Stochastic wind speed modelling including daily wind patterns based on real data

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1. Introduction – Motivation

- UK has ambitious **renewable** energy **targets** (2020) → **increased wind penetration** → system operation and balancing problems → need for more detailed wind modelling [1]
- **Wind speed has stochastic behaviour** → **driven by natural sources** [1,2]
  - ⋄ **Cyclicality** over period of 24 hours (**diurnal cycle**) and longer
  - ⋄ **Noisy short-term** stochastic variations (not analytically tractable)
- **How to model this?** → Stochastic Differential Equations (SDEs) → Existing approaches [2-4]
  - ⋄ Do not account for **daily cycles**
  - ⋄ Lack of **empirical fitting** and validation of the model's parameters
  - ⋄ **Weibull** distribution cannot capture **daily cycles and temporal correlation**

2. The SDE model

Wind speed modelled with Ornstein-Uhlenbeck Geometric Brownian Motion in continuous time [2]

$$lnX(t) = Y(t) + f(t) \tag{1}$$
$$dY(t) = -\kappa\, Y(t)\, dt + \sigma\, dW \tag{2}$$

- $f(t)$ the **deterministic diurnal** cycle based on log-wind speed data
- $Y(t)$ the **mean-reverting stochastic** component of Ornstein-Uhlenbeck type
- κ, σ, dW the **mean reversion** parameter, **volatility** and **Wiener process**

- Probability Density Function (PDF) of wind speed → **log-normal PDF**
- PDF of wind power **not Gaussian** → wind power **cannot** be modelled with an **O-U GBM model**
- **Annual cycle** neglected → short term decisions needed in power system operation and balancing

3. Parametric estimation

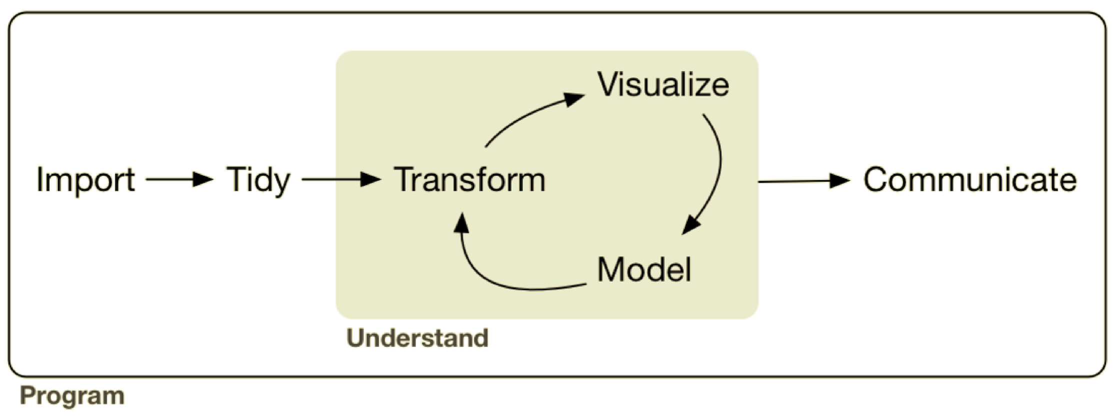

Figure 1: General steps of analysing the wind speed dataset [5]

Import – Tidy

Import data into a data frame → Real data used – collected from Spanish wind farm [6]
- ⋄ 10-minute resolution
- ⋄ summer season (June-July-August) of years 2010-2016 selected to compute **average summer daily cycle**
- ⋄ specific month of June 2016 selected for fitting the **stochastic component**

Tidy the dataset → Columns: variables (date, wind speed, wind power) – Rows: observations [5]
- ⋄ Fix date to specific format **year-month-date**
- ⋄ Change wind speed observations **from factor type to numeric**
- ⋄ No **missing values** observed – remove **outliers** (4 very high unusual wind speed values)

Transform – Visualise

Initial wind speed time series – PDF (Figs 2-3) – **summary statistics** (Table 1)

