# Powering Up with Space-Time Wind Forecasting

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## Goals of This Talk

- Discuss 3 models for forecasting wind speed (2 hour horizon)
  - Investigate role that wind direction plays
  - Discuss the flexible skew-$t$ distribution
- How to compare predictions of speeds
  - Loss function should be based on power curve
- Models including direction are robust on data

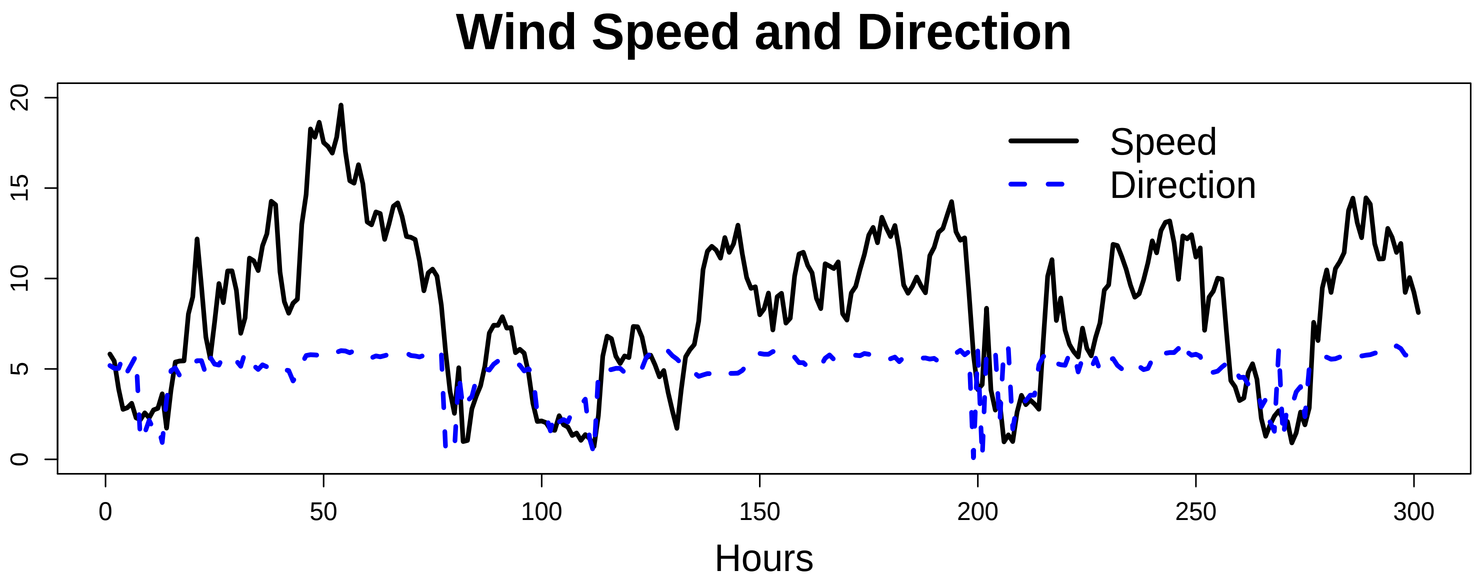
## Importance of Wind Forecasting

- Wind-generated electricity cannot be stored. It enters the grid as soon as it is produced.
- Traditional sources of electricity must supply the balance.
  - May require several hours to come online.
- Demand must meet supply.
- Utilities can impose penalties for electrical shortages or excesses.
- Accurate forecasts will allow wind energy to achieve higher penetrations.

Statistical models are effective in the 0-6 hour forecast horizon, and forecasts have uncertainty intervals which improve their reliability.

# Unique Characteristics of Wind Speed

- Nonnegative and nonnormal
- Temporally and spatially correlated
- Diurnal and seasonal changes
- Changes rapidly and with high frequency
- Highly correlated with wind direction



## Dataset

- Data was collected at 3 sites:
  - Goodnoe Hills, Washington
  - Kennewick, Washington
  - Vansycle, Oregon
- For each hour, the following variables were recorded:
  - Day of the year
  - Hour of the day
  - Wind speed
  - Wind direction
- Two sets of continuously recorded data for all 3 sites:
  - 55 days in 2002, Sep-Oct, Training
  - 269 days in 2003, Feb-Nov, Testing

