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Data-Driven Approaches for Wind Power Ramp Timing at BPA

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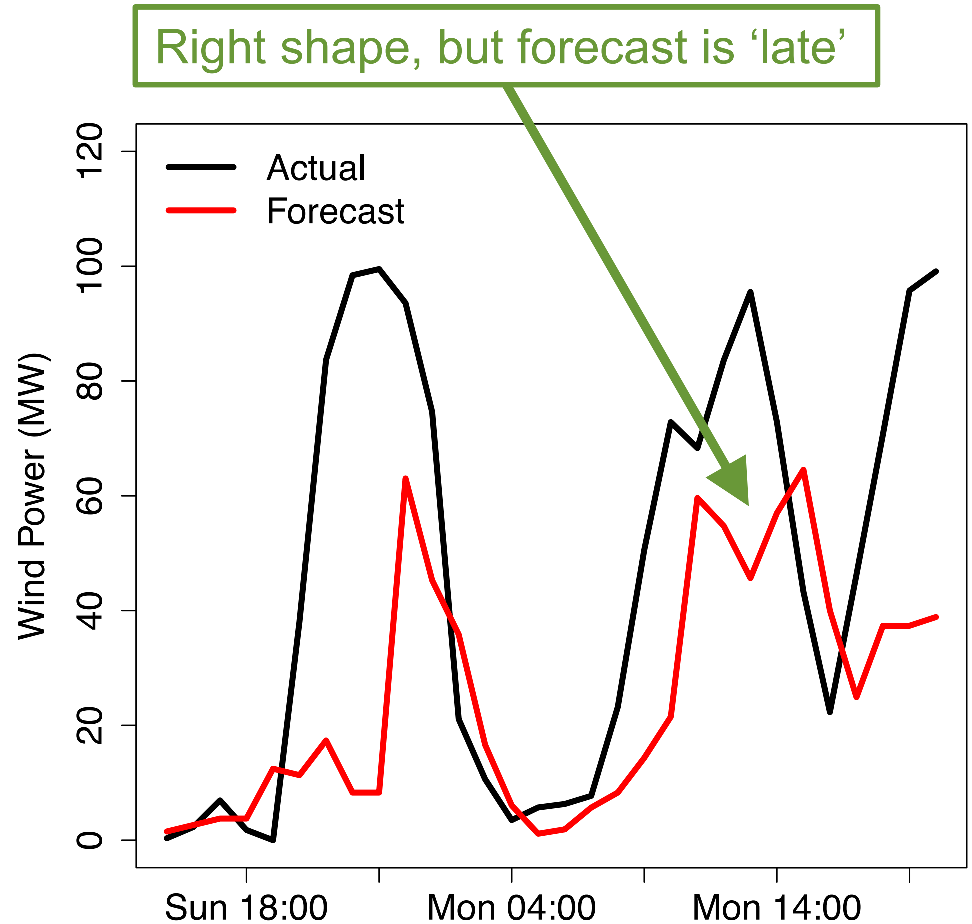
Motivation

- We've been working with BPA forecast and actual wind power data for some time
- Previous work focused on analyzing and trying to reduce forecast errors
- Large focus on errors in magnitude – for an individual hour, improve the power estimate for that hour
- However, many observed forecast errors are errors in time!