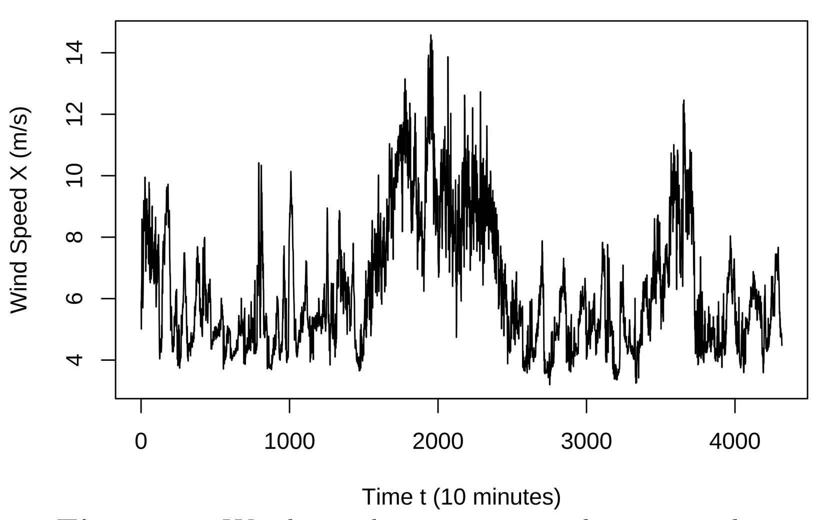

Figure 2: Wind speed time series with time resolution of 10 minutes for June 2016 [6]

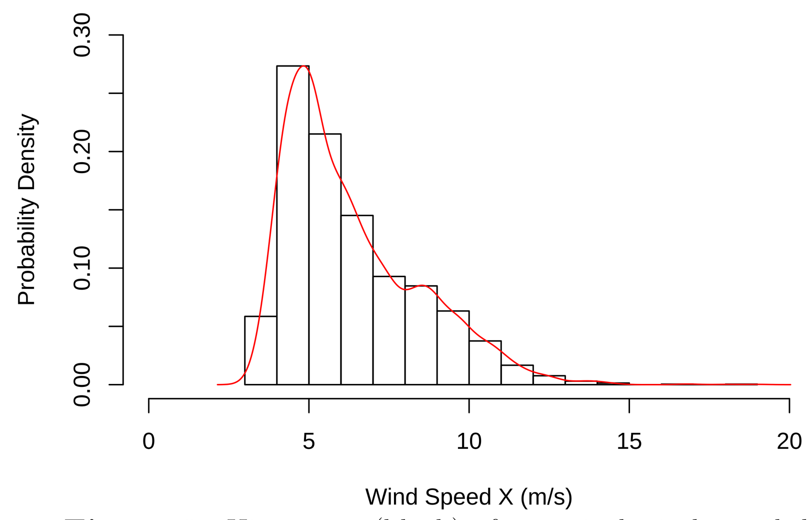

Figure 3: Histogram (black) of empirical wind speed data and kernel PDF (red) of wind speed for June 2016 [6]

Table 1: Main statistical characteristics of the wind speed time series for June 2016 (max, min, mean and sd in m/s)

Time	X-min	X-max	X-mean	X-sd
10-min	3.2	18.98	6.34	2.1

Computed daily averages → existing daily pattern with higher wind speeds during the evening (Fig. 4)
Average summer daily cycle → ensure adequate accuracy (fitted with Fourier series, Fig. 5)

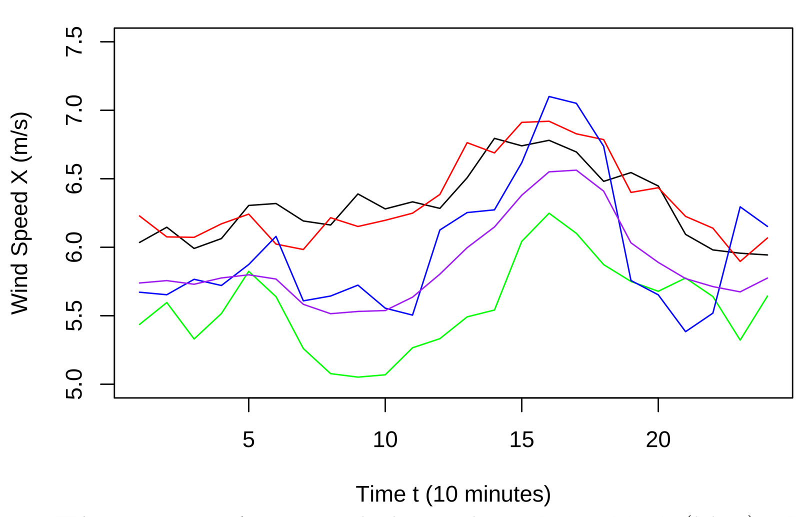

Figure 4: Average daily cycles: June 2014 (blue), June 2015 (green), June 2016 (red), June 2017 (black), average daily cycle for the whole summer season (purple) [6]

