ERA 5 calibration to Elexon power

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Calibration to power

Updates

New

- Curtailment data to obtain potential generation
- Outage data to exclude periods where capacity is constrained
- Updated power curve comparison to data
- ERA 5 wind speed conversion to power

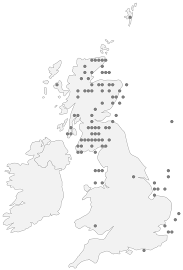
Next steps

- Learn power curve from data
- Benchmark models: Quantile mapping, GAMs
- Calibration spatiotemporal model

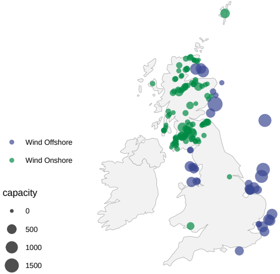
ERA5 vs Elexon generation

Calibrate a ERA5 driven estimate to **potential generation** accounting for spatiotemporal properties.

ERA5 at wind farms



Elexon wind farms map (2025)



Closest grid point to each wind farm location

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

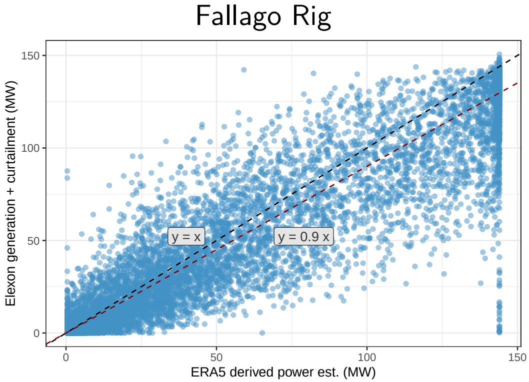
ERA5-derived power estimate $\hat{p}_{it}$ is compared versus potential power p_{it}

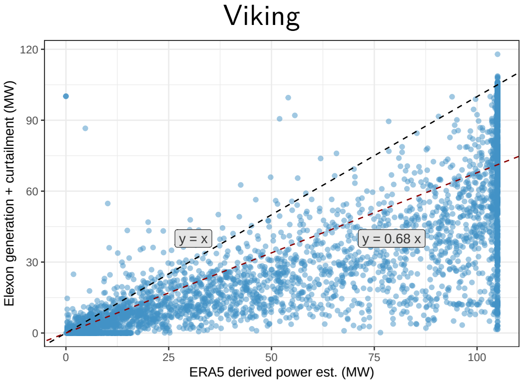
$$\hat{p}_{it} = \hat{PC}_i(w_{it})$$
$$p_{it} = \beta_0 + \beta\hat{p}_{it} + s_i + u_t,$$

where s_i and u_t represent spatial and temporal effects.

Calibration with linear model

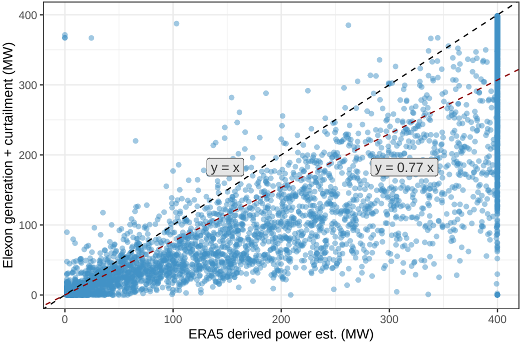
ERA5 based estimates vs Elexon 2024



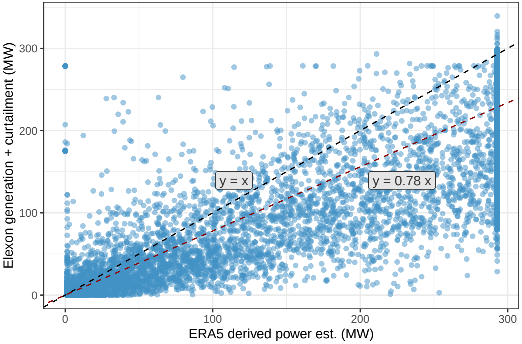


ERA5 based estimates vs Elexon 2024

Hornsea 1

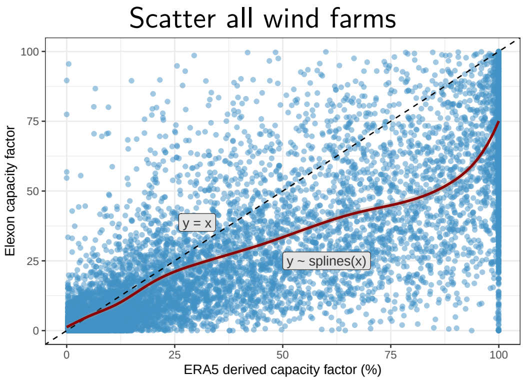


Seagreen 1



Comparison for all wind farms

- Working with 2024 data only
- Each point represents one hour and one location
- Showin a sample of points to simplify plotting



