

# Project 68: Wind Speed

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### Background

- Power generated by wind is projected to increase from the current global total of 1.81% in 2018 to 21.13% by 2050 (Rogelj et al., 2018, p.132)
- Short-term wind speeds forecasts (up to 24 hours ahead) are necessary for efficient grid operations and grid maintanance of wind power plants
- Mathematical models are used for forecasting

#### **Physical models**

- Use partial differential equations to forecast
- Usually deterministic (no measure of forecast uncertainity)
  - Fall under the framework of Numerical Weather Prediction (NWP)

Forecasting models

#### Statistical models

- Use probability theory and regression
- Stochastic (give a measure of forecast uncertainity)

#### Data

- Wind speeds measured hourly at an unknown location in the United Kingdom over a two-year period between the 1st of January 2011 and the 31st of December 2013
- The rest of the data is produced for the same time period and location by MERRA (Modern-Era Retrospective Analysis for Research and Applications) done by NASA

#### MERRA variables:

- wind speed
- zonal wind speed
- meridional wind speed
- relative humidity
- pressure
- Temperature
- wind direction

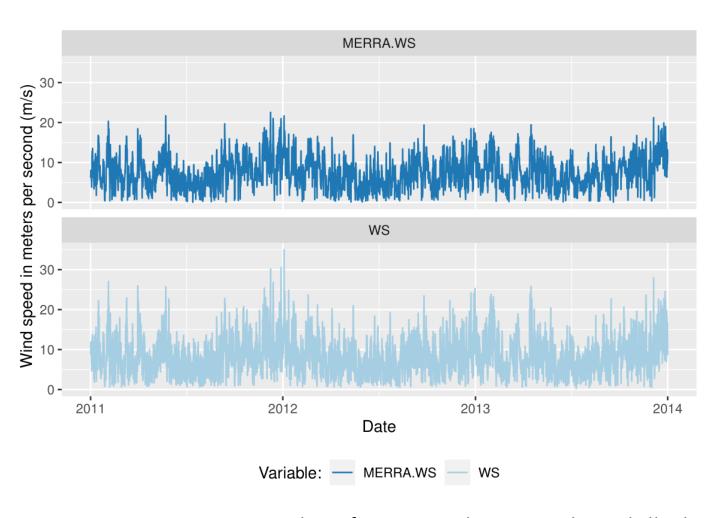


Figure 1: Time series plot of measured (WS) and modelled (MERRA.WS) wind speeds at the location in the UK

#### **Aims**

- Evaluate the cyclical and seasonal patterns, linear trend, as well as identify any extreme values in measured and modelled wind speeds
- 2. Evaluate the performance of the MERRA model at predicting wind speeds for the particular location withing the UK
- 3. Build a probabilistic model that will predict hourly wind speeds in a 24 hour ahead forecast

# Methodology

### Regression model

To evaluate the yearly seasonality and the daily cyclic patters, as well as the linear trend, the following regression model is fitted to the time series data x(t):

$$x(t) = \alpha + \beta t + \sum_{j=1}^{J} (a_{j}cos(\omega_{j}t) + b_{j}sin(\omega_{j}t) + \epsilon(t) \quad (3.3.3)$$

 $\alpha$  is the intercept.

 $\beta$  is the slope.

 $a_j$  and  $b_j$  are the coefficients for the Fourier terms with frequencies  $\omega_j$ .

 $\epsilon(t)$  is the error term.

Assumptions for the model in (3.3.3):

The errors  $\epsilon(t)$  are normally distributed  $\epsilon(t) \sim N(0, \sigma^2)$ , have constant variance and are independent.

### Periodogram

To decide on the frequency of the seasonal and any remaining cyclic patterns, a periodogram is analysed. For that purpose the following function is plotted against a range of different frequencies  $\omega_i$ :

$$I(\omega_j) = \frac{1}{\pi N} [[\sum_{t=1}^n x(t) cos(\omega_j t)]^2 + [\sum_{t=1}^n x(t) sin(\omega_j t)]^2] \quad (3.3.9)$$

where  $\omega_{j} = \frac{2\pi j}{N}$  for j = 1, 2, ..., N/2.

