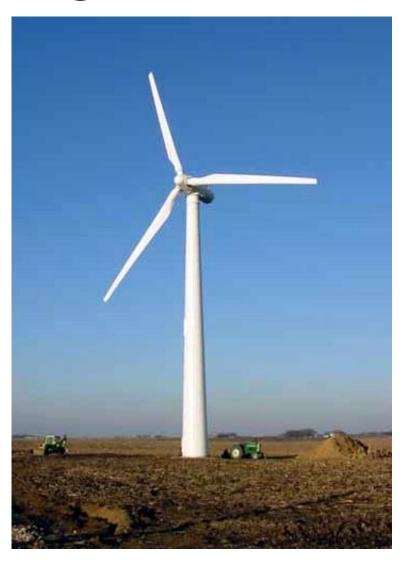
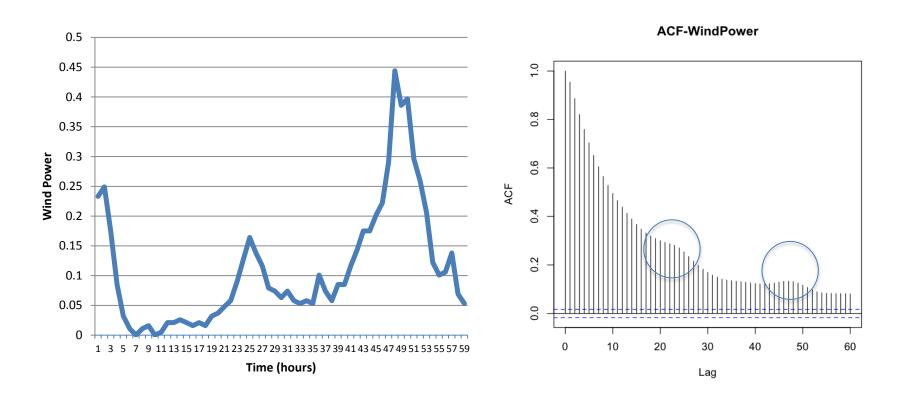
# Wind Power Forecasting Problem

- Kaggle project sponsored by IEEE Power & Energy Society
- Given: Model identification period
- Need to forecast 48 hours ahead based on last 36 hours wind power
- Challenges:
  - Chaotic nature of atmosphere & incomplete understanding
  - Accuracy decreases when we forecast a period far ahead in the future
  - Sudden jumps in data series



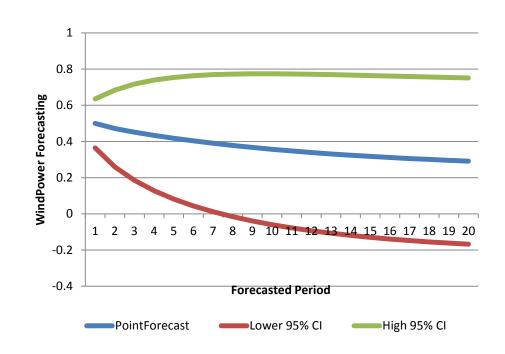
### Data Series And Autocorrelation



- Unpredictability of weather
- Strong correlation at lag 1, lag 24, and lag 48

## **ARIMA**

- Can't use plain off the shelf ARIMA model to forecast 48 periods ahead
  - Wide confidence interval
  - Negative values!
- Need to take advantage of inherent structure in the system



$$y_t = \frac{\phi_0 + \phi_1 y_{t-1} + \dots \phi_p y_{t-p}}{\theta_0 a_t + \theta_1 a_{t-1} + \dots \theta_q a_{t-q}}$$

# **ARIMA Model**

#### Use

- High correlation at lag 1 and lag 24
- Last known good value

$$y_{t} = \phi_{0} + \phi_{1}y_{t-1} + \phi_{2}y_{t-24}$$

$$y_{t+l} = \phi_{0} + \phi_{1}y_{t-1} + \phi_{2}y_{t+l-24} \qquad 1 \le l \le 23$$

$$y_{t+l} = \phi_{0} + \phi_{1}\hat{y}_{t-24} + \phi_{2}y_{t+l-48} \qquad 24 \le l \le 47$$

