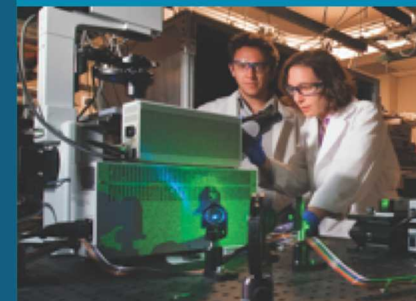
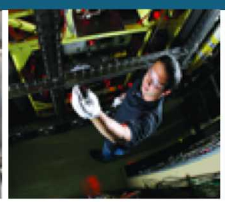
Sandia National Laboratories

SAND2019-6202C

Error Correction in the Timing of BPA Wind Power Ramp Events





Andrea Staid

June 5, 2019

ESIG 2019 Meteorology & Market Design for Grid Services Workshop, Denver, CO

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

A Disclaimer to Start:

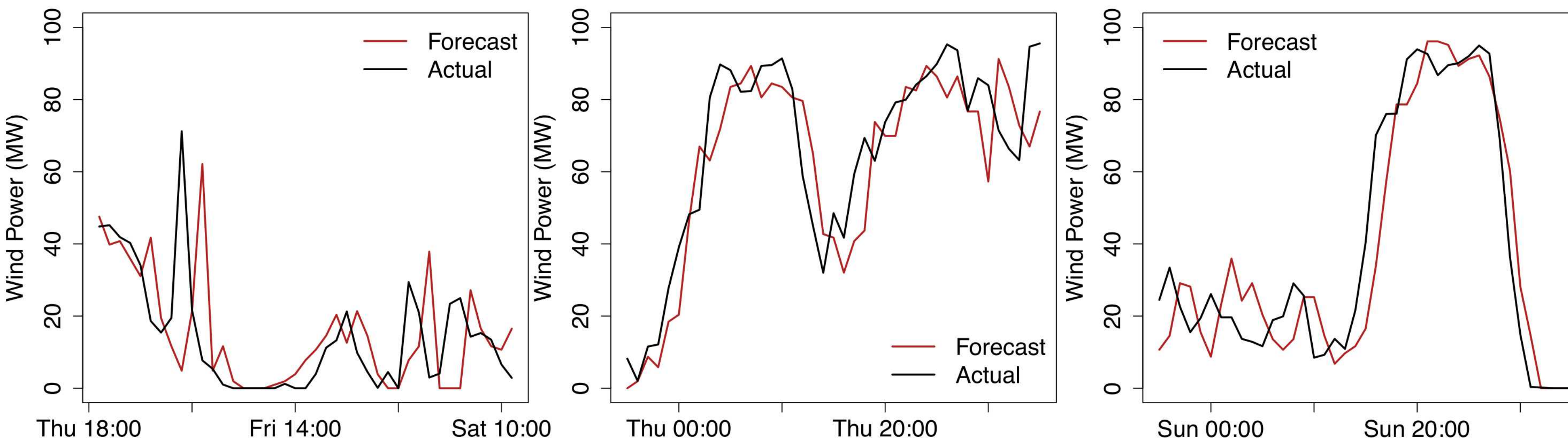
1. This talk is meant to provoke thought about current methods and the potential benefit of alternative approaches
2. This talk is not a prescription for a better wind forecasting method
3. This work focuses on the real-world need to work with what you've already got instead of finding the perfect data
4. The main takeaways of this work are:
   - The data you have is not always the data you want, but you may still be able to make lemonade out of lemons
   - Systematic forecast errors and/or biases are usually detrimental, but they can sometimes be used to your advantage – if they are well understood

Some Observations

Wind forecast errors exist in two dimensions – errors in magnitude and errors in timing

Digging into Bonneville Power Administration wind data, we see forecasts that are generally quite good!

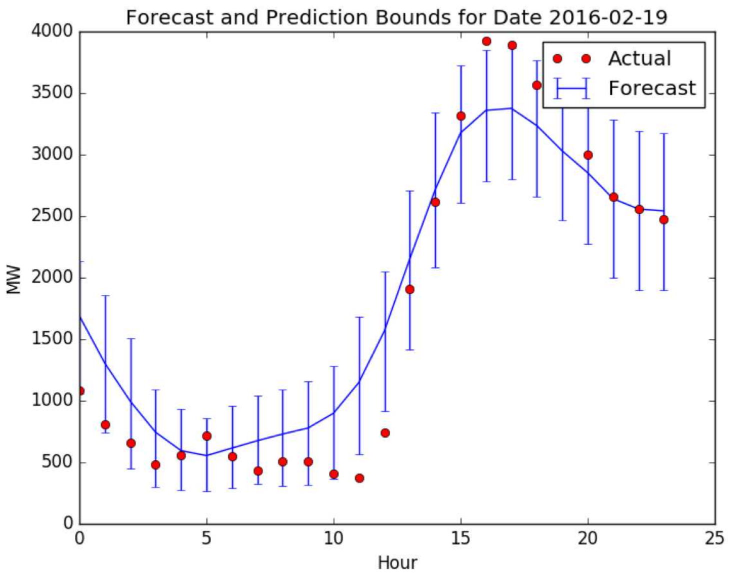
- But, errors in timing occur frequently
- Without access to the models or methods used, we can't say much about why these errors exist or whether there's anything to be done to correct them