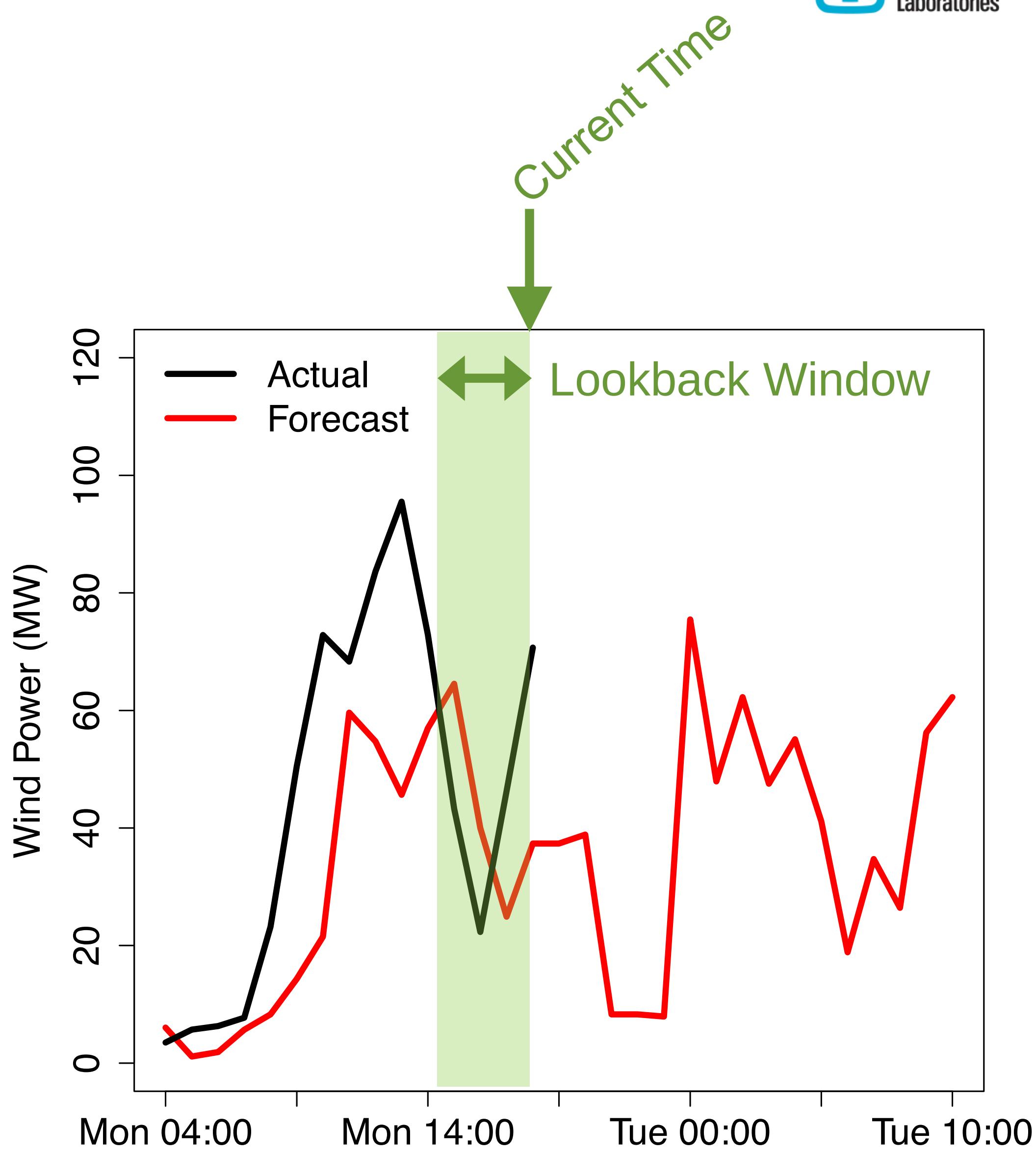


Motivation, Continued

- Forecast errors in time are likely to persist across hours
  - Forecast models may miss the timing of weather events, but not the events themselves
  - E.g., predicting a ramp an hour or two earlier than it occurs
- Hypothesis:
  - If we can detect these timing offsets, we can apply said offset to the near-future forecast hours
  - By studying forecast and actual wind power traces, are there obvious shifts in timing of events?
  - Would a time-shifted forecast vector match the actual values more closely?

Algorithm

- At current time, look back at recent forecast/actual trace of wind power in lookback window
- Calculate integrated error between forecast and actual in window



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- At current time, look back at recent forecast/actual trace of wind power in lookback window
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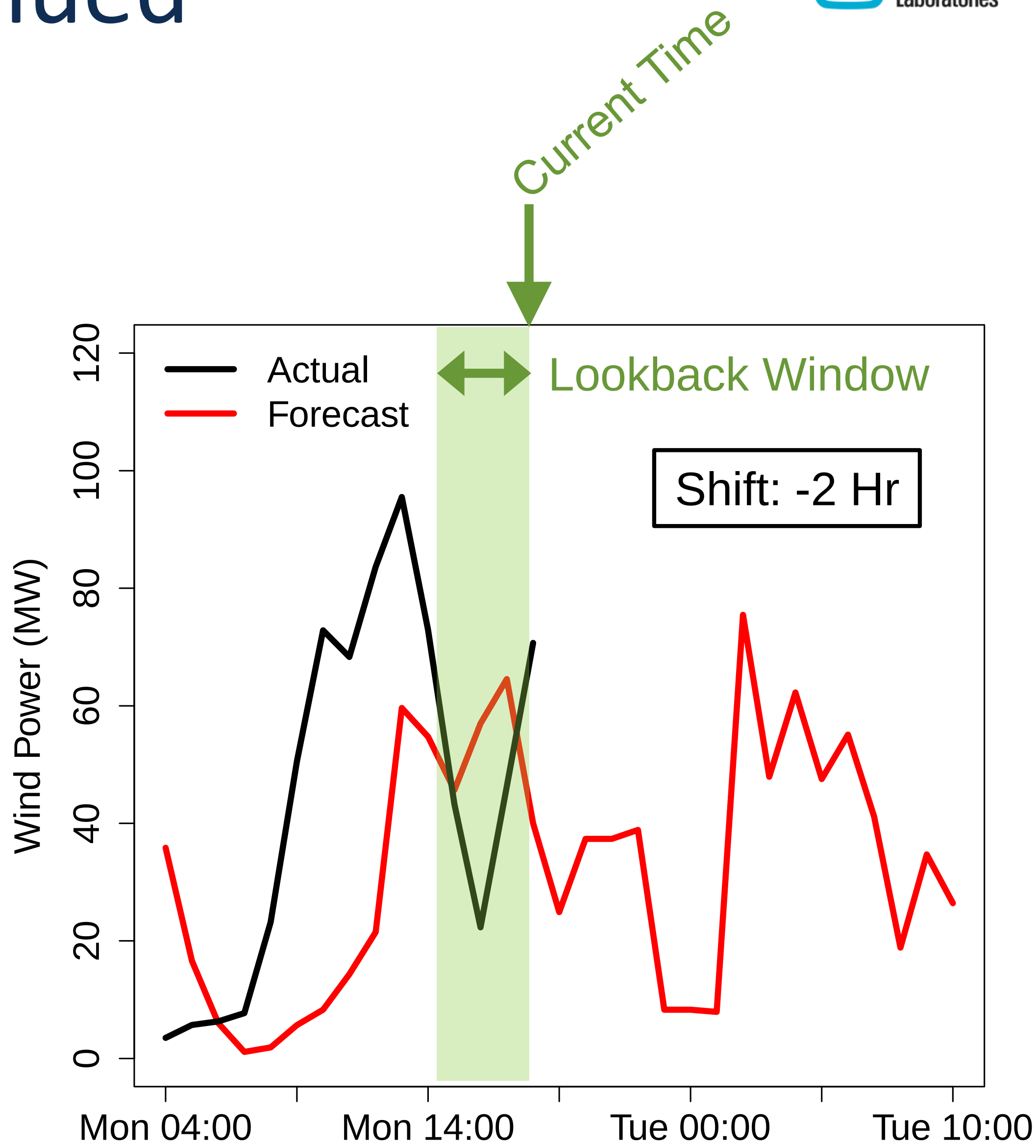
- Assess error if forecast had been shifted forward or backward in time