## Spatial Positions of 3 Sites

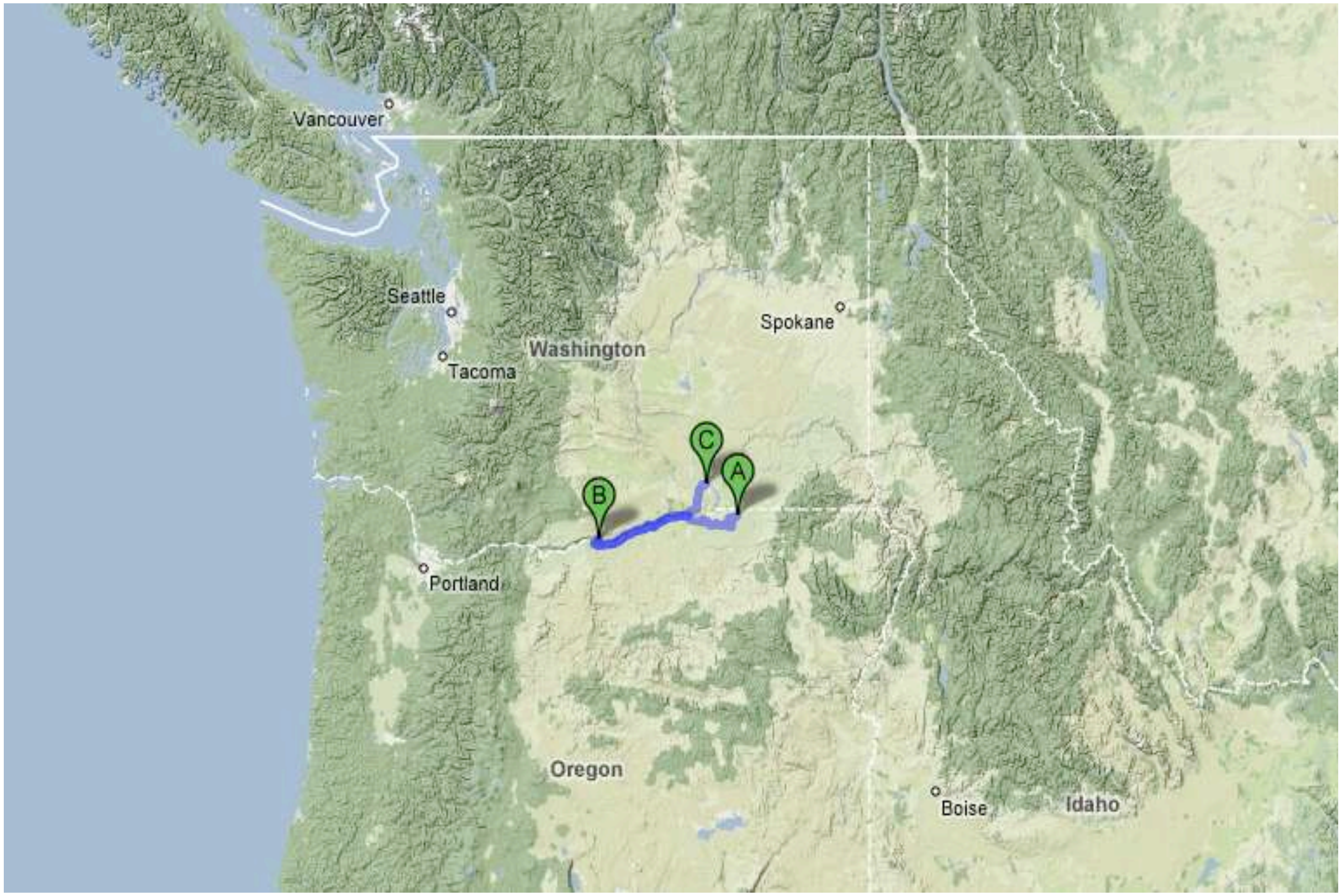



Image from Google Maps

B=Goodnoe Hills, C=Kennewick, and A=Vansycle

## Three Models of Interest

1. RST model: **R**egime-Switching **S**pace-**T**ime Diurnal model
   - Split into 2 regimes based on the wind direction at the westernmost site.
2. TDD model: **T**rigonometric **D**irection **D**iurnal model
   - Incorporates the wind direction directly into the model and eliminates regimes.
3. BST model: **B**ivariate **S**kew-**T** model
   - Transforms speed and direction into Cartesian coordinates.