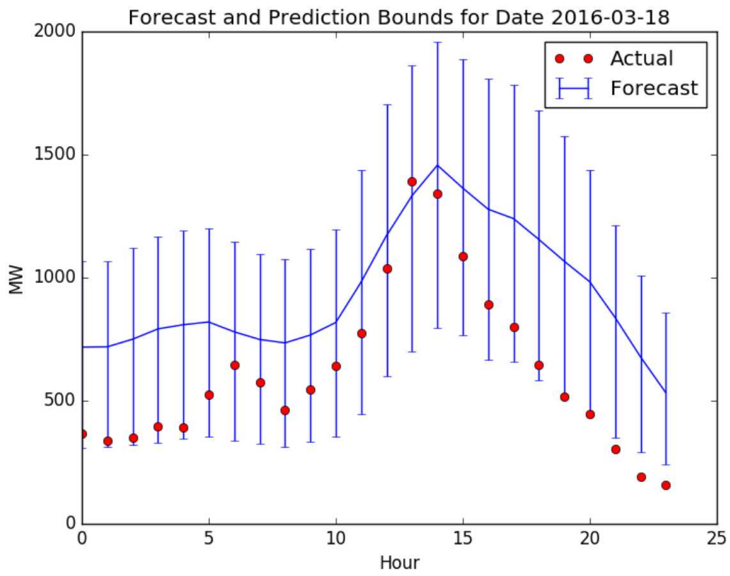


Data-Driven Approaches – Do they work?

Without using weather models or statistical learning, can we use the available data to improve things?

- In a previous project, we worked with BPA to develop more accurate prediction intervals for wind forecasts
- This method is purely data-driven, demonstrating the ability for the data itself to inform areas of improvement*





* I am not advocating for folks to ignore physical constraints and domain knowledge by blindly using data when other information is available

A Data-Driven Hypothesis

Without access to the models and raw data used, can anything be done to improve the timing of forecasts?

We hypothesize that forecast errors persist in time

- If the weather pattern arrived earlier than expected, it will leave earlier than expected as well
- Can we detect a temporal offset, and shift the forecast accordingly to reduce future errors?

This brings up some questions:

- Does this thinking apply only to ramp events, which may be indicative of large-scale weather patterns?
- Is there spatial correlation among wind sites?

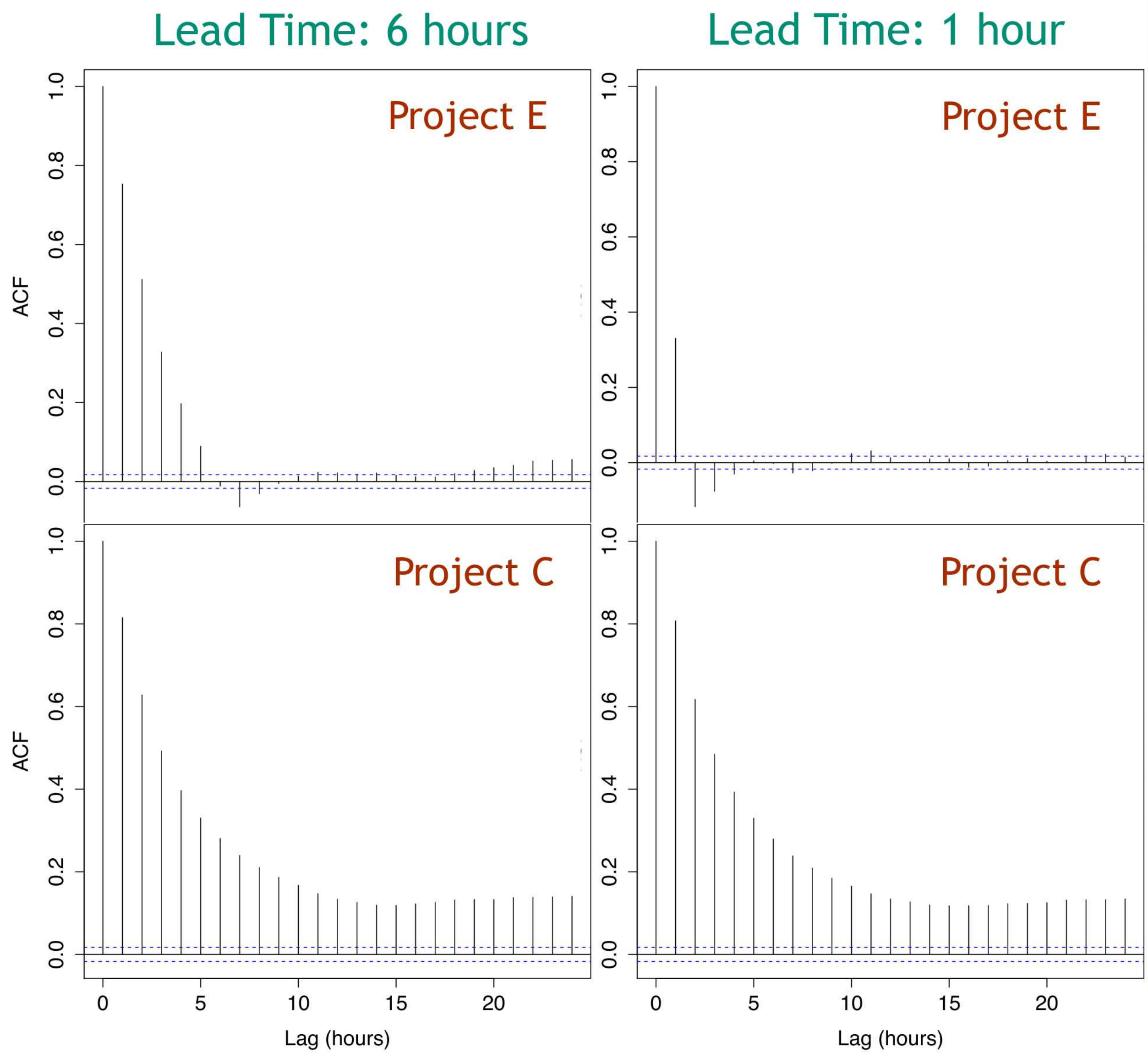
Forecast Error Correlation

Error correlation varies drastically among wind sites

Projects E and C are located nearby but exhibit different behavior

- Project C has errors that are highly correlated across time, and the pattern persists across lead times

Can we take advantage of these relationships?