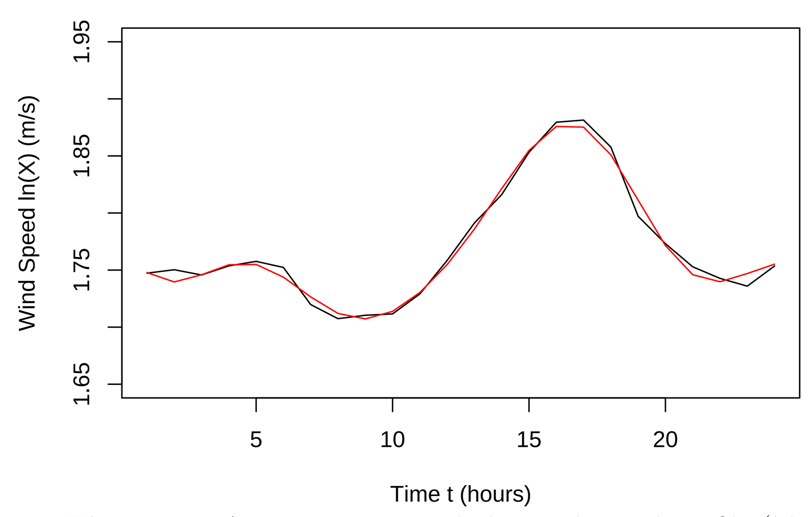

Figure 5: Average summer daily wind speed profile (black) and fitted daily cycle (red) with a Fourier series model (with frequencies of w, $2w$ and $3w$) for log-wind speed [6]

Empirical Validation of SDE Model

- ⋄ Calculate **logarithms** of initial wind speed time series
- ⋄ Remove the average summer daily cycle presented in Fig. 5 [1,3-5]
- ⋄ Estimate κ and σ with maximum likelihood estimators [3,5] (Table 2)
- ⋄ **Residual analysis** → residuals resemble white noise [1,3] (Figs 6-7)

Table 2: Parameter values for the stochastic component of the wind speed model

Parameter	Values	Standard error
$\hat{\kappa}$	0.0368	0.0041
$\hat{\sigma}$	0.0819	0.00088

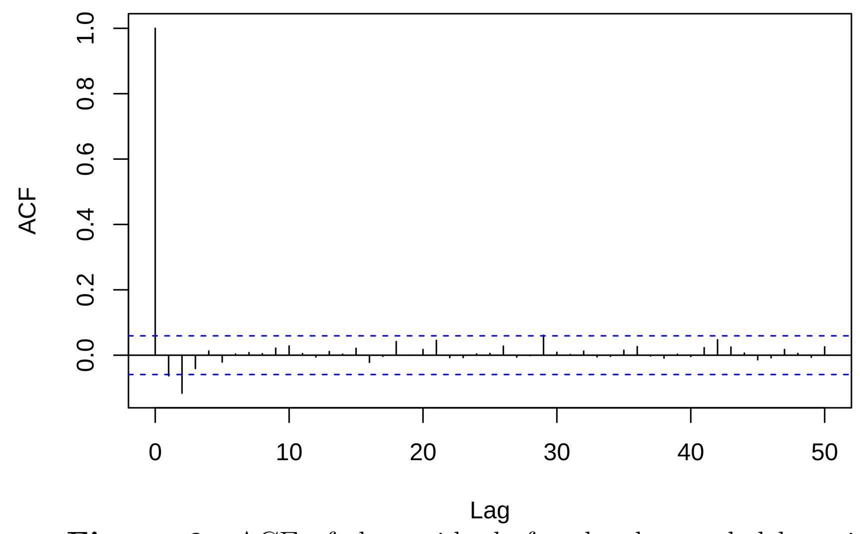

Figure 6: ACF of the residuals for the de-trended log-wind speed data for the Spanish wind farm (95% confidence interval)

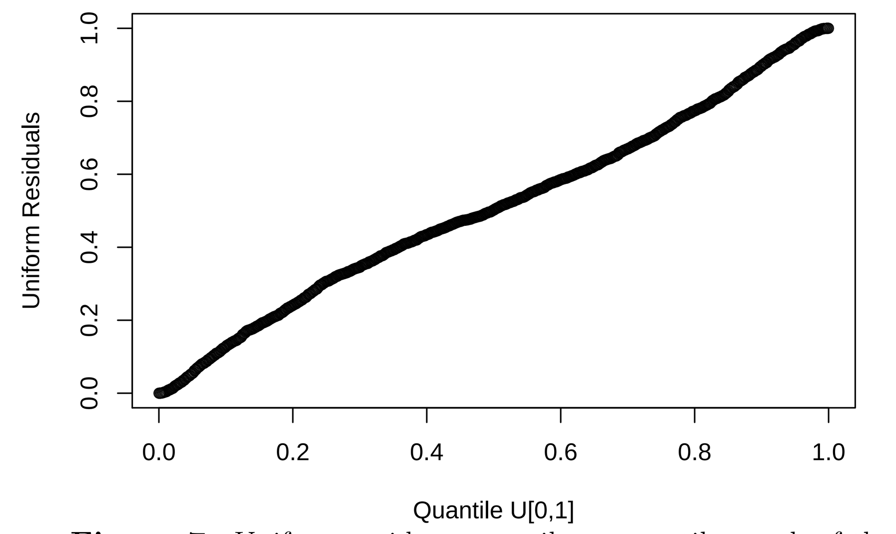

Figure 7: Uniform residues quantile – quantile graph of the de-trended log-wind speed data