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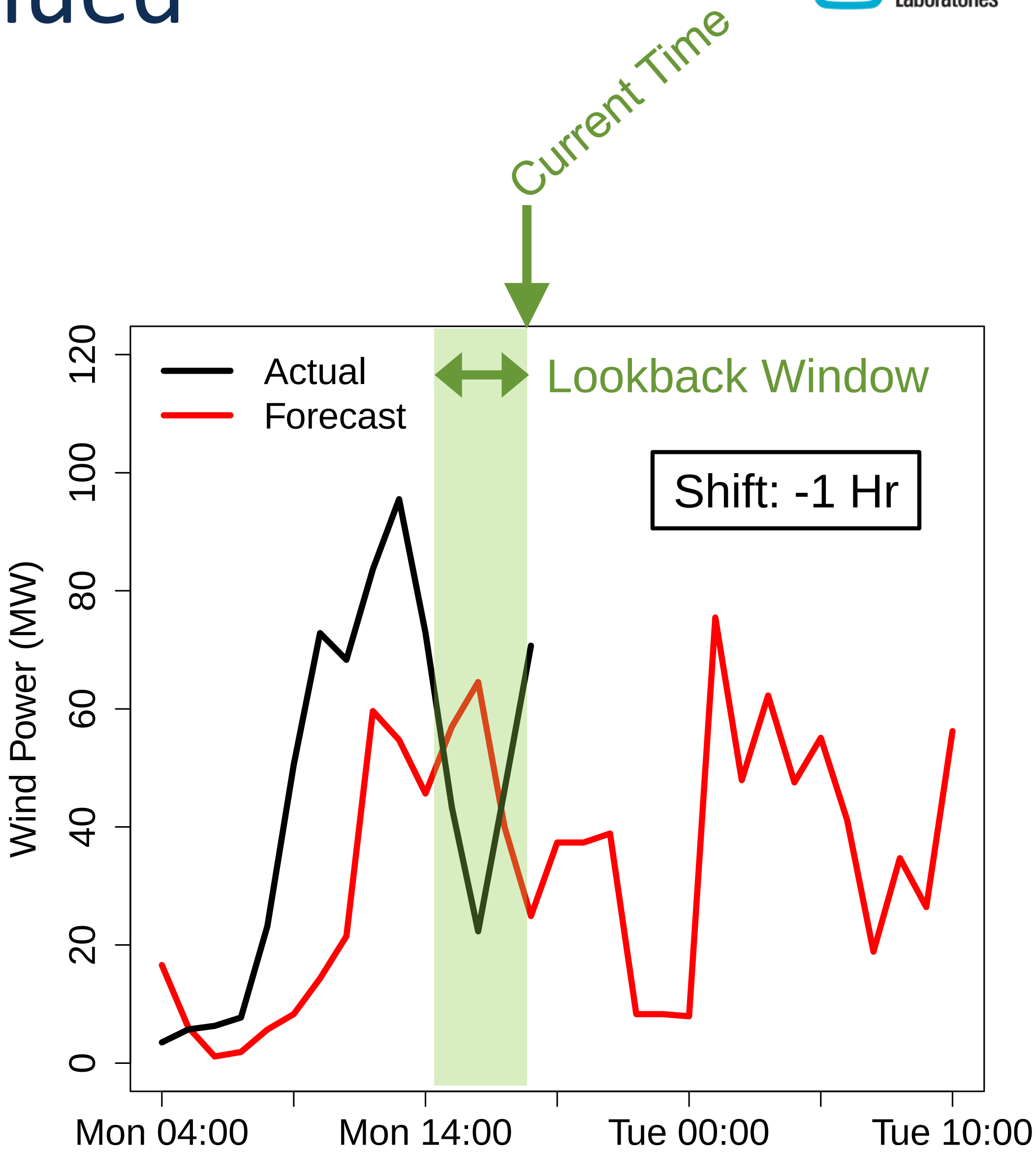