Data and Method

BPA provided us with data from the 33 wind projects in their balancing authority*

- Forecasts with lead times of 1-168 hours
- Hourly actual values

Method:

- For a given hour, calculate the error between forecast and actuals, as the forecast vector is shifted forwards and backwards in time
- Find the minimum error, and assign the corresponding shift as the optimal shift value
- Assign the shifted forecast value as the new forecast for that hour

for $h \in (lb + ms + 1) : (n - ms)$ **do**

  $A = \text{actuals}[(h - lb) : h)$

  for $s \in [-ms : ms]$ **do**

    $F = \text{forecasts}[(h - lb) + s : (h + s))$

    $e_s = \sum_{t=2}^{lb} \frac{|(F_{t-1} - A_{t-1}) + (F_t - A_t)|}{2}$

  end for

  $s_{opt} = \arg\min_s E$

end for

*at the time, this number has changed since then

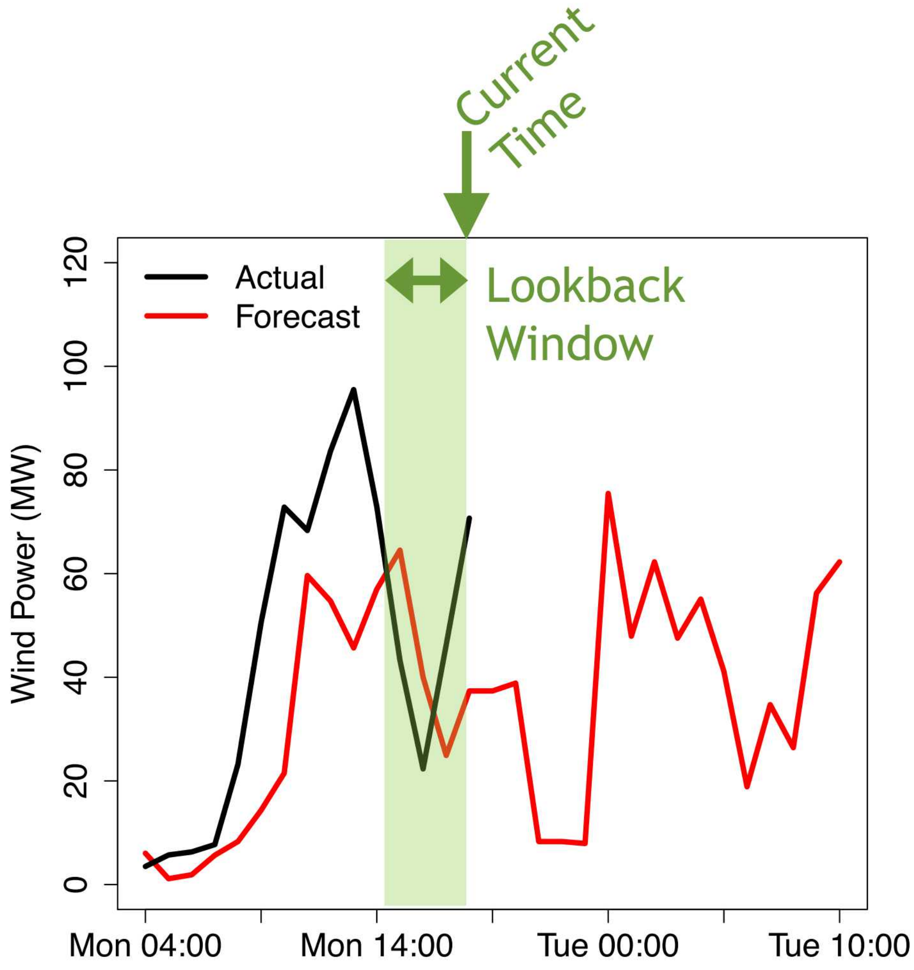
Data and Method

BPA provided us with data from the 33 wind projects in their balancing authority*

- Forecasts with lead times of 1-168 hours
- Hourly actual values

Method:

- For a given hour, calculate the error between forecast and actuals, as the forecast vector is shifted forwards and backwards in time
- Find the minimum error, and assign the corresponding shift as the optimal shift value
- Assign the shifted forecast value as the new forecast for that hour



