Application of a Random Forest Approach to Model Output Statistics for use in Day Ahead Wind Power Forecasts

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Motivation

- Balancing authorities, which include independent system operators and electric utilities, use day-ahead (48-hour) variable generation (e.g. wind and solar) forecasts to plan for and allocate the day-ahead generation resources.
- Currently, wind provides the majority of variable power production.
- The day-ahead wind forecast is an essential tool to estimate wind-generated power that will be available on the grid during the next operating day.
- New techniques that can reduce day-ahead wind power forecast error will provide additional value to balancing authorities and ultimately reduce the cost of integrating wind into electric systems.
- Day-ahead wind power forecasts are primarily produced from an ensemble of numerical weather prediction(NWP) forecasts which exhibit systematic non-linear error patterns.
- Systematic NWP forecast error can vary by:
  - Location
  - Season
  - Time of Day
  - Weather Regime
- Various forms of statistical models, known as model output statistics (MOS), are commonly used to minimize the impact of systematic model error on forecasts.
- Traditional MOS techniques have several limitations:
  - Artificial neural networks require long training periods and tend to overfit
  - Support vector machines are slow to train over large datasets and depend on the choice of kernel parameters
  - Linear regression assumes normal distribution and is overly sensitive to outliers
- These limitations make the ensemble decision tree technique known as "random forest" a promising and interesting method that may be applied to NWP forecasts in order to more effectively reduce model forecast error.

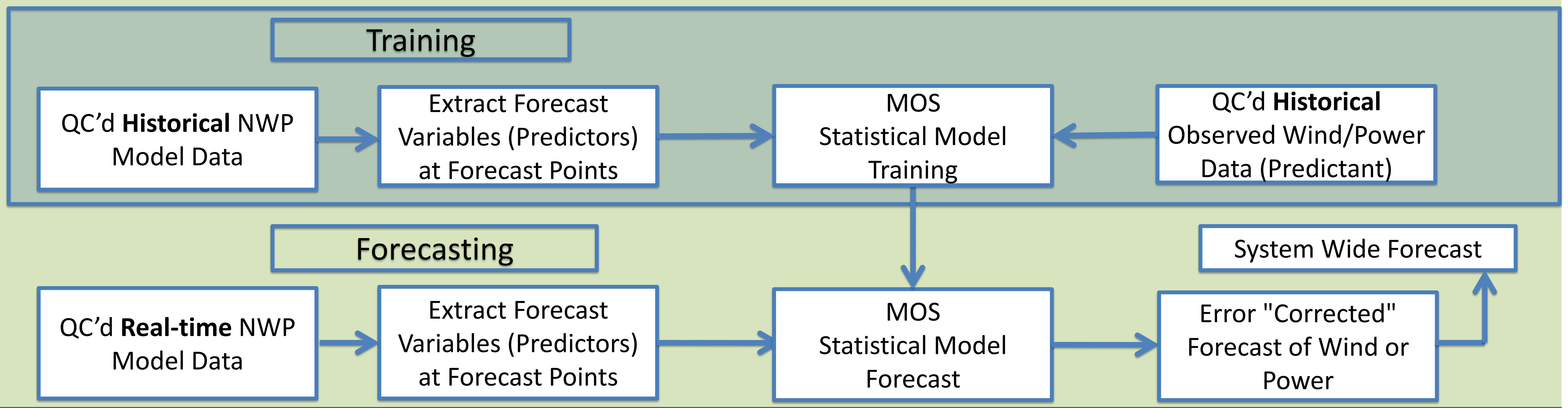
Method

- Random forest (RF)[1] is a non-parametric machine learning method that improves on the decision tree approach[2] in several ways:
  - Random forest trains from an ensemble of trees on resampled versions of the original training set using a bootstrap technique to explore the range of dataset variability.
  - At each node of the tree, only a random subset of the data attributes are evaluated.
- Unlike other techniques random forest trains quickly, is less prone to overfitting and can account for non-linear relationships.

