

**1. Intraday on-shore wind power generation measured every hour for one year is available from the csv file WindGeneration.csv. Load the data into your computer and produce a graphic showing the time series of the wind generation over time. Is there evidence of annual seasonality?**

Graphs depict annual seasonality, illustrating a steady fall from January to May. May to September, rising from Sept to December. Wind power generation reduces at the beginning of the year January 2014. Plummeting from May to September rising steadily to December.

**2. Plot the change in wind generation over time as a percentage of the maximum generation. Is there evidence of annual seasonality?**

Percentage change of Wind Generation time series does reflect evidence of seasonality, the picks are independent, where June to July was the highest. Lowest being January to February.

**3. Consider positive and negative ramps in wind power generation,  $x(t)$ , as a percentage of the maximum, over the hourly timescale. An hourly ramp is therefore defined as  $r(t,d) = 100 * [x(t+d) - x(t)] / \max(x)$  where  $d=1$  for an hourly sampling period. Construct empirical cumulative distribution functions (CDF) for both the positive and negative ramps and plot these with the probability on a vertical logarithmic axis. Plot the CDF for a normal distribution with mean-zero and standard deviation from the observations. Is the normal distribution a good model for wind power extremes?**

Normal distribution on positive ramps and negative ramps is a good model for power extremes, since they are statistically displayed effectively.

**4. National power system operators are tasked with the challenge of balancing supply and demand. They need to understand the variability in wind generation over different timescales. Investigate variability over timescales from one hour to one day by plotting the 1%, 5%, 95% and 99% percentiles. This can be achieved using distributions of the ramps  $r(t,d)$  with  $d = 1, 2, \dots, 24$ .**

The spread or variability of wind generation around the mean differed over timescale in 24 hours, the 1 percentile was in negative 0 to -20, 5 percentile stayed at 0. 95 percentile increased 0-40, and lastly 99 percentile reached 60.

**5. Calculate and plot the autocorrelation of wind generation for lags over 10 days. Comment on the structure of the autocorrelation.**

The wind generation autocorrelation for 10 days displayed a shift from 1 to slightly below 0.25, which was maintained for that period. It reveals the feature's autocorrelation.

**6. Calculate and plot the autocorrelation of change in wind generation for lags over 10 days. Include horizontal lines to detect statistically significance values ( $p < 0.05$ ). Is there**

**any evidence of diurnal seasonality? Might it be more appropriate to model the change in wind generation than the wind generation?**

There is evidence of diurnal seasonality for 10 days with change in wind generation, yet wind generation data from Q5 models better than change in wind generation.

**7. Use a variance ratio test to investigate the structure of the wind generation time series. Can the null hypothesis of a random walk be rejected? Is there evidence of either mean-reversion or mean-aversion?**

ADF P-value  $3.322198217670297 \times 10^{-16}$ , we reject the hypothesis given our ADF result  $-9.507227276824727$  more negative than critical values 1%  $-3.4310990236088363$

**8. Estimate the optimal window for simple moving average. Is there a simple benchmark that improves on the persistence benchmark?**

The optimal window of simple moving mean equals 0.0

**9. Evaluate the mean-Absolute-error (MAE) performance of the persistence benchmark forecast over forecast horizons from one hour to one day. Plot MAE as a percentage of the maximum generation for the persistence benchmark.**

Mean absolute error from one hour to one day persists with time, for the 24 hours.  
With minimum of mean absolute error of 6662.908675799086

**10. Loop over the number of parameters to use in an ARIMA model for describing wind generation and use information criteria (AIC and BIC) to find the optimal ARIMA model.**

The optimal BIC 98828.30335976055 and AIC 98776.47210723053