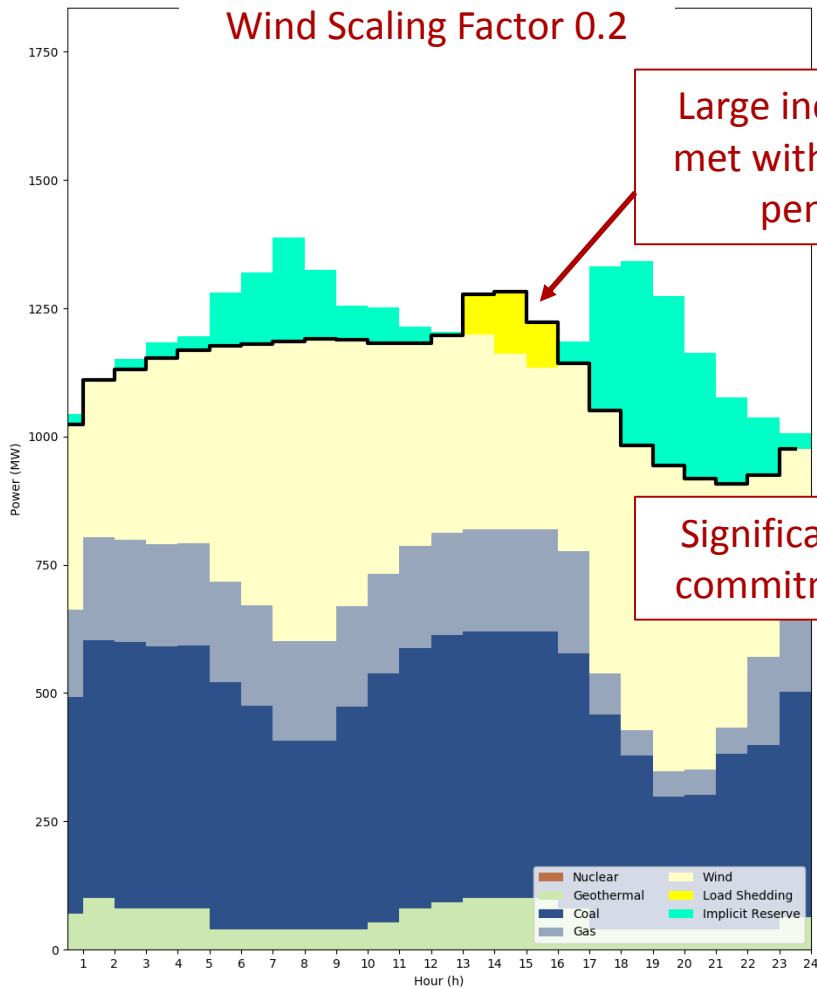


- Increased wind results in more out-of-market load, but the differences are small
- Still only see this happen on very few days overall

Single Day Commitments

2017-04-02

CP: 0 – 0.33 – 0.66 – 1
Wind Scaling Factor 0.2

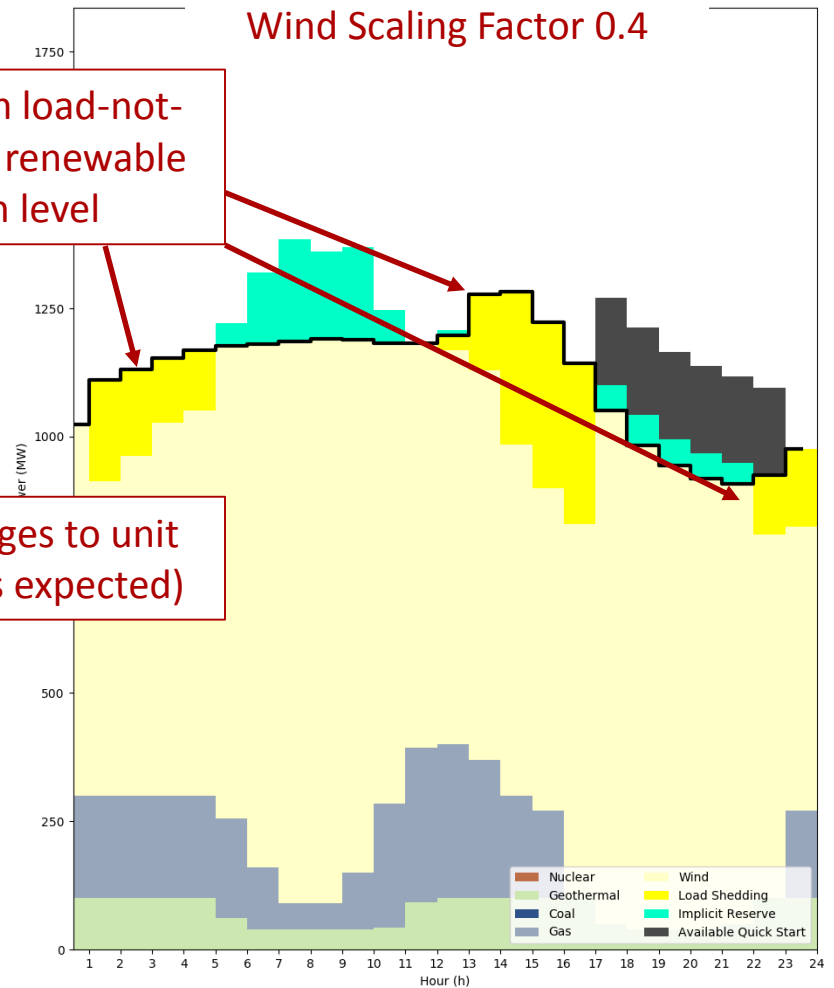


Large increase in load-not-met with higher renewable penetration level

Significant changes to unit commitment (as expected)

2017-04-02

CP: 0 – 0.33 – 0.66 – 1
Wind Scaling Factor 0.4



Variable costs: 298129.21
Fixed costs: 307123.20
Renewables penetration rate: 38.83%

Variable costs: 103376.18
Fixed costs: 96262.60
Renewables penetration rate: 74.00%

Future Work

- Evaluation of additional scenario sets
 - Assess value of scenarios that explicitly incorporate wind power ramp events
 - Look at performance of simple methods used in literature, compare to methods presented here
- Run re-enactment on larger test cases
 - Have started on WECC 240 case, with results pending
 - Increase wind penetration levels to assess scenario performance at high renewable levels
- Assess performance over a longer date range
 - Incorporate more variability, both in seasonal wind and load
- Different wind dataset, if possible
 - Evaluate scenario creation methodology on additional wind sites, as ramp behavior and wind variability vary by location

Questions?

- Contact:
 - Jean-Paul Watson, jwatson@sandia.gov

- Acknowledgements
 - Bonneville Power Administration for providing access to their data and for partial funding of this work
 - U.S. Department of Energy's Grid Modernization Laboratory Consortium, Project 1.4.26
 - U.S. Department of Energy's ARPA-E, Green Energy Network Integration (GENI) Project Portfolio