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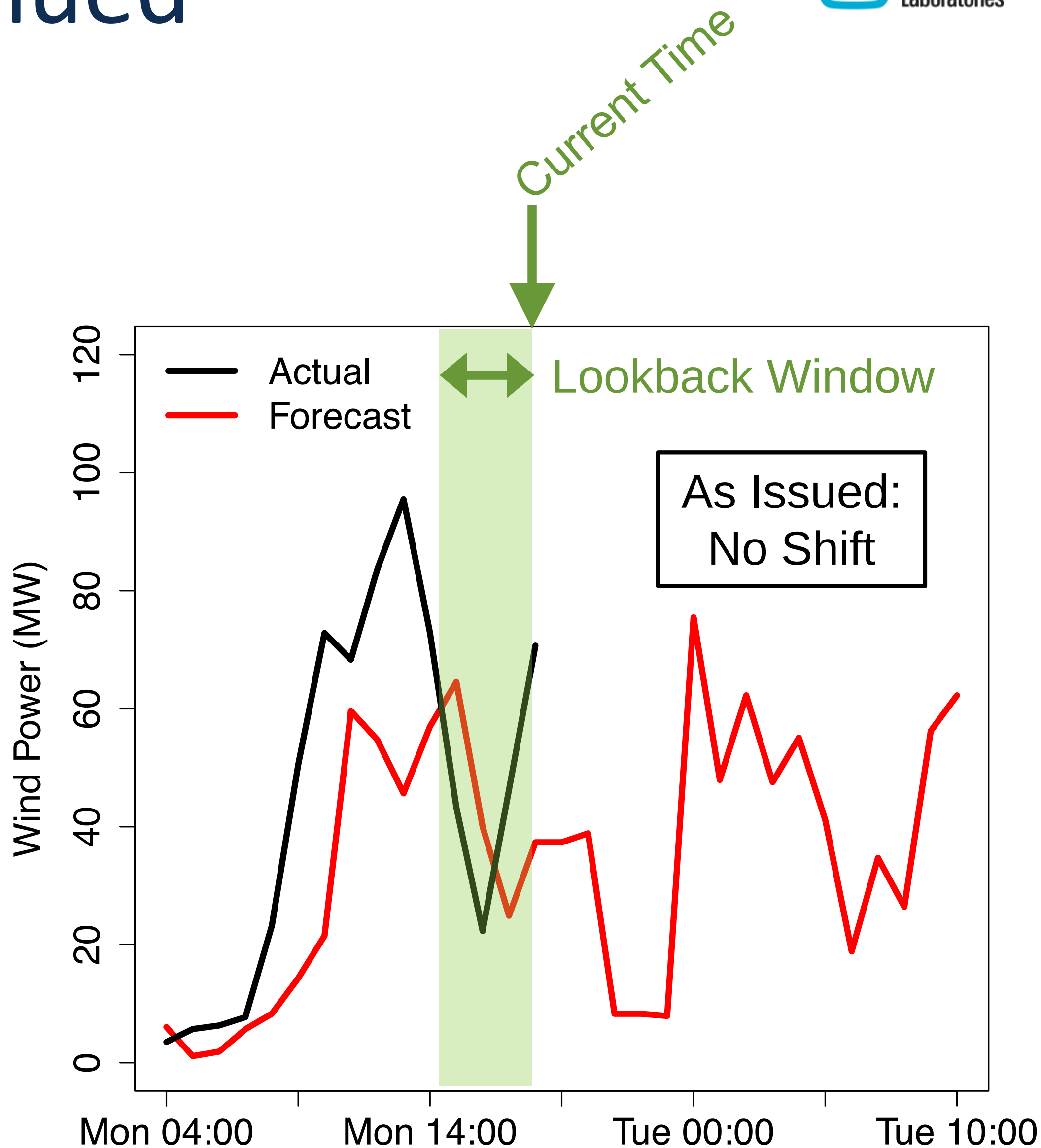