*at the time, this number has changed since then

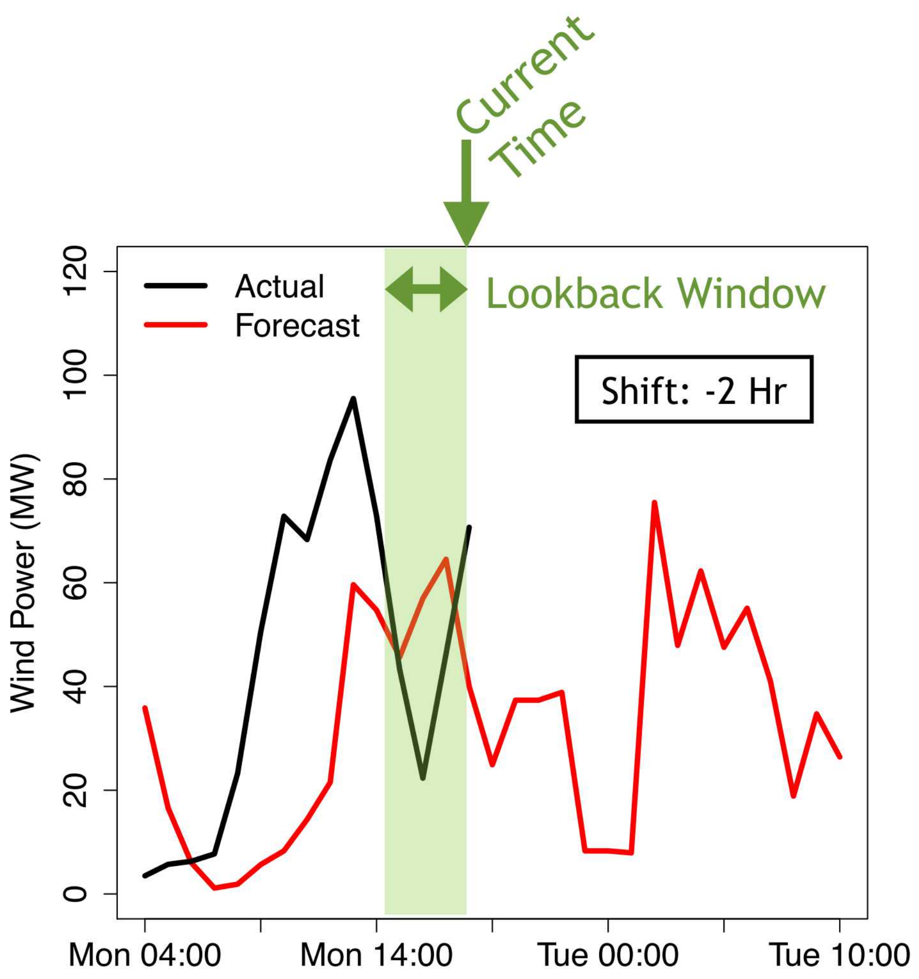
Data and Method

BPA provided us with data from the 33 wind projects in their balancing authority*

- Forecasts with lead times of 1-168 hours
- Hourly actual values

Method:

- For a given hour, calculate the error between forecast and actuals, as the forecast vector is shifted forwards and backwards in time
- Find the minimum error, and assign the corresponding shift as the optimal shift value
- Assign the shifted forecast value as the new forecast for that hour



*at the time, this number has changed since then

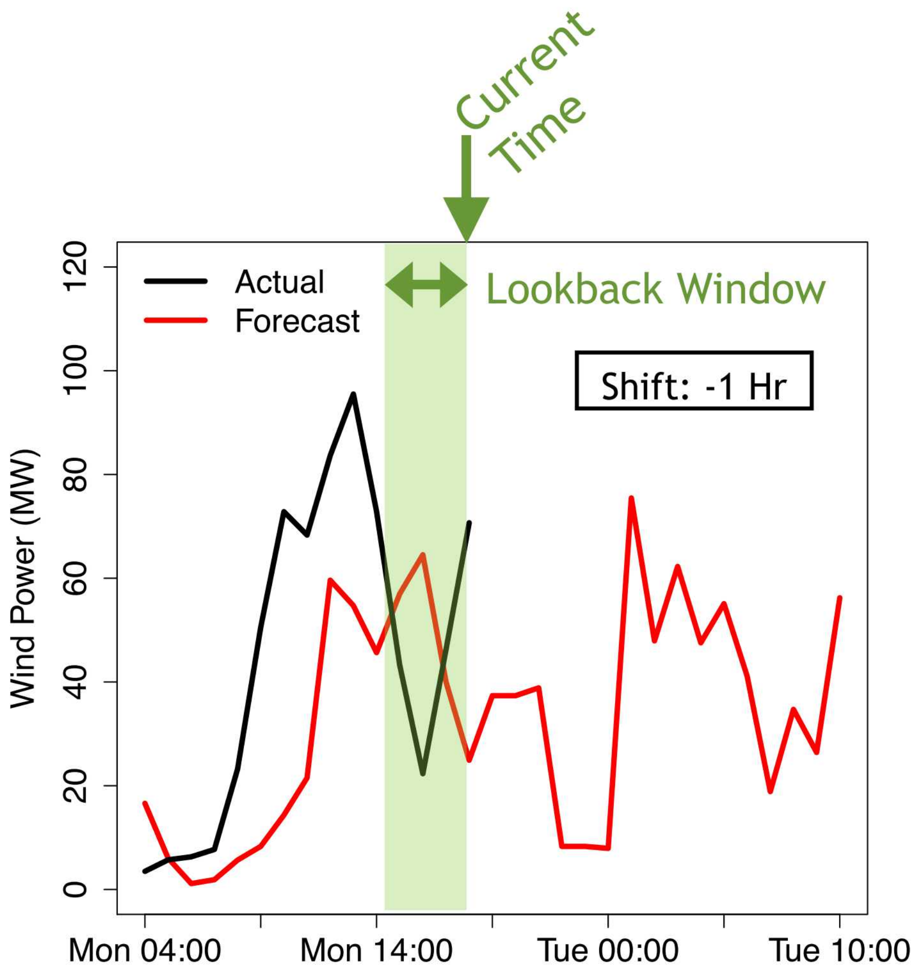
Data and Method

BPA provided us with data from the 33 wind projects in their balancing authority*

- Forecasts with lead times of 1-168 hours
- Hourly actual values

Method:

- For a given hour, calculate the error between forecast and actuals, as the forecast vector is shifted forwards and backwards in time
- Find the minimum error, and assign the corresponding shift as the optimal shift value
- Assign the shifted forecast value as the new forecast for that hour