GB level aggregation

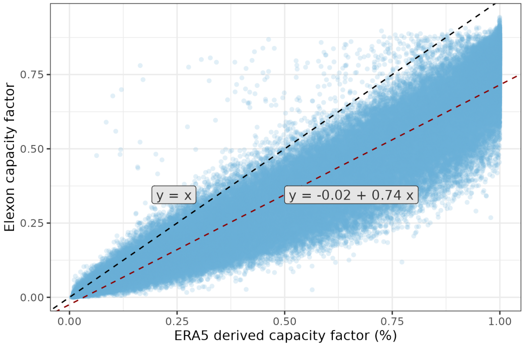
GB level aggregation

- 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

Scatter aggregated power



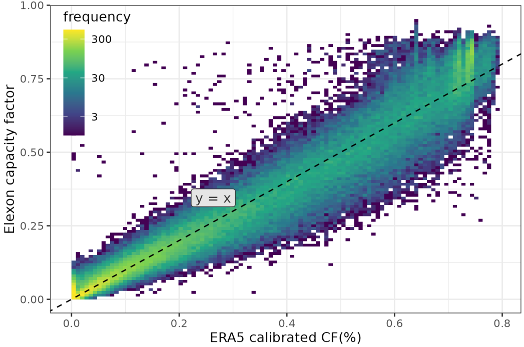
Calibration with linear model

Features of importance: - month - Turbine 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

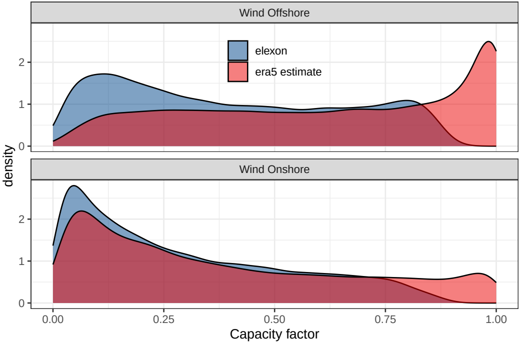
Scatter aggregated power



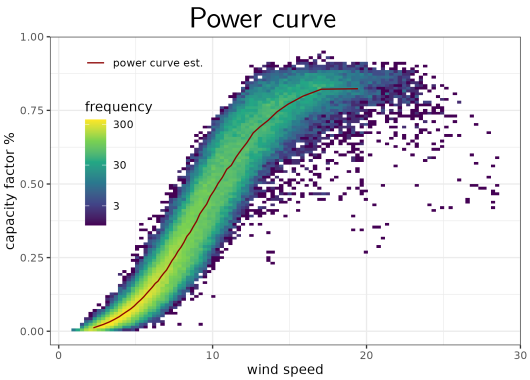
Density of aggregated power

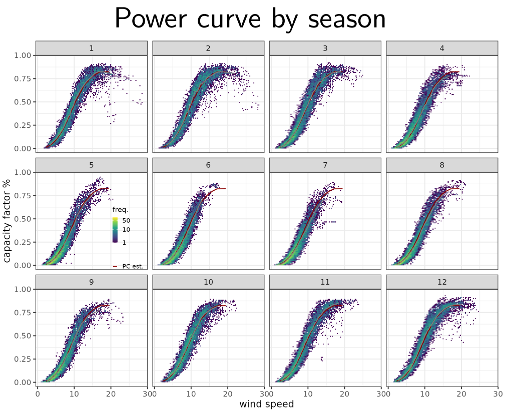
- Cut-off wind speed isn't capture well by generic power curves
- This issue is markedly present in offshore data