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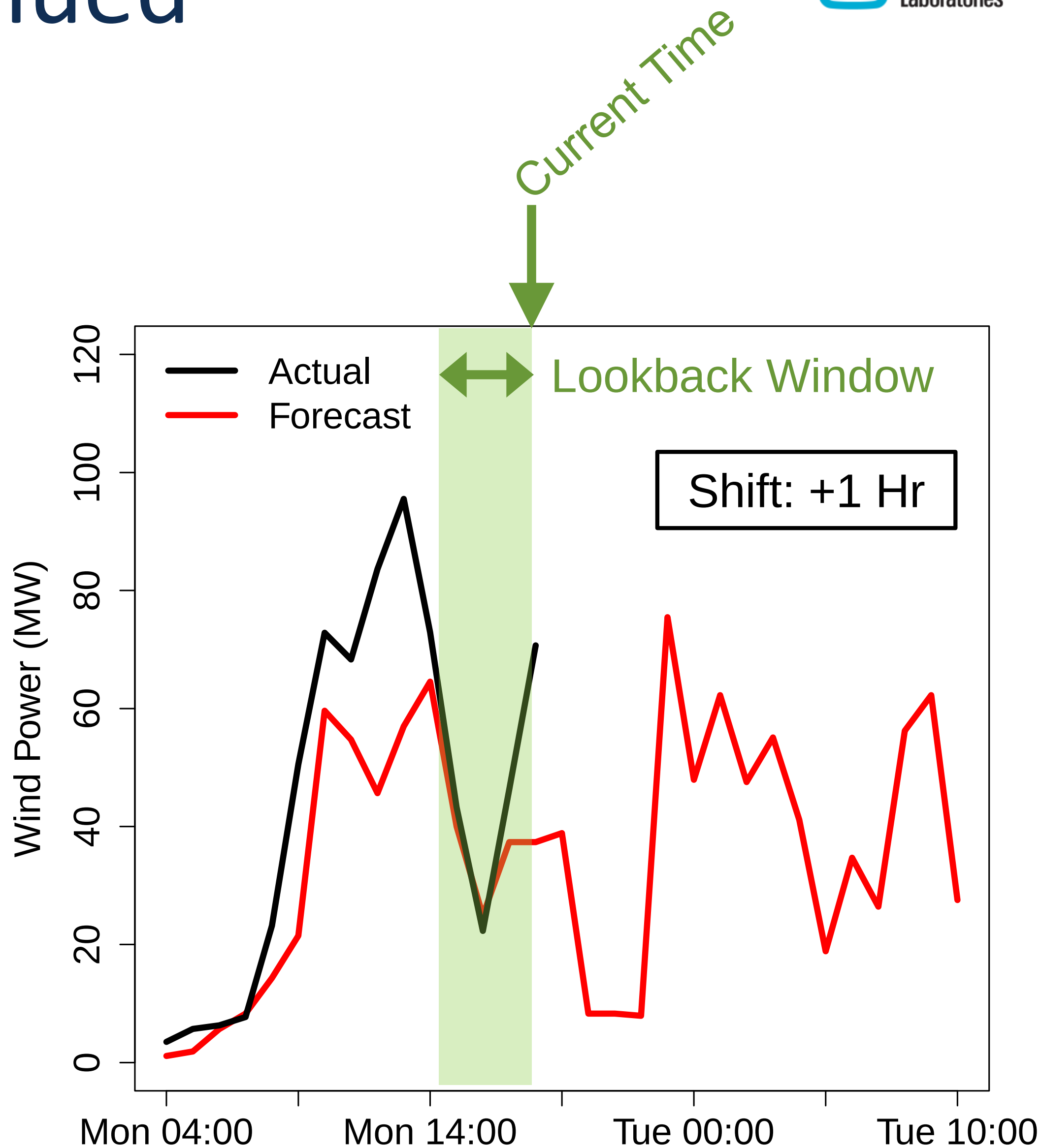

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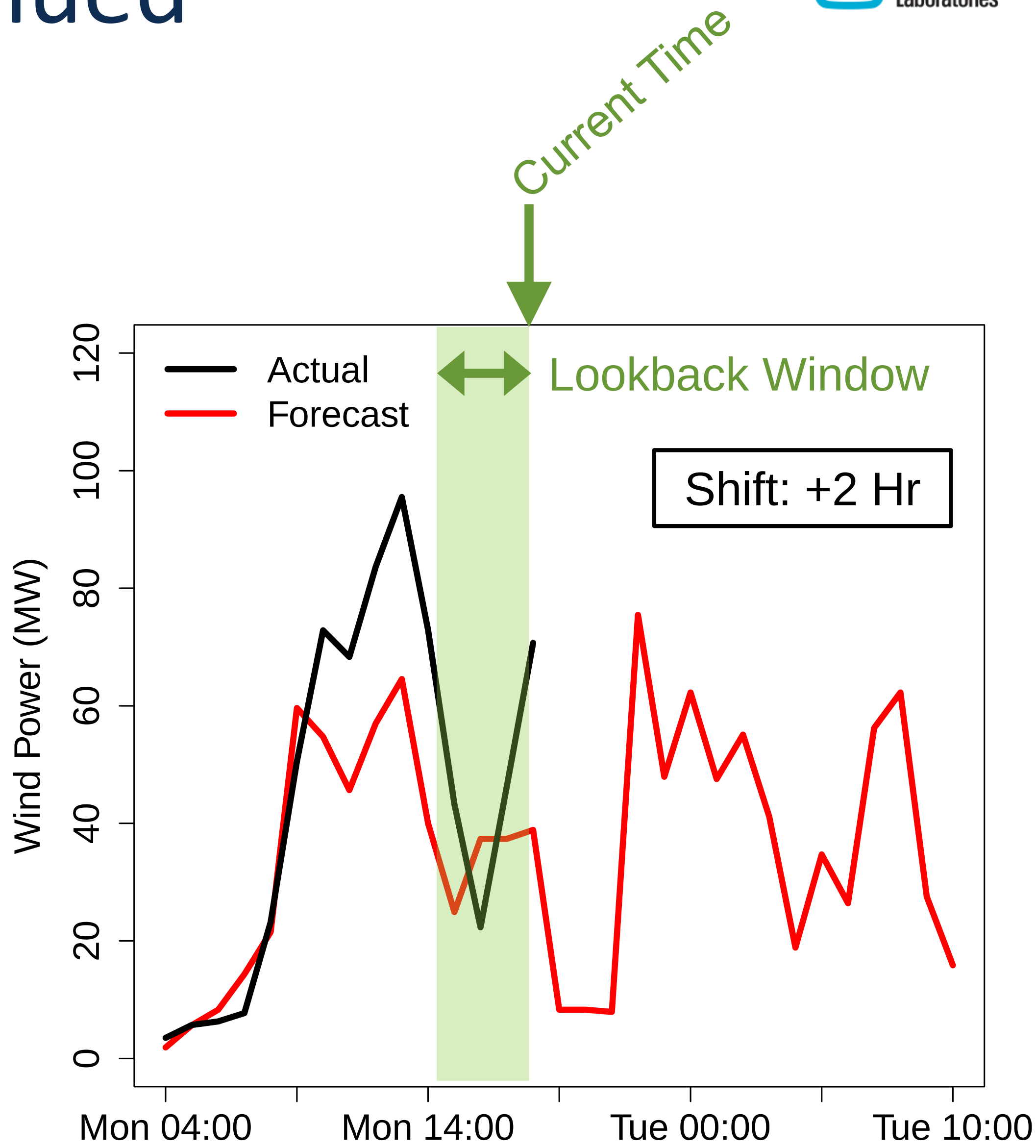