## Results

### Frequencies

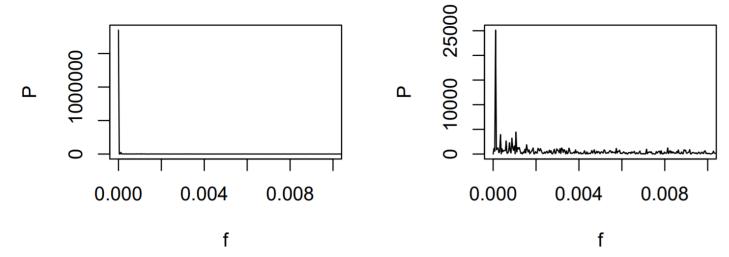


Figure 2: Periodograms (from (3.3.9)) of the WS data (on the left) and detrended WS data (on the right)

From the periodograms, it can be identified that the suitable periods for the Fourier terms are: 8767 hours (yearly seasonality), 939 hours and 2922 hours. An additional 24 hour term is added to account for the daily cyclicity.

### Fitted model

The following harmonic regression model from (3.3.3) is fitted to the data with frequencies identified by the periodogram function:

$$x_{\lambda=0.44}(t) = 1.381 + 1.455 * 10^{-9} \ t - 0.036 \ sin(\frac{2\pi t}{24}) - 0.061 \ sin(\frac{2\pi t}{939}) - 0.229 \ cos(\frac{2\pi t}{939}) + 0.054 \ sin(\frac{2\pi t}{2922}) + 0.225 \ cos(\frac{2\pi t}{2922}) - 0.102 \ sin(\frac{2\pi t}{8767}) + 0.588 \ cos(\frac{2\pi t}{8767}) + 0.588 \ cos(\frac{2\pi t}{8767}) + 0.061 \ sin(\frac{2\pi t}{939}) + 0.061$$

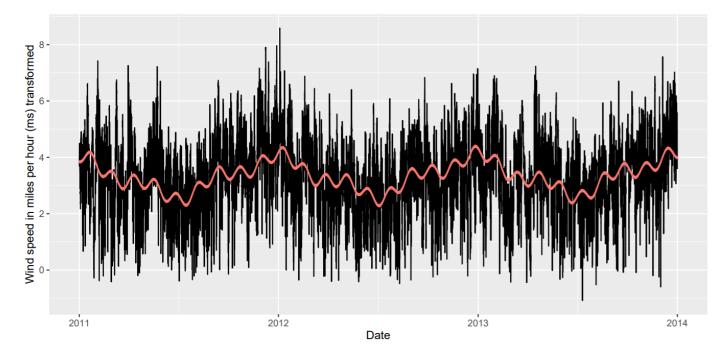


Figure 3: Fitted values from the harmonic regression model in (4.1.1) plotted in red

#### Residual series/error terms

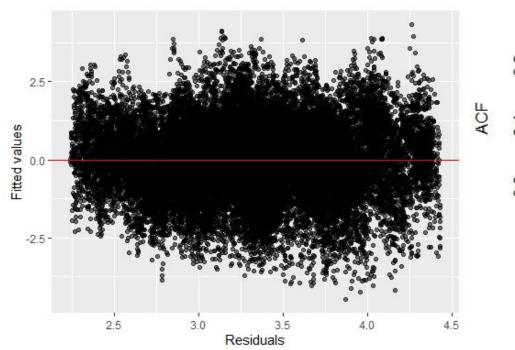


Figure 4: Residual series from the regression model in (4.1.1)

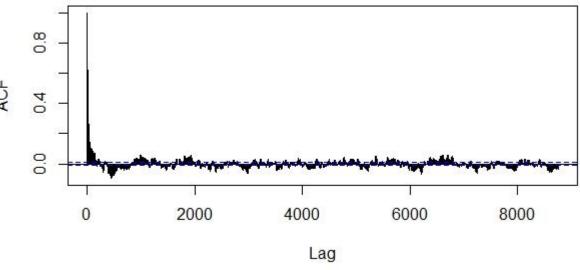


Figure 5: Autocorrelation function for the residual series from the regression model in (4.1.1)

#### **Discussion**

#### Regression:

Remove extreme values before fitting the regression

#### Errors:

- Fit a vector fractional ARIMA model to model the longterm dependance in the error terms
- Aggregate the data to a lower temporal resolution (for example, daily) and forecast daily wind speeds instead

## The End

Thank you for listening.