Statistical Analysis and Modeling for Wind Power Forecasting

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Project Overview

- Address various scientific and practical challenges encountered in wind power forecasting, including power curve modeling

- Just completed a 3-year project funded by internal research money

- Five-member LLNL team
  - Wayne Miller (PI, turbine mechanics)
  - Sonia Wharton (atmospheric science, data collection)
  - Vera Bulaevskaya (statistics/machine learning)
  - Matthew Simpson (WRF modeling)
  - Don Lucas (WRF modeling, climate modeling)

- In collaboration with Andy Clifton at NREL (machine learning, turbine mechanics, remote sensing)

- Close collaboration with industry partners
LLNL Field Campaigns

United States - Land-Based and Offshore Annual Average Wind Speed at 80 m

LLNL wind field campaigns

Our goal

Advance power curve models through:

1. Expanding the set of meteorological predictors to the power model
2. Statistical modeling
Atmospheric and power data

- Wind farm in northern CA with moderately complex terrain
- June - August 2012
- Power output data:
  - 38 1-MW turbines
  - 10-minute means
- Lidar wind data
  - 10-minute summaries
  - Wind speed means, SDs, and wind direction means at 40, 50, …, 150 meters
- Other relevant data
  - Air density
  - Nacelle wind speed and direction
We applied several filters to the data

- Focus on one turbine that is most often directly downwind of the lidar
- Only included observations with wind directions favorable to the turbine we considered
- Only included observations with the wind speed means roughly corresponding to region II of the power curve (non-constant power)
- Lidar measurement at **90 meters** is the closest to the hub height in terms of the elevation and wind speeds measured at the turbine, so it was used as proxy for the hub-height wind speed
We investigated several sets of meteorological inputs

- Wind inputs (density-adjusted w/ IEC standard)
  1. Wind speed 10-min mean at 90 meters (proxy for hub height)
  2. Wind speed 10-min mean + standard deviation at 90 meters
  3. Rotor-equivalent wind speed: wind speed averaged across the rotor disk
  4. Entire profile of wind speed means (40, 50, …, 150 m)
  5. Entire profile of wind speed means and standard deviations
    - For sets 4 and 5, performed principal component analysis (PCA) to reduce the dimension

- Other atmospheric variables
  - Air density (added separately to the unadjusted wind inputs)
  - Wind veer (standard deviation of wind directions at heights 40-90 meters)
We investigated 3 models

1. Neural networks (NN)

   ![Neural Network Diagram]

   - Inputs
   - Weights
   - Activation Function
   - Output

2. Random forest (RF)

   ![Random Forest Diagram]

   - $x_1 \leq 49$
   - $x_1 > 49$
   - $x_2 \leq 0.4$
   - $x_2 > 0.4$
   - $x_3 \leq 0.7$
   - $x_3 > 0.7$

3. Gaussian Process Model (GPM)

   \[ Y(x) = Y(x_m, x_e) = g^T(x_m)\beta + Z(x_e) \]

   - Inputs used to model the mean function
   - Inputs used to model the error process

   \[ g = \text{just the intercept term or natural spline of order 3} \]

   \[ E(Z(x_e)) = 0 \]

   \[ Cov(x_i, x_j) = \sigma^2 \left[ \exp \left( -\frac{\sum_{p=1}^{P} |x_{pi} - x_{pj}|^2}{d_p} \right) + q\delta_{ij} \right] \]

   - $d_p = \text{range parameter for the } p^{th} \text{ predictor}$
   - $q = \text{nugget}$
Model comparison

- Estimating uncertainty associated with point forecasts is more natural with GPM than NN and RF

- NN and RF scale better with the number of predictors than GPM, making computation faster
  - But training can be done offline, so speed is not critical
Performance study

- Randomly divided the data (1737 points) into training and validation sets (50/50)

- Using each of the models, fit power using the training data, predicted power for the validation set and obtained the root mean squared error (RMSE) of prediction

- Repeated 30 times
Results

Boxplots of RMSEs from 30 experiments

If only using the hub height speed as an input, there is no gain from using the statistical models (color) relative to the bias-corrected power curve (grey)

Pronounced improvement when using the entire profile of wind speeds: average change of **0.02 MW** in a 10-min period, 2% of the rated power

Statistical models perform more or less equally

Using reduced wind profiles (PCA) performs almost as well as using the original profile, so only the reduced ones are shown
Using shear exponent and TI

Boxplots of RMSEs from 30 experiments

Shear exponent: Less accuracy than using the entire vertical profile of wind

Turbulence intensity (TI): Same accuracy as using the standard deviation if adding to hub-height wind speed alone, but less accuracy if using a profile of TIs versus profile of standard deviations
Additional atmospheric variables (GPM and NN)

- Typically, adding more variables results in greater gains for smaller wind speed input sets
- Adding density on its own results in more accurate predictions than using density-adjusted wind inputs (median reduction up to 28%)
- Veer resulted in marked improvements, as well (median reduction up to 27%)
Summary

- Case study of a complex terrain site
- Identified avenues for improving power modeling
  - Additional inputs
  - Statistical modeling
- Quantified improvement
- Illustrated an approach for building a more accurate power curve model at other sites and during other seasons
Ongoing and future work

1. Other sites, seasons, turbines

2. Extending this framework to *forecasts* of inputs to the power curve model

3. Modeling power of an entire wind farm

4. Performance metrics other than RMSE
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