## The RST Model

- The **R**egime-Switching **S**pace-**T**ime Diurnal model was developed by Gneiting et al. (2006) to predict hourly average wind speed at Vansycle two hours ahead.
- The wind speed at Vansycle is modeled using a truncated normal distribution which has two parameters, $\mu$ and $\sigma$.
- The mean of the truncated normal distribution is the point forecast

$$\mu^{+} = \mu + \sigma \cdot \phi\left(\frac{\mu}{\sigma}\right) / \Phi\left(\frac{\mu}{\sigma}\right).$$

- The parameters $\mu$ and $\sigma$ are regime-dependent.
- In each regime, $\mu$ is a linear combination of present and past wind speeds at the 3 sites.

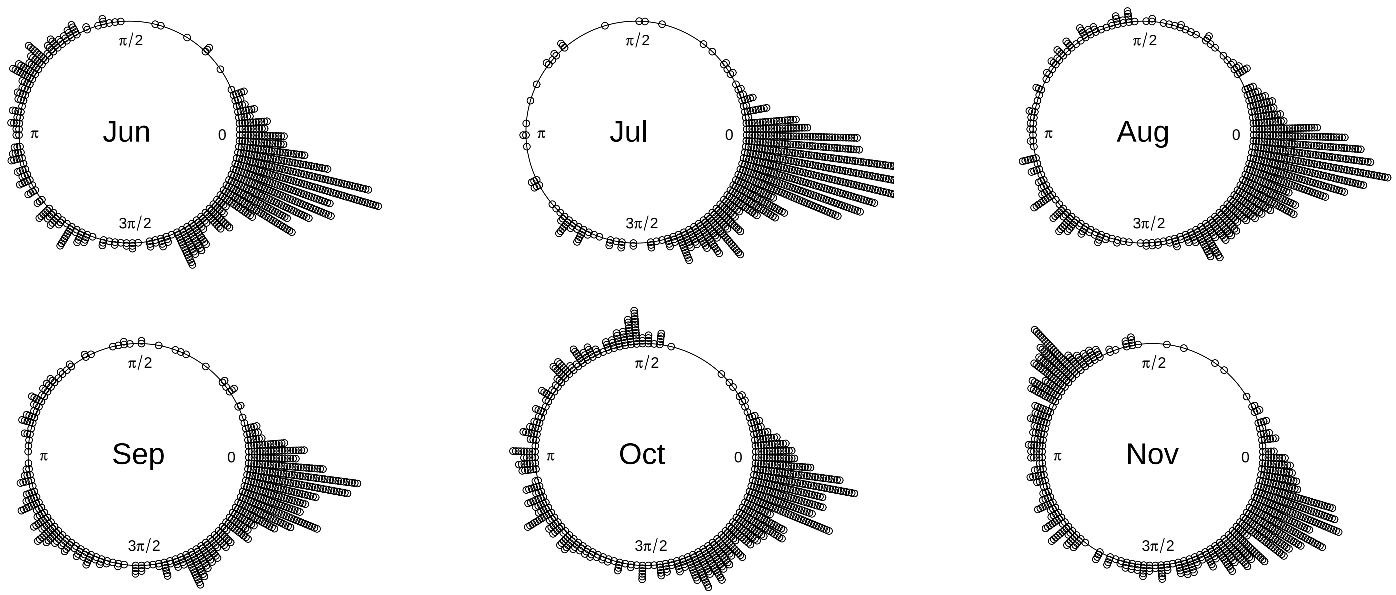
# The RST Regimes

Two regimes are based on the current wind direction at Goodnoe Hills.

**Westerly Regime**: right half of the circle

**Easterly Regime**: left half of the circle

Goodnoe Hills Wind Direction Distributions by Month



## Motivation to Generalize RST

- The RST model addresses many characteristics of the wind speed:
  - Nonnormality and nonnegativity
  - Diurnal variability
  - Spatial and temporal correlation
  - Conditional heteroscedasticity of wind speeds
- However, it is based on a regime structure specific to the topography of this geographic region.
- Defining the regimes is subjective and difficult, making the model difficult to apply elsewhere.

**Goal:** Eliminate the regimes and incorporate wind direction directly into the model.

## The TDD Model Idea

- The **T**rigonometric **D**irection **D**iurnal Model

  Eliminates the RST regimes by including wind direction as a variable.

- Wind direction is a circular variable, meaning the endpoints of its range, $[0^\circ, 360^\circ]$, meet.