*at the time, this number has changed since then

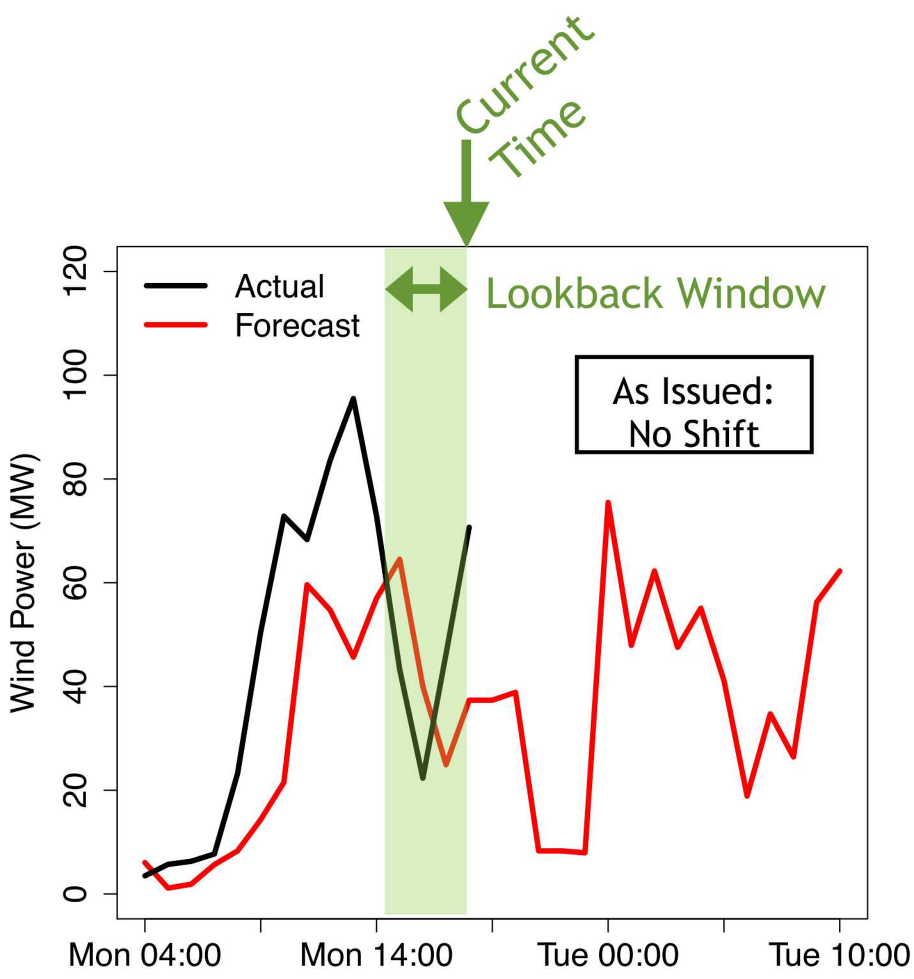
Data and Method

BPA provided us with data from the 33 wind projects in their balancing authority*

- Forecasts with lead times of 1-168 hours
- Hourly actual values

Method:

- For a given hour, calculate the error between forecast and actuals, as the forecast vector is shifted forwards and backwards in time
- Find the minimum error, and assign the corresponding shift as the optimal shift value
- Assign the shifted forecast value as the new forecast for that hour



*at the time, this number has changed since then

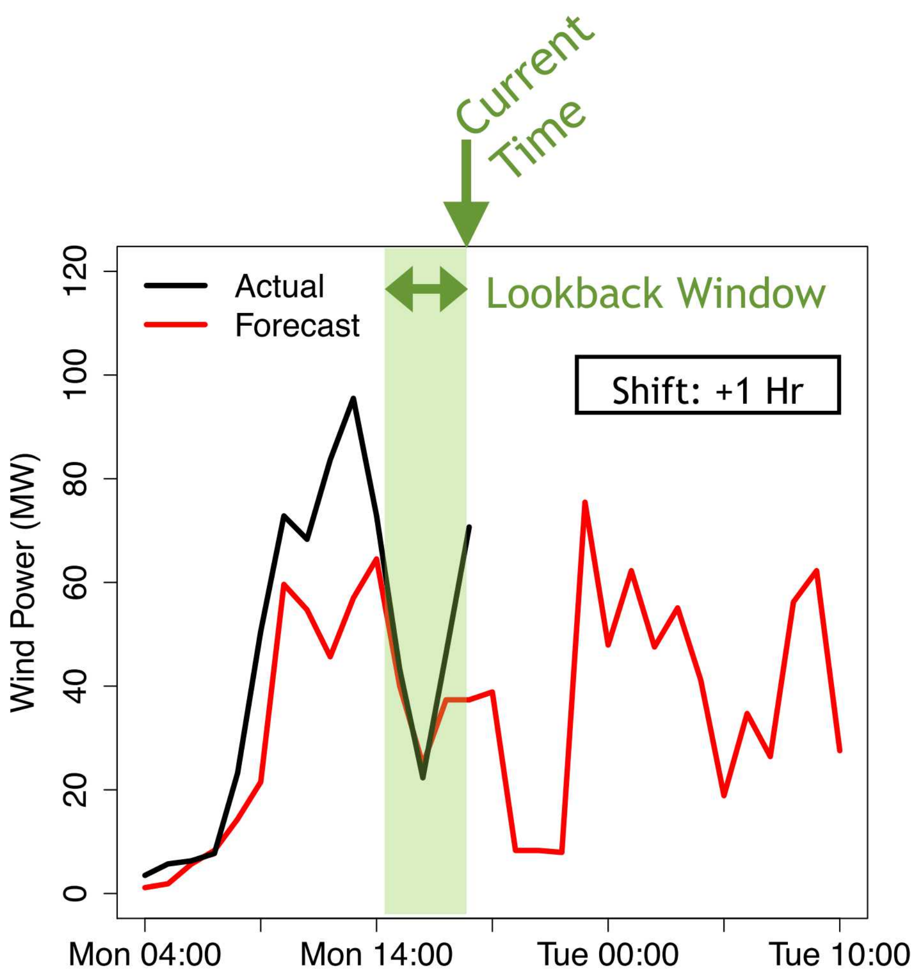
Data and Method

BPA provided us with data from the 33 wind projects in their balancing authority*