Experimental Design

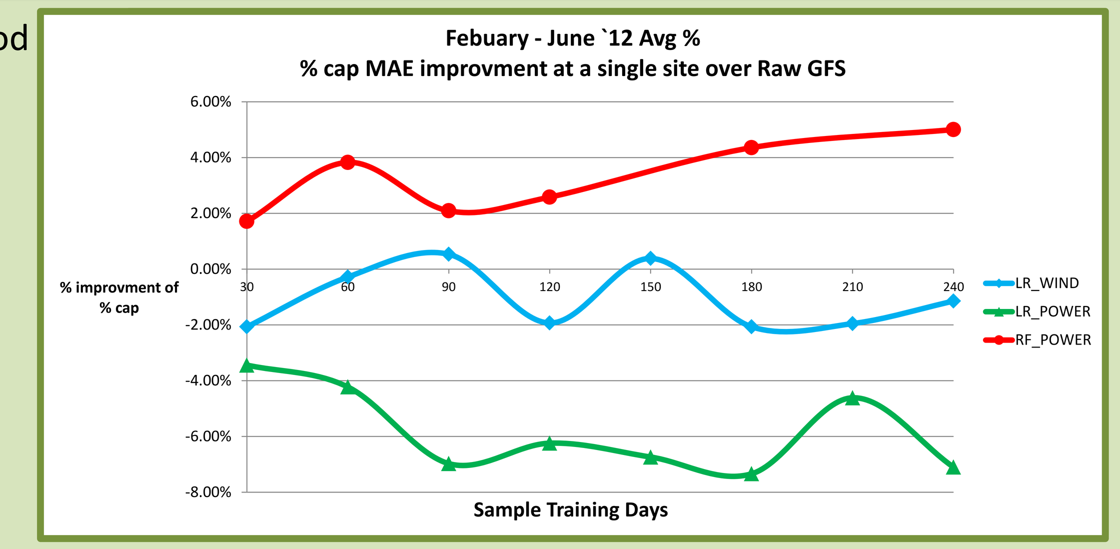
- A RF approach was used to directly predict wind power production (% of plant capacity) and compared to a screening multiple linear regression (LR) technique and model forecasts without bias correction (raw).
- Forecasts were produced for a number of wind farms in Texas and aggregated to generate a system wide forecast (AGG) using two years of observations and model data.
- Predictor variables (input) from the North American Mesoscale Model (NAM) and Global Forecast System (GFS) NWP models at selected heights for each forecast location included:
  - Wind Speed and Direction
  - Temperature
  - Geopotential height
- The RF model was retrained monthly using various training periods sizes
- Each method can be trained to predict either wind or power

Forecast Technique



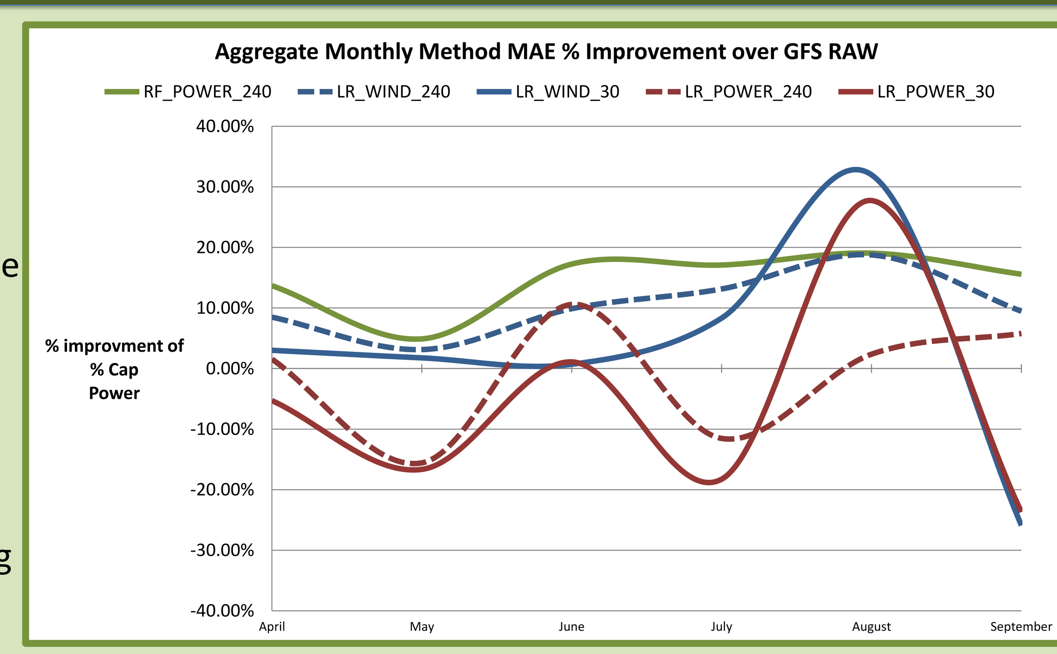
Single Site Sensitivity to Training Sample Size by Method Type