- Wind direction must be "linearized" before including it in any regression for linear variables, such as wind speed.

- Wind speed is still modeled with a truncated normal distribution, but the sine and cosine of wind direction at each site can be included in the model for $\mu$.

- Variables are selected with a BIC-selection method.

## Variable Selection for TDD

Correlations with $V_{t+2}$ in 2002 Data

| | Time Lag | | | |
|---|---|---|---|---|
| Variable | t | $t-1$ | $t-2$ | $t-3$ |
| V | 0.90 | 0.85 | 0.80 | 0.75 |
| $\cos(\theta_V)$ | -0.55 | -0.54 | -0.51 | -0.48 |
| $\sin(\theta_V)$ | -0.22 | -0.20 | -0.18 | -0.16 |
| K | 0.74 | 0.72 | 0.69 | 0.66 |
| $\cos(\theta_K)$ | -0.63 | -0.63 | -0.62 | -0.62 |
| $\sin(\theta_K)$ | -0.04 | -0.02 | -0.02 | 0.00 |
| G | 0.60 | 0.60 | 0.58 | 0.56 |
| $\cos(\theta_G)$ | -0.32 | -0.32 | -0.32 | -0.33 |
| $\sin(\theta_G)$ | -0.45 | -0.44 | -0.43 | -0.41 |

## The BST Model

- The **B**ivariate **S**kew-**T** model converts wind speed and direction into Cartesian coordinates using $\mathsf{x} = \mathsf{r}\cos(\theta)$ and $\mathsf{y} = \mathsf{r}\sin(\theta)$.
- An hourly diurnal component is removed from the coordinate at each location and is divided by an overall standard deviation. For example, at Vansycle we have

$$\mathbf{V}_t^r = \left(V_{t,x}^r, V_{t,y}^r\right)' = \left(\frac{V_{t,x} - D_{s,x}}{\hat{\sigma}_x}, \frac{V_{t,y} - D_{s,y}}{\hat{\sigma}_y}\right)'.$$

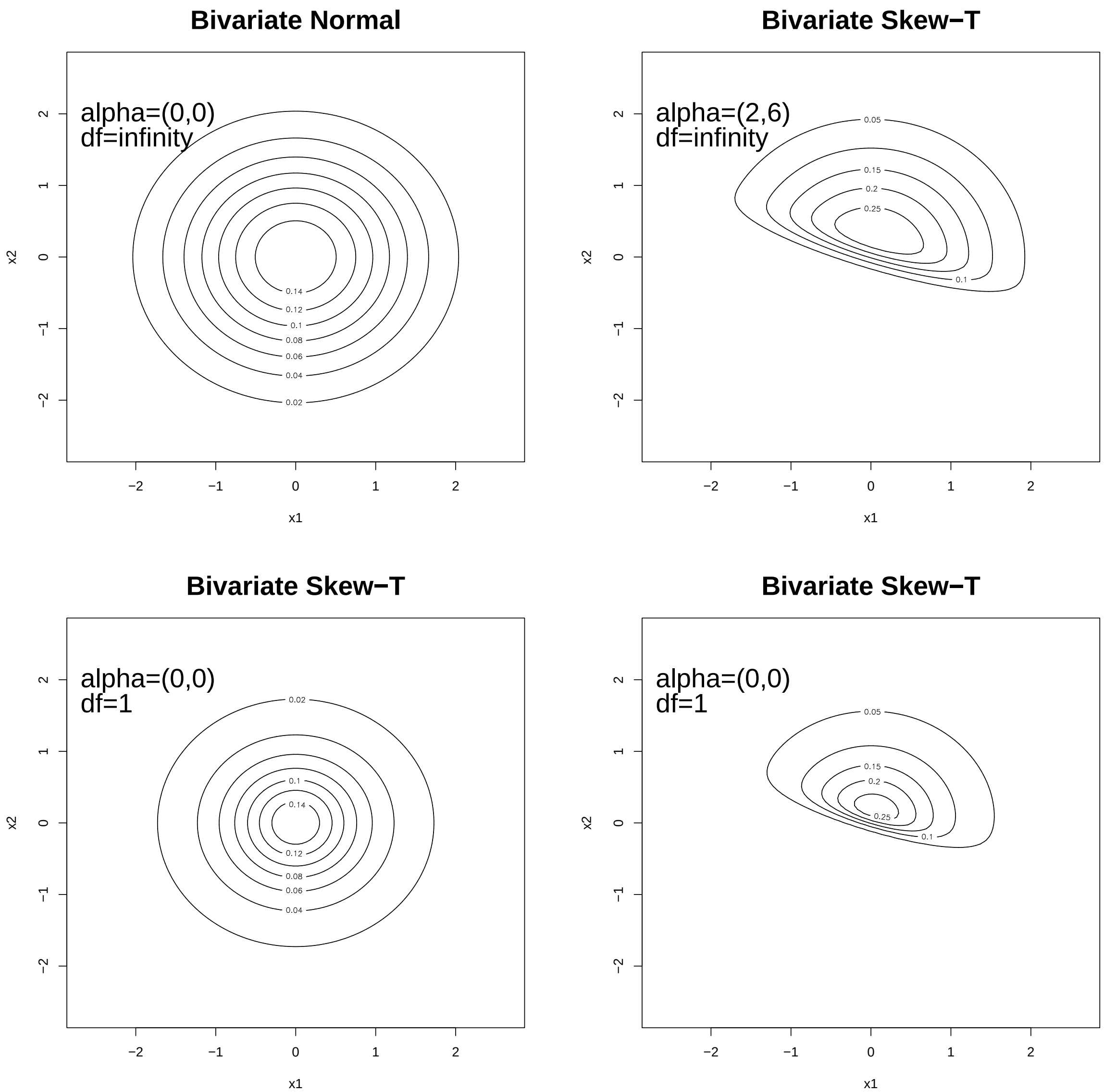
- The residual series at time $t + 2$ at Vansycle is modeled with