- Forecasts with lead times of 1-168 hours
- Hourly actual values

Method:

- For a given hour, calculate the error between forecast and actuals, as the forecast vector is shifted forwards and backwards in time
- Find the minimum error, and assign the corresponding shift as the optimal shift value
- Assign the shifted forecast value as the new forecast for that hour



*at the time, this number has changed since then

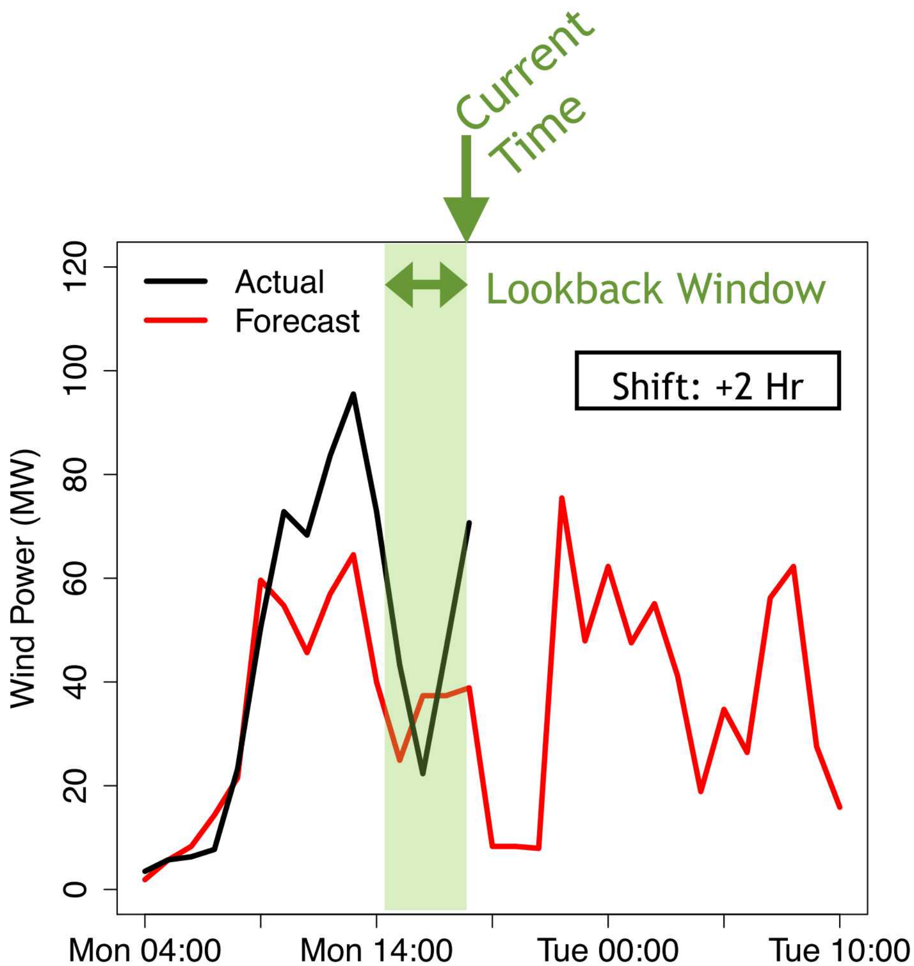
Data and Method

BPA provided us with data from the 33 wind projects in their balancing authority*

- Forecasts with lead times of 1-168 hours
- Hourly actual values

Method:

- For a given hour, calculate the error between forecast and actuals, as the forecast vector is shifted forwards and backwards in time
- Find the minimum error, and assign the corresponding shift as the optimal shift value
- Assign the shifted forecast value as the new forecast for that hour

