ERA 5 calibration to Elexon power

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Calibration to power

Updates

New

- Spatial correlation check
- Updated linear models
- Power curve modelling

Next steps

- Combine PC model with calibration
- Benchmark models: Quantile mapping, GAMs
- Calibration spatiotemporal model

Overview

Data sources

Wind speed

- ERA5 at wind farms
  - Hourly data
  - Spatial resolution 0.25° x 0.25°
  - 10m and 100m heights

Wind power

- Elexon BMU data (since 2019)
  - Half hourly data
  - Generation, curtailment, potential, capacity
  - Outage data (REMIT)
- REPD database
  - Location, turbine height, capacity

Overview

1. ERA 5 to wind farm

Vertical interpolation to turbine height h.

$$w(h) = w_{100} \left(\frac{h}{100} \right)^{\alpha}, \text{ where } \alpha = 1/7$$

2. Wind speed to power

Generic power curves rescaled to wind farm capacity.

$$\hat{PC}_i(w) = PC_i(w) \times \frac{C_i}{\text{Rated power}},$$

where C_i is the capacity at location i

Overview of power conversion

3. Potential generation

Curtailment and outages are two main events that impact observed generation o_{it}

- Curtailment is added giving rise to potential generation:

$$p_{it} = o_{it} + \mathsf{curt}_{it}$$

- Outage data shows additional limits on capacity
- Currently outage periods are excluded

Calibration

4. Calibration

ERA5-derived power estimate $\widehat{p}_{it}$ is compared versus potential power p_{it}

$$\widehat{p}_{it} = \widehat{PC}_i(w_{it})$$
$$p_{it} = \beta_0 + \beta\widehat{p}_{it} + s_i + u_t,$$

where s_i and u_t represent spatial and temporal effects.

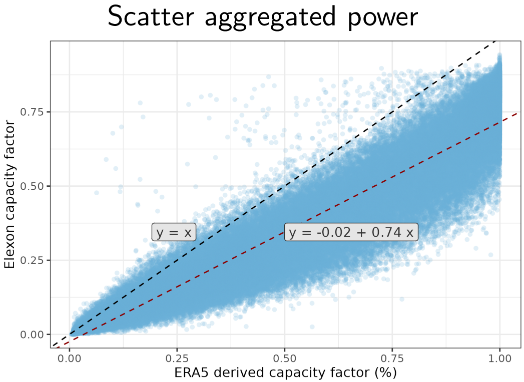
Calibration with linear model

GB level aggregation

- Power aggregated at GB level

$$p_{\text{tot},t} = \sum_i p_{it} / \sum_i C_i$$

- Each point represents one hour
- Overestimation persits but dispersion is lower now

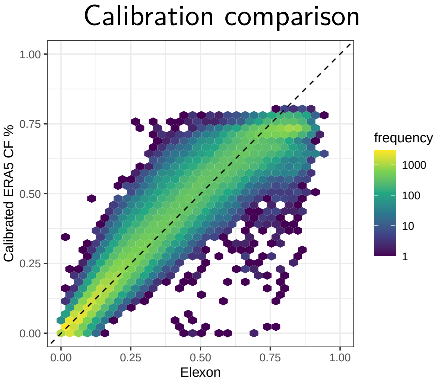


Initial linear model

- Features of importance:
  - m: month
  - k: Type (offshore / onshore)

$$p_t^{calib} = \alpha_{k,m} + \beta_{k,m}\hat{p}_t,$$

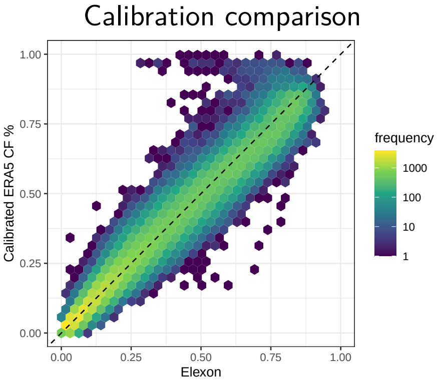
where $\alpha_{k,m}$ and $\beta_{k,m}$ represent the intercept and slope, varying by type and month



Updated linear model

- Using step AIC criteria selection:
  - k: Type (offshore / onshore)
  - m: month, h: hour
  - w_t: wind speed

$$p_t^{calib} = \alpha_{k,m,h} + \beta_{k,m}\hat{p}_t + \sum_{j=1}^{3} \phi_j w_t^3$$