$$\mathbf{V}_{t+2}^r = \mathbf{A}_0 + \mathbf{A}_1\mathbf{V}_t^r + \mathbf{A}_2\mathbf{V}_{t-1}^r + \mathbf{A}_3\mathbf{K}_t^r + \mathbf{A}_4\mathbf{K}_{t-1}^r + \mathbf{A}_5\mathbf{G}_t^r + \boldsymbol{\epsilon}_t.$$

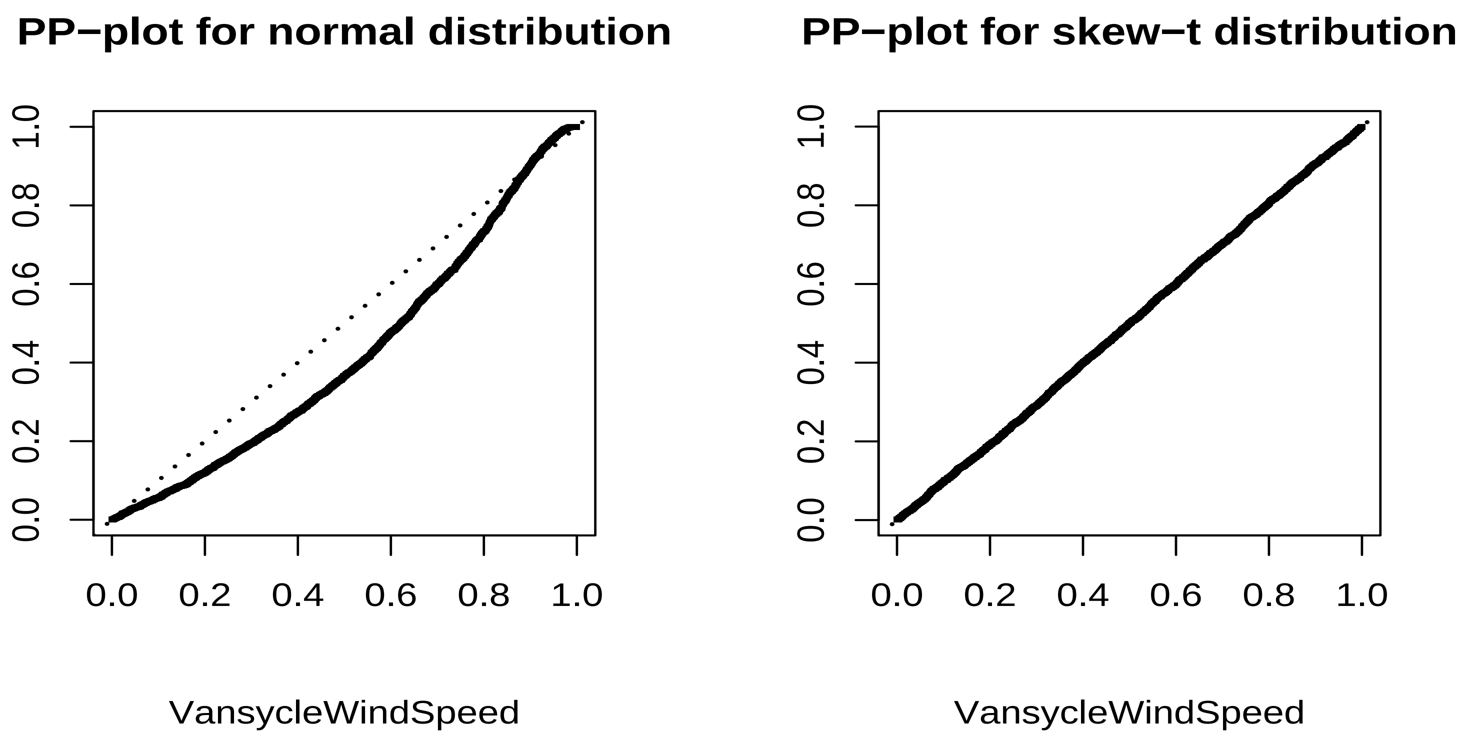
## The Skew-t Distribution

- $\boldsymbol{\epsilon}_{\mathrm{t}}$ follows a bivariate skew-t distribution with skewness parameters $\boldsymbol{\alpha} = (\alpha_1, \alpha_2)'$ and degrees of freedom $\nu$ controlling kurtosis.
  - If $\boldsymbol{\alpha} = (0, 0)'$, then the distribution of $\boldsymbol{\epsilon}_{\mathrm{t}}$ is symmetric.