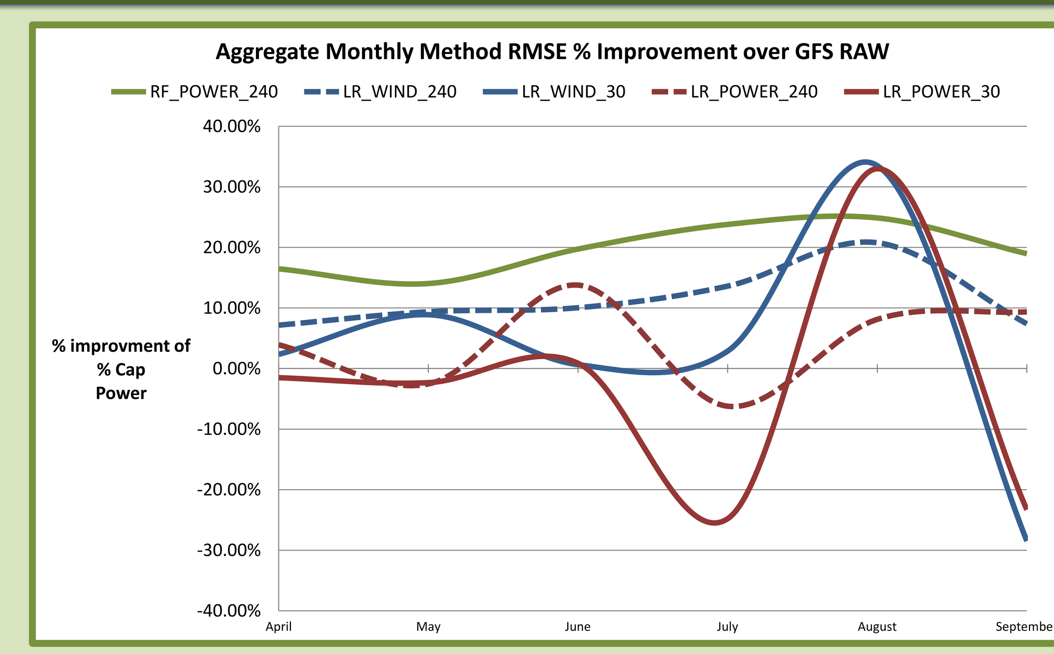
- 48-hour forecasts of hourly power production were produced daily for one site over a 5 month period
- Each method was retrained monthly using 30 -240 training days
- 3 Methods were trained using the GFS model variables (predictors):
  - **LR_Wind:** Linear regression trained to wind speed then converted to power
  - **LR_Power:** Linear regression trained directly to power
  - **RF_Power:** Random forest trained directly to power
- Methods are compared to the raw GFS wind speed forecast put through a power curve
- RF_Power performed the best, with increased improvement for larger training sample sizes
- LR_Power performed the worst most likely due to non-linear correlation from model state to power



Aggregate Forecast Performance by Month

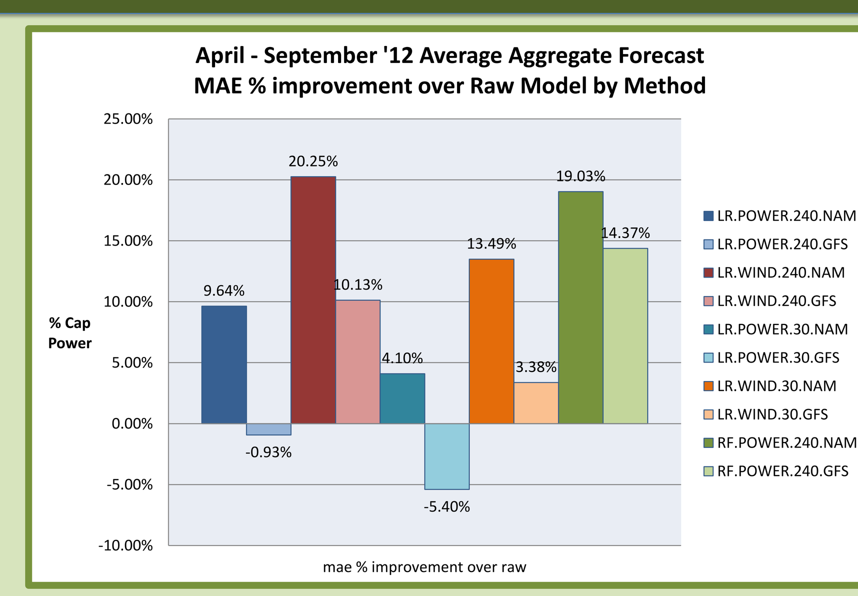
- Trained for both **30** and **240** days once per month
- Aggregate of 50 wind sites
- RF 6 month average RMSE improvement was 19.64% over the raw GFS method as compared to 11.39% and 4.40% for wind and power LR methods (240 training days).
- 30-day training linear regression methods did best in August during a very persistent weather regime.