4. Communicate Results

- ⋄ SDE of Eqs (1)-(2) solved numerically with **Milstein scheme**
- ⋄ **Parameters used:** $\kappa = 0.0368$, $\sigma = 0.0819$, $n = 4320$, $\delta t = 0.167$, fitted average summer daily cycle, $f(t)$, first observation of the initial wind speed time series used as starting point, random variable drawn from the $N(0,1)$ distribution multiplied by $\sqrt{\delta t}$

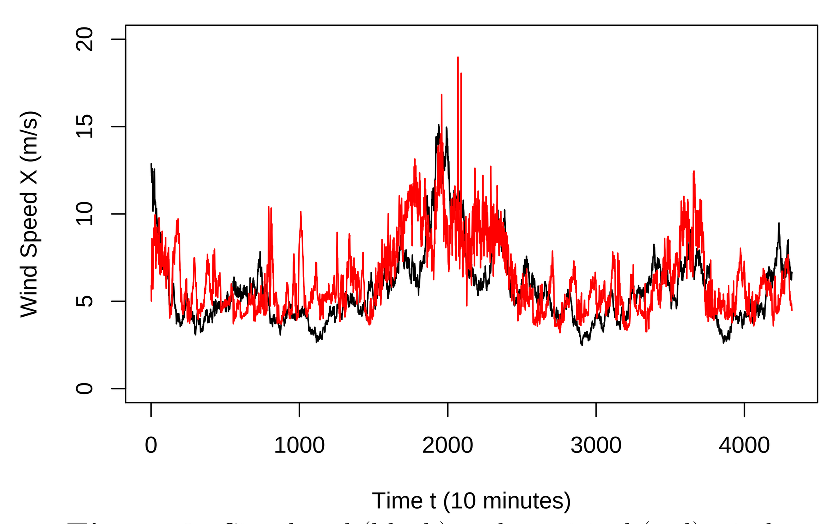

Figure 8: Simulated (black) and empirical (red) wind speed time series for the 10-minute data for June 2016

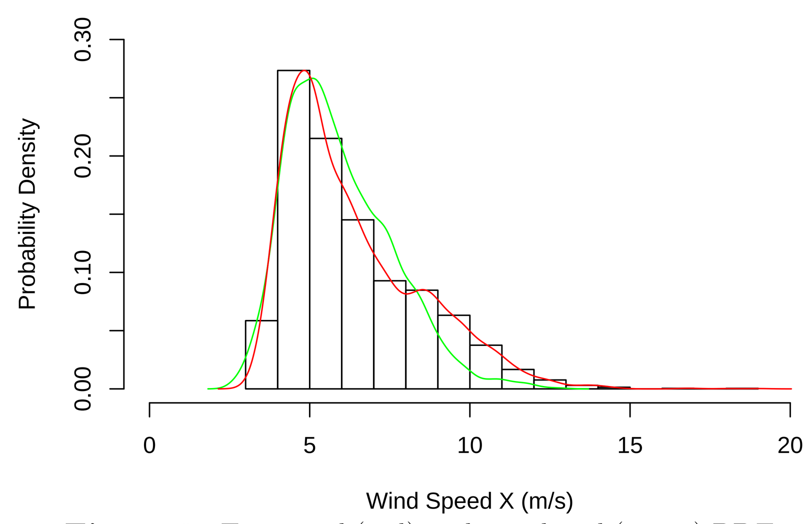

Figure 9: Empirical (red) and simulated (green) PDFs with histogram (black) for the 10-minute data for June 2016

1. **Simulated wind speed** follows empirical time series closely – they **change similarly over time** and remain **within the same limits** as also shown from histogram and PDFs (Figs 8-9)
2. **Correlation** between empirical and simulated wind speed: 0.61, **Root Mean Square Error** between PDFs: 0.073
3. **Mean-reverting nature of the model** → simulated wind speed starts at higher value than the long-term mean but it reverts back to the mean daily cycle

5. Conclusion

- ⋄ Proposed model **fitted and validated with real data**
- ⋄ Proposed model **adequately represents wind speed variations** in continuous time
- ⋄ Proposed model easily **adjusted to other time resolution** from that of the given data
- ⋄ Proposed model can be used for various applications – **optimal energy storage or system balancing**

Future work:
- ⋄ **Different data sets** → different daily cycles and examine their impact on the stochastic wind model
- ⋄ **Wind power curve** → compute and analyse wind power output

6. References

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