  - If $\nu = \infty$, then the distribution of $\boldsymbol{\epsilon}_{\mathrm{t}}$ has the same tail behavior as a normal distribution.
  - If both $\boldsymbol{\alpha} = (0, 0)'$ and $\nu = \infty$, then the distribution of $\boldsymbol{\epsilon}_{\mathrm{t}}$ is bivariate standard normal.

# Examples


Bivariate Normal
alpha=(0,0)
df=infinity
Bivariate Skew−T
alpha=(2,6)
df=infinity
Bivariate Skew−T
alpha=(0,0)
df=1
Bivariate Skew−T
alpha=(0,0)
df=1
x1
x2

## The Skew-t Error Choice



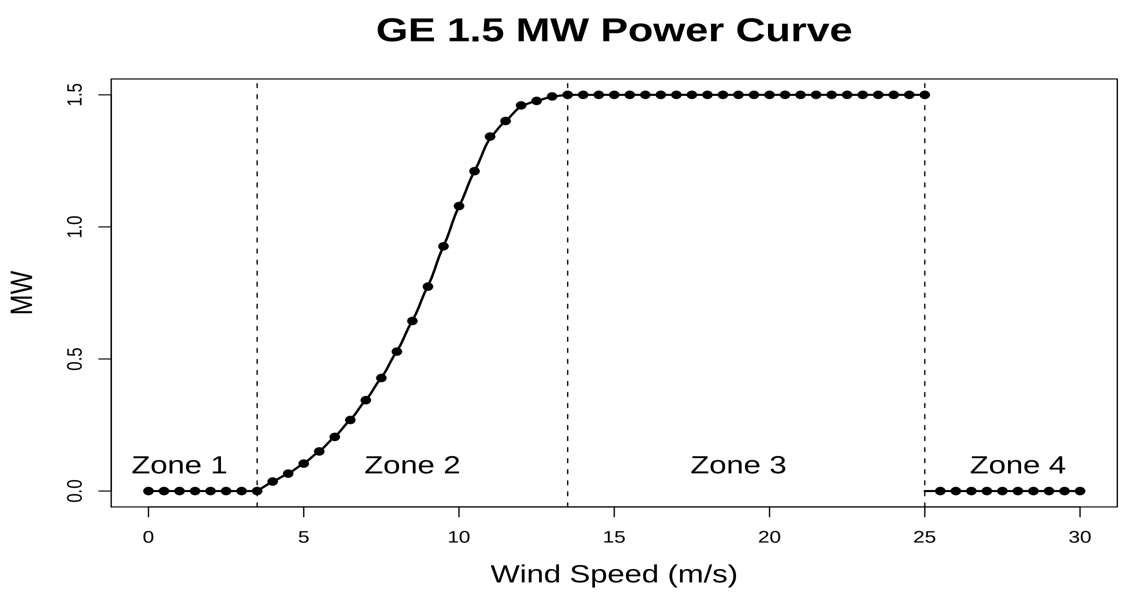

The BST model predictions are made with the following formula:

$$\hat{\mathbf{V}}_{t+2} = \left(\hat{\mathbf{A}}_0 + \hat{\mathbf{A}}_1 \mathbf{V}_t^r + \hat{\mathbf{A}}_2 \mathbf{V}_{t-1}^r + \hat{\mathbf{A}}_3 \mathbf{K}_t^r + \hat{\mathbf{A}}_4 \mathbf{K}_{t-1}^r + \hat{\mathbf{A}}_5 \mathbf{G}_t^r + \hat{\epsilon}_t\right) \cdot \hat{\boldsymbol{\sigma}} + \mathbf{D}_{s+2}$$

and then take the norm of $\hat{\mathbf{V}}_{t+2}$.

## Comparing the Speed Predictions

- Predictions are commonly compared with Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).
- However, are these the most appropriate comparisons since the wind power is the main interest, not the wind speeds?
- We should use the relationship between wind speed and wind power.



## Power Curve Error Measure

- The true power output is proprietary.
- True wind speeds $\rightarrow$ "true" power output

  Predicted wind speeds $\rightarrow$ "predicted" power output
- To transform speeds to power in Zone 2, a nonparametric regression method is used.
- The true power and predicted power are compared and summarized with the Power Curve Error, or

$$\mathrm{PCE} = \frac{1}{n}\sum_{i=1}^{n} |P_{i,t+2} - P^{mod}_{i,t+2}|.$$

## Model Comparison Summary

| | Mod | May | Jun | Jul | Aug | Sep | Oct | Nov | All |
|---|---|---|---|---|---|---|---|---|---|
| RMSE | PER | 2.14 | 1.97 | 2.37 | 2.27 | 2.17 | 2.38 | 2.11 | 2.21 |
| | RST | **1.73** | 1.56 | 1.69 | 1.78 | 1.77 | 2.07 | 1.87 | 1.79 |
| | TDD | 1.74 | **1.55** | **1.65** | **1.77** | **1.73** | **2.02** | **1.85** | **1.77** |
| | BST | 1.79 | 1.64 | **1.65** | 1.86 | 1.88 | 2.13 | 2.03 | 1.86 |
| MAE | PER | 1.60 | 1.45 | 1.74 | 1.68 | 1.59 | 1.68 | 1.51 | 1.61 |
| | RST | **1.31** | 1.19 | 1.32 | **1.31** | 1.36 | 1.48 | 1.38 | 1.34 |
| | TDD | 1.34 | **1.18** | **1.28** | **1.31** | **1.32** | **1.47** | **1.37** | **1.33** |
| | BST | 1.34 | 1.23 | 1.29 | 1.38 | 1.42 | 1.50 | 1.52 | 1.38 |
| PCE | PER | 197.8 | 145.6 | 228.6 | 189.7 | 151.8 | 184.1 | 118.8 | 174.3 |
| | RST | 154.6 | **114.6** | 167.0 | 138.6 | 126.5 | 163.3 | 110.4 | 140.0 |
| | TDD | 156.9 | **114.6** | 162.7 | **135.8** | **124.5** | 161.1 | **105.2** | **137.6** |
| | BST | **154.4** | 119.2 | **160.6** | 136.4 | 129.6 | **160.3** | 113.3 | 139.4 |

Note: Fitting a bivariate skew-$t$ distribution to the data performs similarly to any robust fitting technique—it downweights extremes and estimates parameters that fit well for the majority of the data.

# Conclusions

**Models:**

- RST model is limited to few locations and known physics.
- TDD & BST can be applied to a wide variety of locations and topographical conditions.
- Incorporating wind direction improves predictions.

**Loss Function:**

- PCE gives a more realistic assesement of wind speed forecasts.
- Greater penalties on wind speeds are assessed in the region where power is proportional to the cube of speed.
- Can be modified for other turbines and for wind farms.

## Continuing Work

- Improve BST forecasts with uncertainty intervals.
- Improve uncertainty intervals for all models to include parameter estimation uncertainty.
- Simulate speed and direction data over space and time using bivariate skew-$t$ approach for utility system experiments.
  - Reproduces the heavy tails of the wind vector, making long runs of realistic data.

## Some References

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