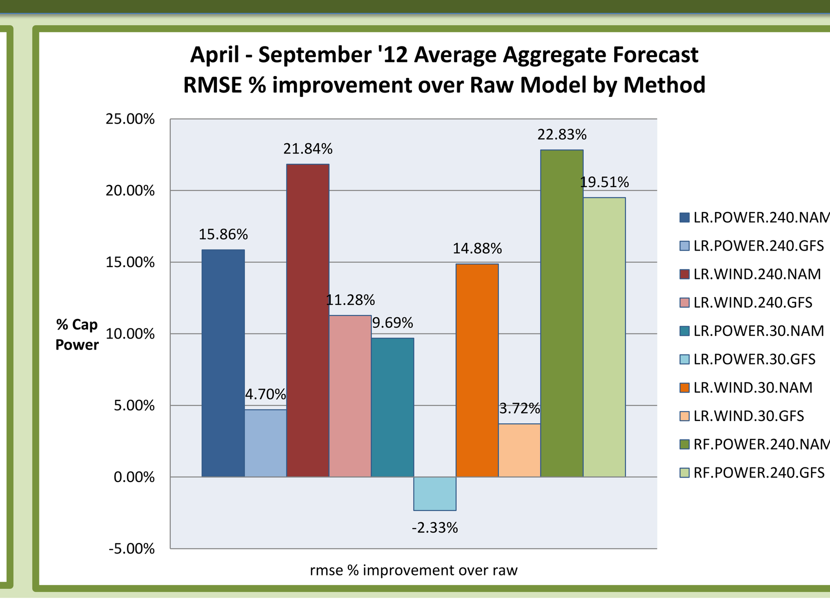




Sensitivity to Input Model

- Compared linear regression to random forest for both GFS and NAM models with 30 and 240 training days.
- Results show % decrease in MAE and RMSE over either NAM or GFS (raw) model wind forecast put through a power curve.
- Darker colors denote NAM methods compared to raw NAM and lighter colors denote GFS methods compared to raw GFS.
- **RF decreases RMSE more than MAE and improves the NAM forecast more than GFS.**
- RF with 240 training days is slightly better than RF for MAE using NAM input, mostly due to the improved performance in July-August months (shown above).