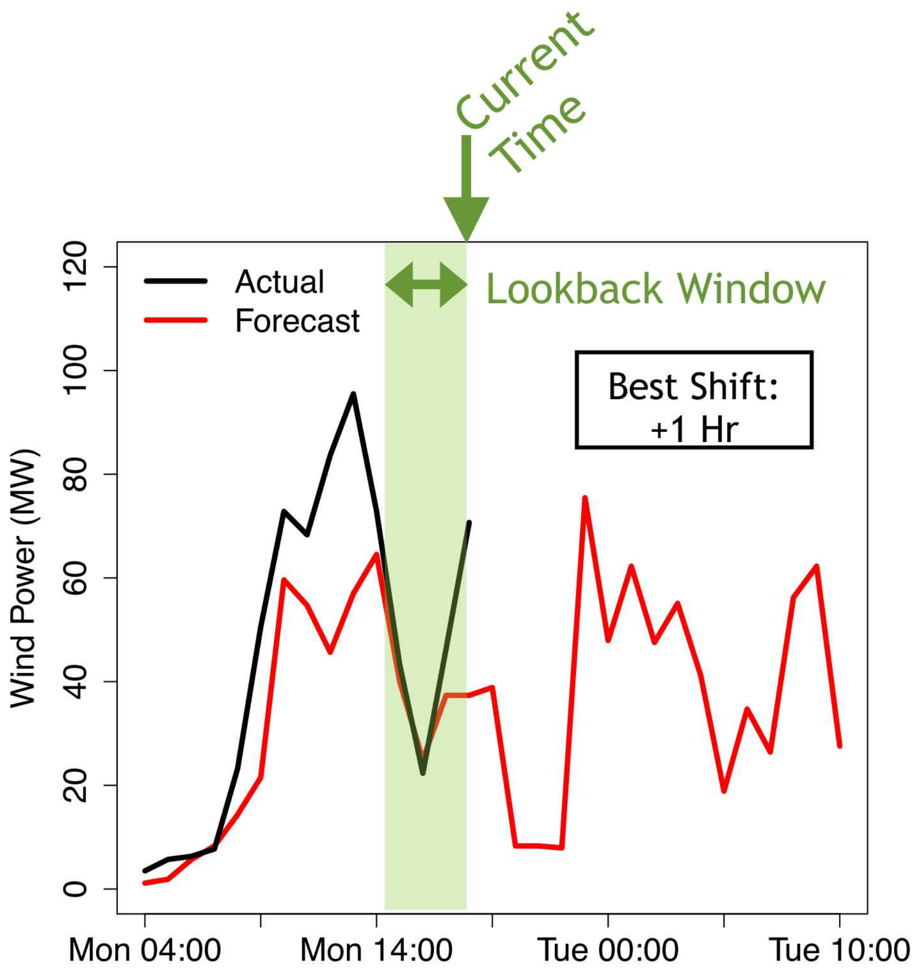


*at the time, this number has changed since then

Data and Method

BPA provided us with data from the 33 wind projects in their balancing authority*
- Forecasts with lead times of 1-168 hours
- Hourly actual values

Method:
- For a given hour, calculate the error between forecast and actuals, as the forecast vector is shifted forwards and backwards in time
- Find the minimum error, and assign the corresponding shift as the optimal shift value
- Assign the shifted forecast value as the new forecast for that hour



*at the time, this number has changed since then

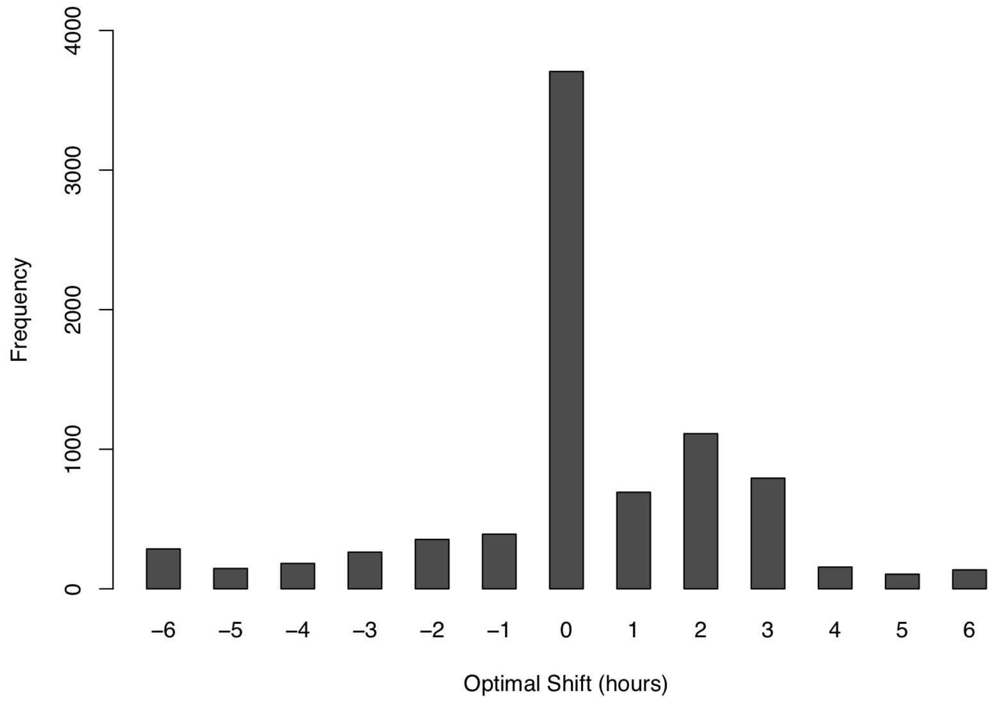
Options and Extensions

We experimented with options surrounding:

- Maximum allowed shift
- Size of lookback window
- Strength of error reduction
- Assigning only forecast data vs using actuals if the shift value allows
- Varying forecast lead time

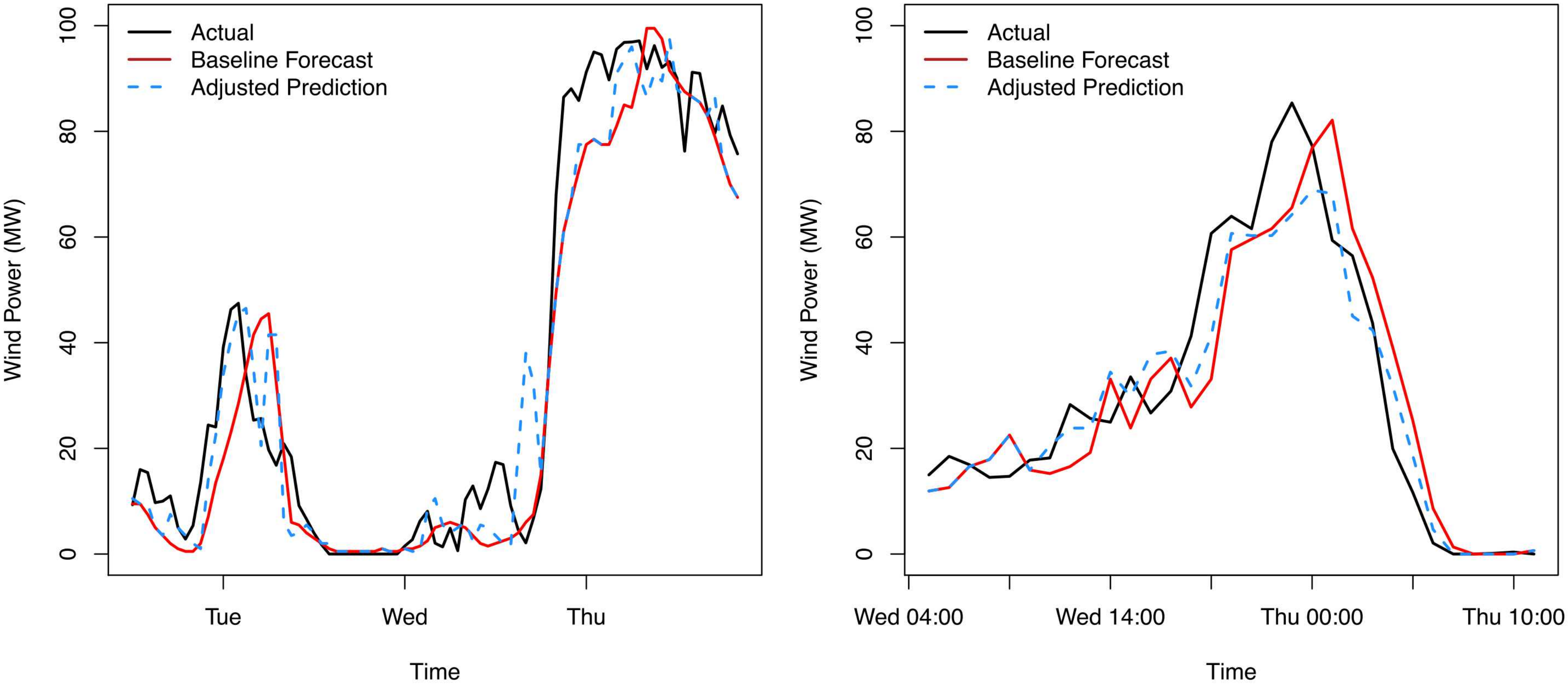
Overall, the optimal forecast shift was generally small