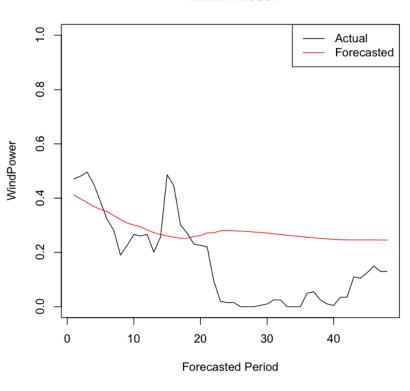
#### Regularization

$$\hat{\phi} = \underset{\phi}{\operatorname{arg\,min}} ||y_t - \phi^T y_{t-l}||^2$$

$$0 \le \phi_1 \le C$$

$$0 \le \phi_2 \le C$$

#### **ARIMA Model**



RMSE = 0.2609

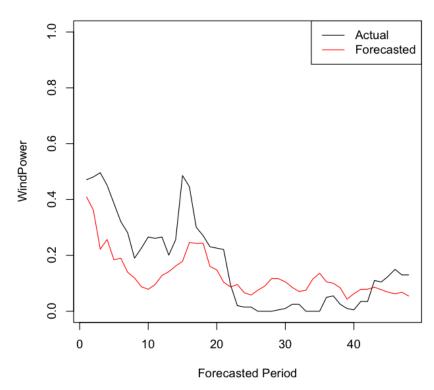
# Locally Weighted Regression

- Divide the model identification data in chunk of 36+48 periods
- Use the similarity of first 36 period to forecast the next 48 period

$$w^{(i)} = \exp\left(-\frac{(x^{(i)} - x)^2}{2\tau^2}\right)$$

- Cross-Validation
  - Use cross-validation to find the value of bandwidth parameter

#### **Locally Weighted Regression Model**



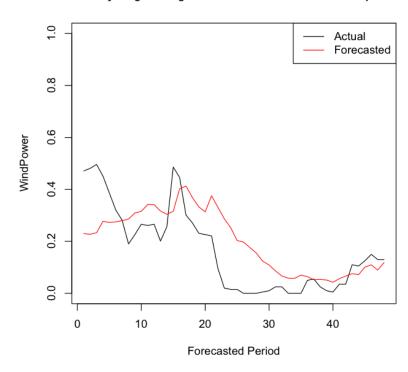
$$RMSE = 0.3343$$

# Locally Weighted Regression With Forecasted Wind Speed

- Instead of relying only on univariate wind power, use
  - Forecasted wind speed
  - Forecasted direction
  - Forecasted zonal component
  - Forecasted meridional component
- Using cross-validation test set:
  - Only forecasted wind speed was had a significant impact

$$w^{(i)} = \exp\left(-\frac{(x^{(i)} - x)^2}{2\tau^2}\right)$$

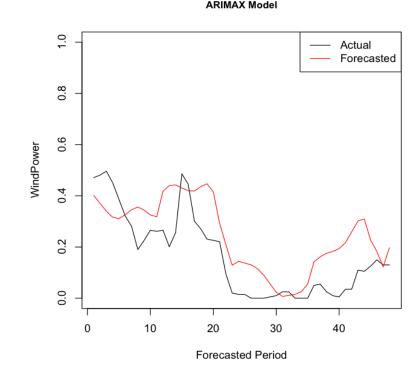
Locally Weighted Regression Model with forecasted wind speed



RMSE = 0.2050

## ARIMAX Model with Forecasted Wind Speed

- High correlation between wind power and wind speed
- Wind direction, zonal, meridional components were not found to have significant correlation
- Include as part of linear regression model



$$RMSE = 0.19$$

$$y_{t} = \phi_{0} + \phi_{1}y_{t-1} + \phi_{2}y_{t-24} + \phi_{3}w_{t}$$

$$y_{t+l} = \phi_{0} + \phi_{1}y_{t-1} + \phi_{2}y_{t+l-24} + \phi_{3}w_{t+l} \qquad 1 \le l \le 23$$

$$y_{t+l} = \phi_{0} + \phi_{1}\hat{y}_{t-24} + \phi_{2}y_{t+l-48} + \phi_{3}w_{t+l} \qquad 24 \le l \le 47$$

# Summary

- Best indicators for forecasting wind power in a given hour:
  - Predicted wind power generated over the past hour
  - Wind power generated over the same hour one day ago
  - Most recent wind speed forecast for the current hour
  - Forecasts for wind direction, zonal and meridional wind components were not significant

- Performance of ARIMAX model is comparable to Kaggle's best entries
- ARIMAX model is more interpretable

# Results

Model	RMSE
Best Kaggle Entry	0.15
ARIMAX Model with Wind Speed	0.19
Locally Weighted Regression with Wind Speed	0.21
ARIMA Model	0.26
Locally Weighted Regression	0.33
Benchmark	0.35