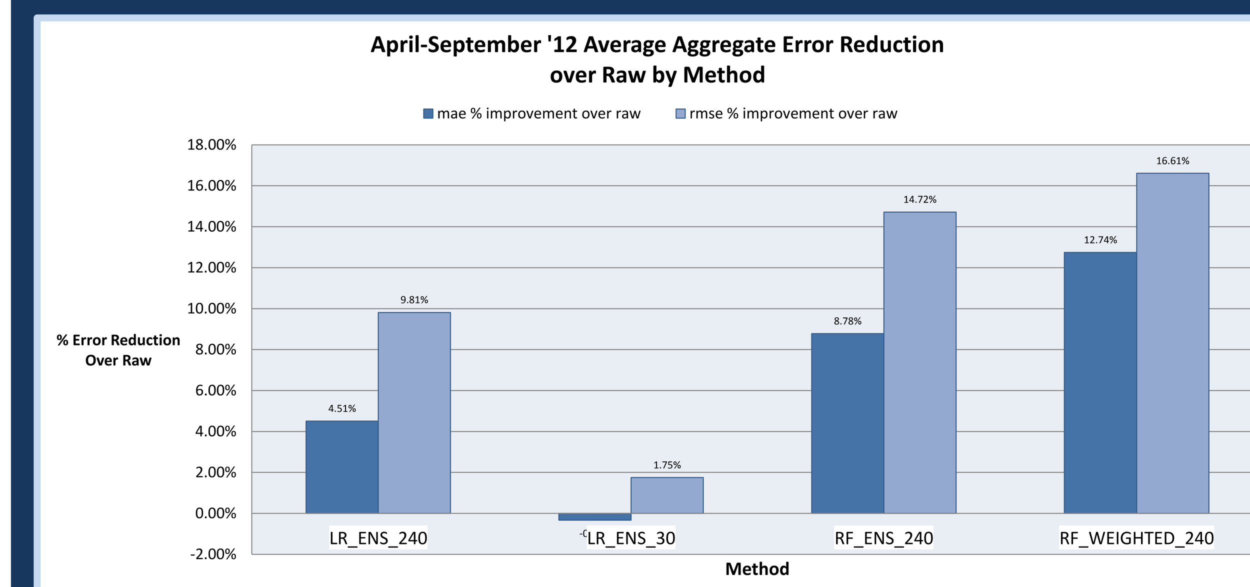


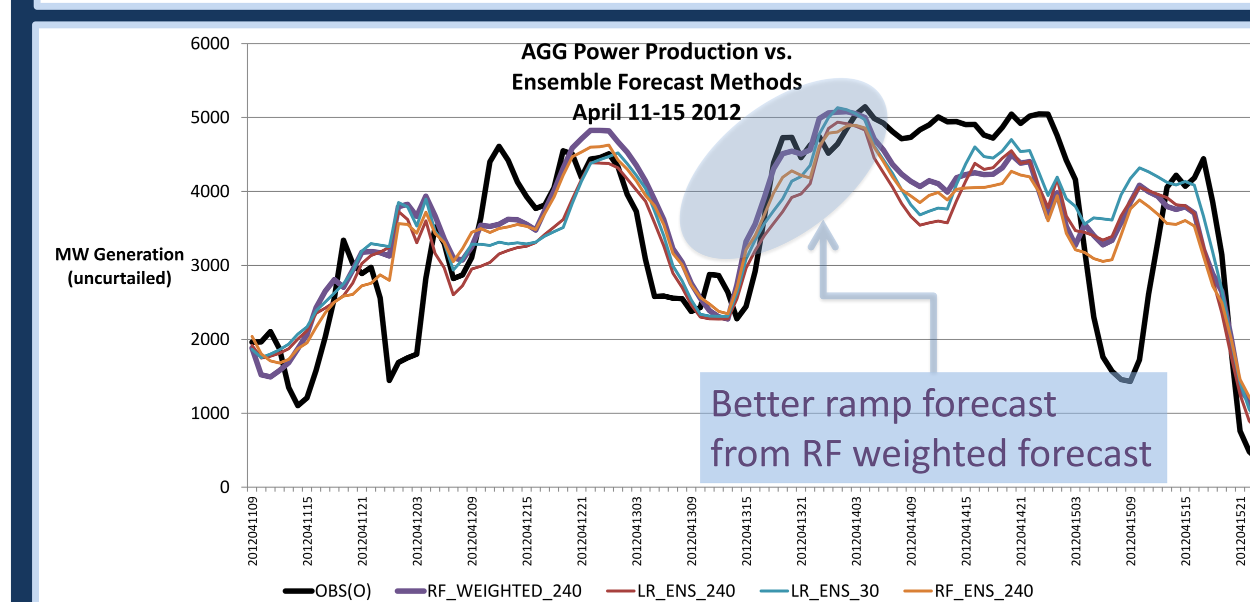


1. Breiman, L., 2001 Random Forests. *Machine Learning*,**45**, 5-32.
2. Breiman, L.,1984: *Classification and Regression Trees*, Chapman & Hall, 358 pp.

Ensemble Results

- To determine the impact of using predictors from more than one model, several ensemble aggregate forecasts were generated for a six month period from April – September 2012:
  - **Raw**: unweighted average of both the GFS and NAM wind speed forecast after a power curve is applied.
  - **LR_ENS_240**: unweighted average of 4 methods; LR_Wind and LR_Power for GFS and NAM data using 240 training days.
  - **LR_ENS_30**: unweighted average of 4 methods; LR_Wind and LR_Power for GFS and NAM data using 30 training days.
  - **RF_ENS_240**: unweighted average of RF_Power for GFS and NAM data using 240 training days.
  - **RF_WEIGHTED_240:** RF weighting predictors from both GFS and NAM data using 240 training days.
- Uneven weighting of model state variables in RF reduces the power production forecast error by 3.96% for MAE and 1.89% for RMSE over an average of RF-adjusted NAM and GFS for a 6 month period.





Conclusions and Future Work

- RF is an efficient machine learning technique that can reduce the error of NWP-based day-ahead wind power generation forecasts.
  - RF trains quickly, is less prone to overfitting than other methods, and can account for non-linear interactions among predictors.
- RF took advantage of larger training samples more effectively than a screening linear regression technique for a 5-month evaluation period.
- RF-based forecasts using predictors from 2 NWP models improved upon a simple average of RF-adjusted forecasts from each model suggesting that RF has skill in unevenly weighting the individual forecasts.
- Area for further development:
  - Screening of candidate predictors to identify which are most useful in order to limit predictor to a smaller set of the most effective predictors without overfitting.
  - Regime-based training (pre-partitioning of sample into subsamples or addition of regime based predictors)