Algorithm, Continued

- At current time, look back at recent forecast/actual trace of wind power in lookback window
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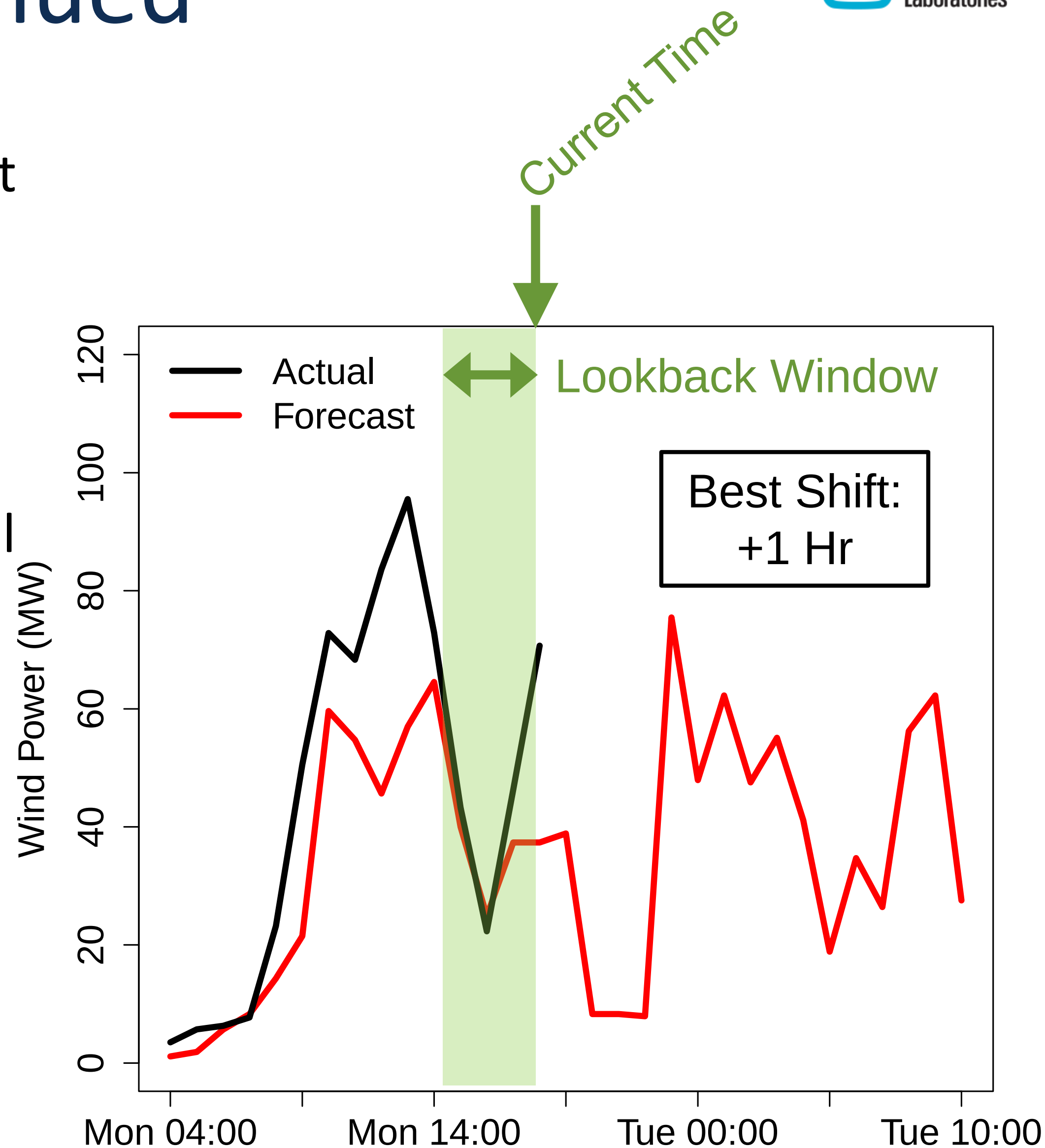
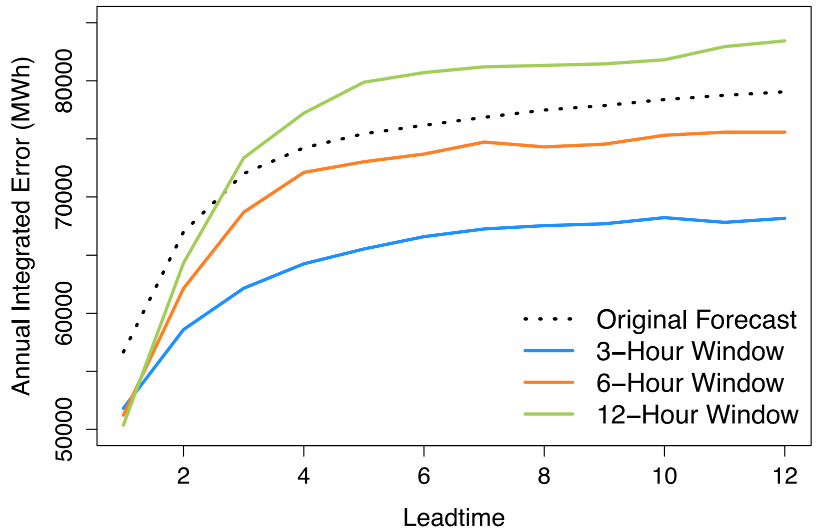
- Assess error if forecast had been shifted forward or backward in time
- **Identify shift with lowest error and take corresponding forecast value as new prediction**