- These forecasts are quite good to start with!



Sample Results

What would this look like in practice?



Overall Results

Wind Project	Lead Time	Lookback Window	Maximum Shift	Algorithm Option	Forecast MAE	Adjusted MAE	Percent Improvement
A	1	2	3	2	9.40	9.14	2.78%
B	1	5	3	1	9.92	9.47	4.55%
C	1	2	3	1	8.52	8.09	5.12%
D	1	2	3	2	8.58	8.35	2.74%

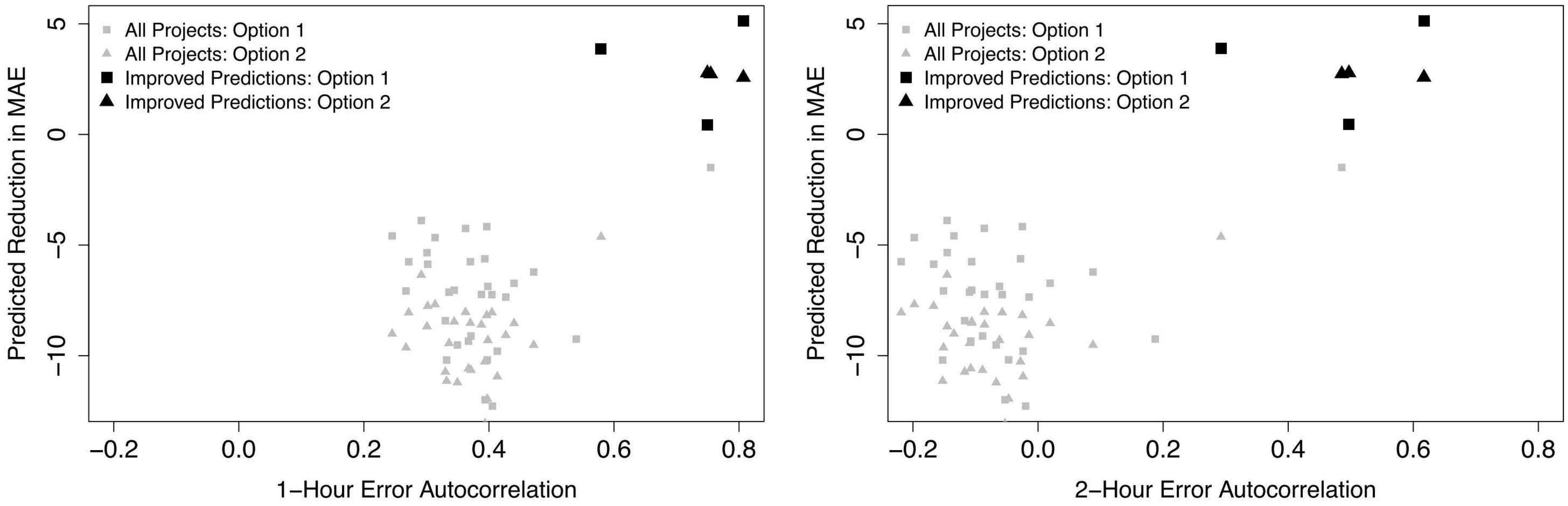
Out of 33 wind projects, we only see improvements in 4

However, from an economic standpoint, 2-5% improvements are significant, if the savings can be realized

So what is it about those 4 projects?

The projects that see improvements all have something in common:

- Errors are highly correlated in time
- This allows those particular projects to take advantage of our algorithm, which relies on consistency over short time periods



Caveats

The results shown are specific to the data used here – Is this a problem?

- If the forecast vendor were to change their model, for example, there's no guarantee that this algorithm would still work
- The high temporal error correlation is likely indicative of insufficient forecast updates; if this is corrected, the improvements shown here would disappear

This isn't a perfect solution, but going back to my disclaimers from the beginning…

1. This talk is meant to provoke thought about current methods and the potential benefit of alternative approaches
2. This talk is not a prescription for a better wind forecasting method
3. This work focuses on the real-world need to work with what you've already got instead of finding the perfect data
4. The main takeaways of this work are:
   - The data you have is not always the data you want, but you may still be able to make lemonade out of lemons
   - Systematic forecast errors and/or biases are usually detrimental, but they can sometimes be used to your advantage – if they are well understood