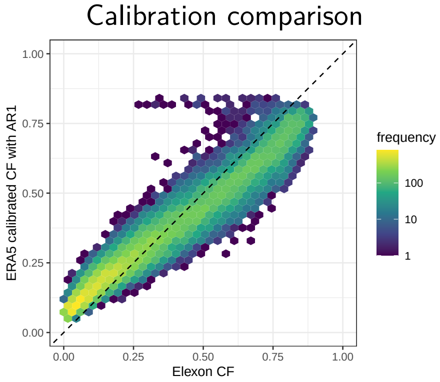


Autoregressive error

- Using step AIC criteria selection:
  - k: Type (offshore / onshore)
  - m: month, h: hour
  - w_t: wind speed
  - u_t: AR1

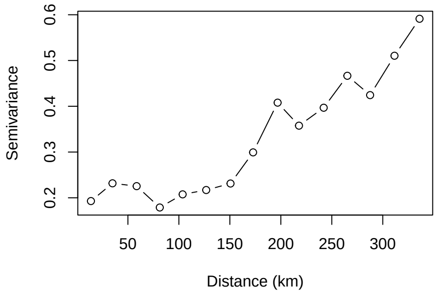
$$p_t^{calib} = \alpha_0 + \sum \alpha_e + \beta_k \hat{p}_t + f_w(w_t) + u_t$$

where α_0 is the intercept, the α_e $e \in k, m, h$ represent random effects (cyclic for month and hour), β_k is a random slope, f_w is smooth effect (RW2).

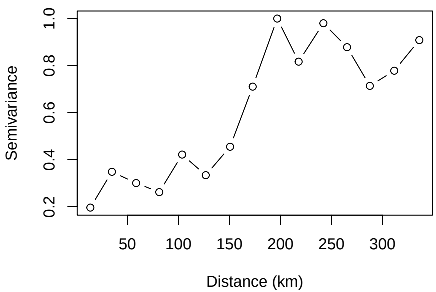


Spatial correlation

Variogram for Elexon generation



Variogram for ERA5 uncalibrated estimate



Power curve modelling

Using a two-likelihood approach for power curve estimation:

- **1st likelihood:** Observed power is modelled as a smooth function of wind speed
  - Random walk of order 2
  - Beta with logit link for output [0,1]
- **2nd likelihood:** Penalisation towards a generic PC
  - Gaussian noise; strength controlled via precision
  - Estimate is pulled to typical turbine behaviour
- **Cut-off speed estimation?**
- **Outcome:** Smooth, physically realistic power curve informed by both data and prior knowledge

Next Steps

- Power curve parametric model from data
- Check for spatial correlation
- Quantile mapping calibration

Appendix

Previous research

Power curve modelling

Binning method

$$P_i = \frac{1}{n_i} \sum_{j=1}^{n_i} P_{ij}$$

where: P_{ij} is the j th power observation in bin i and n_i no. of observations in bin i

Logistic

$$P(u) = a \frac{1 + m \exp(-u/\tau)}{1 + n \exp(-u/\tau)}$$

where a represents the upper asymptote, n, m shape the lower asymptote, and τ controls the transition.

Power curve modelling

5 parameter curve

$$P(u) = D + \frac{A - D}{(1 + (u/C)^B)^G}$$

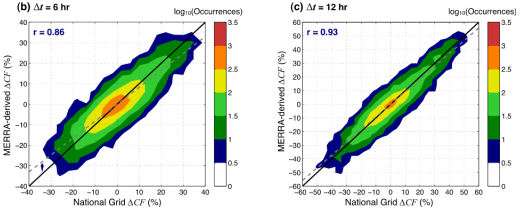
where: A and D are the upper and lower asymptotes, C is the inflection point, B the slope at inflection point, adn G controls the asymmetry.

Reanalysis data to quantify extreme wind power statistics

D. Cannon, D. Brayshaw, et. al (2015)

- MERRA wind speed validated with MIDAS
- Vertical interpolation with a logarithmic change
- Calibrated power curves based on manufacturers PC
- Use that to analys extreme low and high levels, and ramps

ΔCF comparison

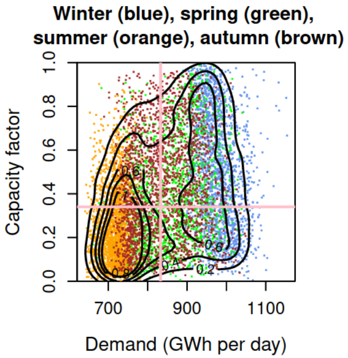


Balancing energy

H. Thornton, D. Brayshaw analyse the relationship between weather, energy demand, and wind power.

- ERA Interim wind speed
- Cubic power curve with air density correction
- CF compared with GB average from other studies
- Seasonal effects on Demand and

ΔCF comparison



Analysis of extreme wind droughts

Panit Potisomporn, C. Vogel (2024) perform a extreme value analysis of wind droughts in GB.

- Use ERA5 wind speeds calibrated to MIDAS with QM
- Build a ML algorithm that learns how to extrapolate wind speed from 10m to hub height
- Use a 5 parameter logistic function to model power curve
- Model energy losses with factors by type.

CF calibration