Initial Analysis

- Early attempts at demonstrating functionality of our method:
  - Evaluating data with set lead-time, applying shift to next hour
- Results showed promise
  - Large error reductions compared to original forecast



- Smaller lookback windows resulted in largest error reductions
  - Most recent past is most indicative of near-future
- However, this approach relied on outdated data!
  - E.g., applying 4-hr lead-time data to the next hour
  - In reality, you'd use 1-hr lead-time forecast
- Need to change to a real-time data context; using the best possible data that an operator would actually have available

Real-Time Forecast Shift

- After identifying 'best' shift, apply new forecast value as prediction for the hour of interest
  - If shift is positive, take value for later lead-times from forecast vector for the same issue-time
  - If shift is negative, take value for earlier lead-times from forecast vector until current time
    - If you reach current time, use actual values

Original Forecast

For Example:

Issue Time	Hr1	Hr2	Hr3	Hr4	Hr5	Hr6
6/3/16 9:00	30.6	44.9	64.9	73.0	73.0	66.5
6/3/16 10:00	90.5	90.5	90.5	86.9	78.1	69.7
6/3/16 11:00	90.5	90.5	90.5	83.3	71.3	47.5
6/3/16 12:00	24.5	28.5	32.8	31.7	15.1	3.1
6/3/16 13:00	1.6	3.1	4.2	2.1	0.3	0.0
6/3/16 14:00	1.4	1.6	0.8	0.1	0.0	0.0
6/3/16 15:00	12.2	5.9	0.9	0.1	0.0	0.0
6/3/16 16:00	53.0	20.8	4.2	0.9	0.3	0.3

Real-Time Forecast Shift

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    - If you reach current time, use actual values going back in time

For Example:

Original Forecast

Shift: +2 Hr

Issue Time	Hr1	Hr2	Hr3	Hr4	Hr5	Hr6
6/3/16 9:00	30.6	44.9	64.9	73.0	73.0	66.5
6/3/16 10:00	90.5	90.5	90.5	86.9	78.1	69.7
6/3/16 11:00	90.5	90.5	90.5	83.3	71.3	47.5
6/3/16 12:00	24.5	28.5	[illegible]	31.7	15.1	3.1
6/3/16 13:00	1.6	3.1	4.2	2.1	0.3	0.0
6/3/16 14:00	1.4	1.6	0.8	0.1	0.0	0.0
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  - If shift is negative, take value for earlier lead-times from forecast vector until current time
    - If you reach current time, use actual values going back in time

Shift: ≤ -2 Hr

Original Forecast

For Example:

You’ve gone too far! Use actual measured values instead

Issue Time	Hr1	Hr2	Hr3	Hr4	Hr5	Hr6
6/3/16 9:00	30.6	44.9	64.9	73.0	73.0	66.5
6/3/16 10:00	90.5	90.5	90.5	86.9	78.1	69.7
6/3/16 11:00	90.5	90.5	90.5	83.3	71.3	47.5
6/3/16 12:00	24.5	28.5	32.8	31.7	15.1	3.1
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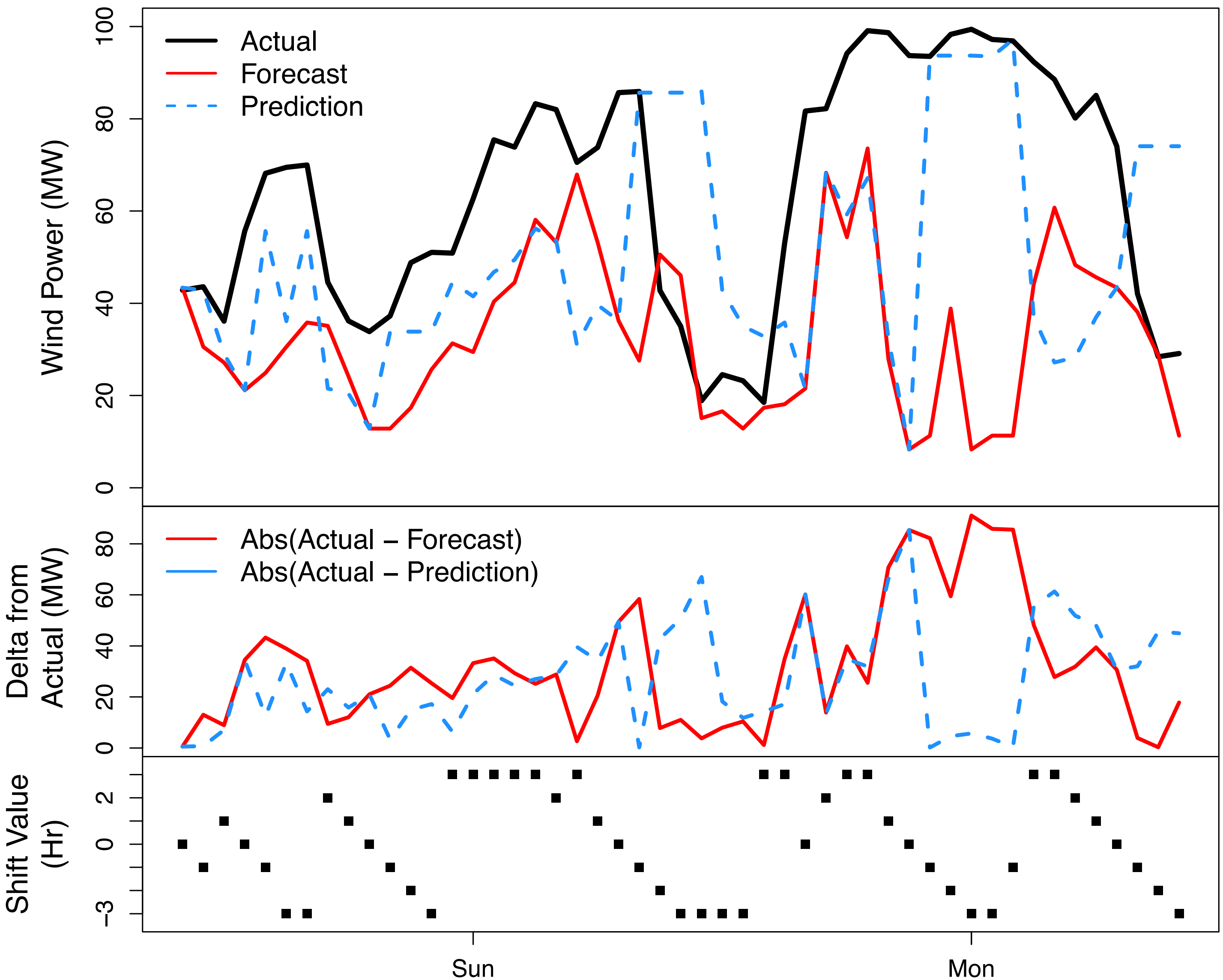
Testing the Algorithm

- Data from 33 wind projects in BPA balancing area
- Applied algorithm at the project level, using vendor-issued forecasts for each project
  - Assessed forecast performance vs ‘prediction’ from algorithm for one year, stepping forward in hourly increments
- Tested for varying lead-times, lookback window sizes, and maximum allowed shift values

What does this look like?



Single wind project, 1-hour lead time

Errors are smaller on average, but still miss some hours

For this time period:

- RMSE of Original Forecast: 40.5
- RMSE of New Prediction: 34.6

Preliminary Results

- Error reductions seen for some wind projects, but not all
  - More analysis needed to determine why, and under what conditions it fails
- In real-time data context, improvements seen only for very short lead times (1-2 hours)
- Greatest improvements seen for small lookback window, and small maximum shift value
  - This is good news! The forecasts are generally fairly accurate, and benefit the most from small adjustments

Preliminary Results

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Error results for projects that see forecast improvements:

1-Hour Lead Time

Wind Project	RMSE: Forecast	RMSE: Prediction	Annual Production (MWh)	Annual Savings (MWh)	Annual Savings (%)
A	18.3	17.6	236,021	6,022	2.6%
B	21.2	19.2	204,509	7,136	3.5%
C	18.6	17.6	244,459	4,597	1.9%
D	17.3	16.8	185,649	4,344	2.3%
E	22.9	19.8	201,838	12,018	6.0%
F	20.0	17.8	196,161	6,728	3.4%
G	22.7	20.0	203,610	9,548	4.7%

2-Hour Lead Time

Wind Project	RMSE: Forecast	RMSE: Prediction	Annual Production (MWh)	Annual Savings (MWh)	Annual Savings (%)
A	18.6	18.7	235,309	(108)	0.0%
B	21.6	21.7	204,082	(3,160)	-1.5%
C	18.8	18.8	243,837	(2,271)	-0.9%
D	17.4	17.5	185,084	(890)	-0.5%
E	23.0	22.5	201,394	260	0.1%
F	20.2	19.6	195,715	263	0.1%
G	23.1	22.3	203,254	1,237	0.6%

* All projects have been normalized to 100MW capacity

Conclusions

- This is very much research in progress… but results look promising
  - Small per-project forecast improvements can lead to large aggregate savings in system operations
  - Better estimates of timing offsets can be combined with improvements in prediction intervals of wind power magnitude
  - The shift estimate alone can be used as a useful metric for improved situational awareness, indicative of whether or not forecasts are running late or early across the system

- Much more to be done here, but suggestions are welcome!

Questions?

Contact:

- Andrea Staid, astaid@sandia.gov

Thanks to the Bonneville Power Administration for providing access to their data!