Density of Elexon and ERA5 based estimate



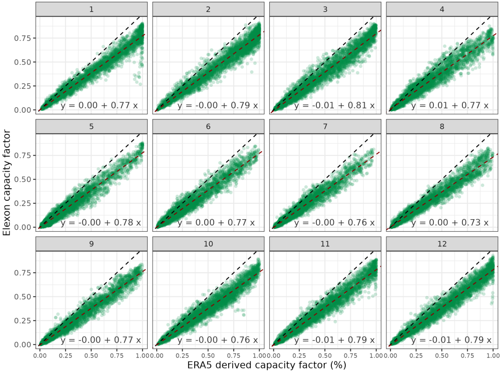
Power curve by season



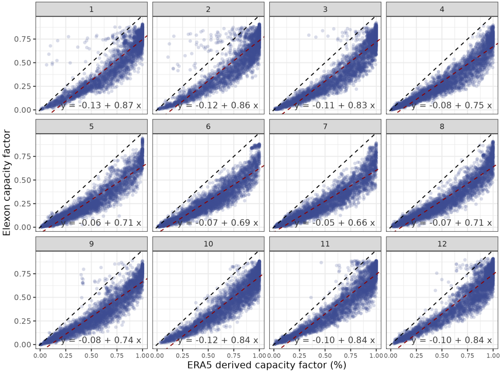


Linear calibration by season

Onshore power

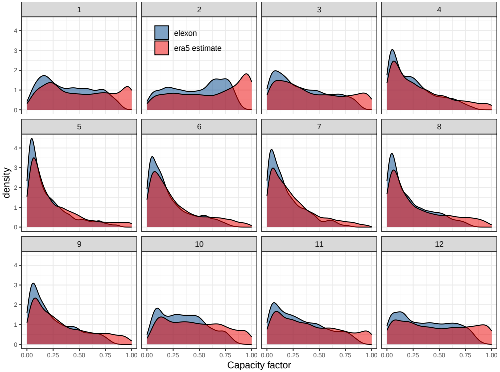


Offshore power

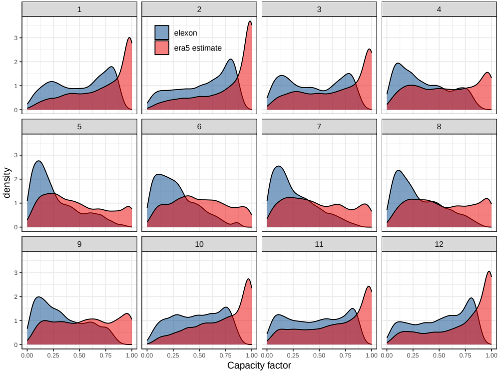


Difference in density by season

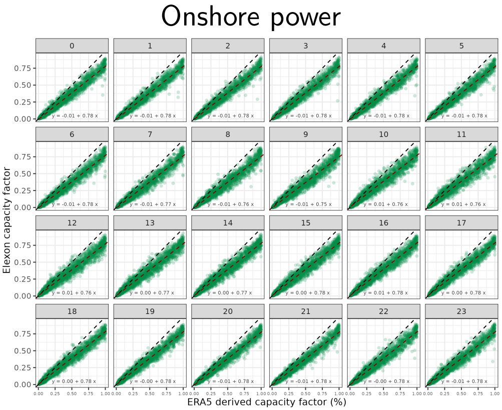
Onshore power

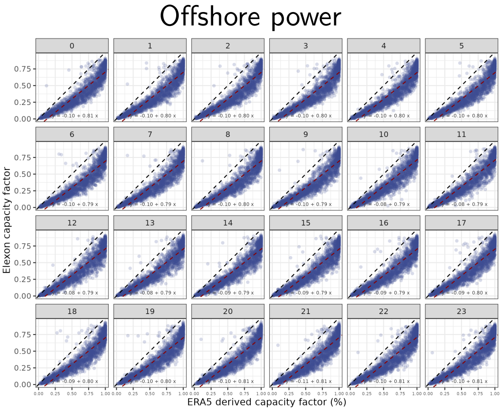


Offshore power



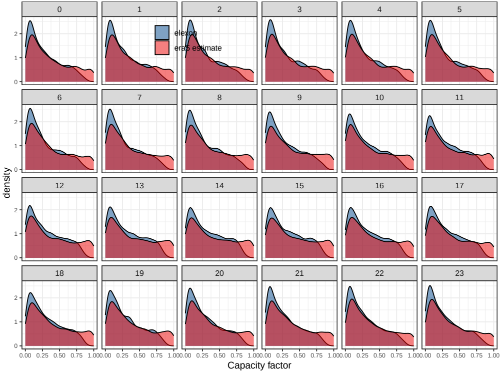
Linear calibration by time of day



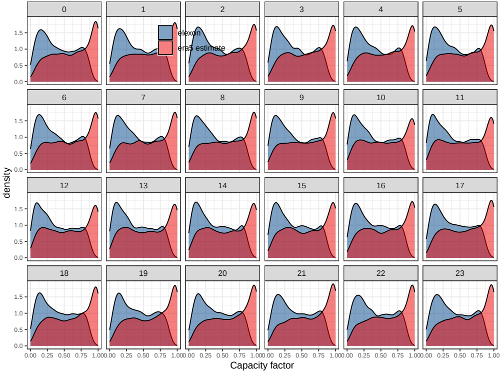


Difference in density by hour

Onshore power



Offshore power



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

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

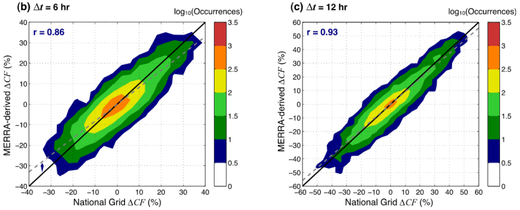
where: A and D are the upper and lower asymptotes, C is the inflection point, B the slope at inflection point, adn G controls the asymmetry.

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

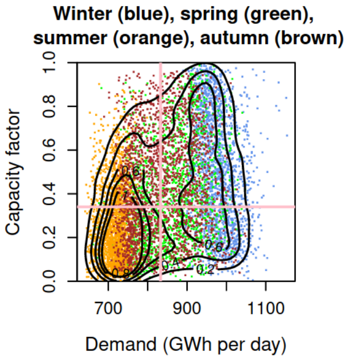


Balancing energy

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

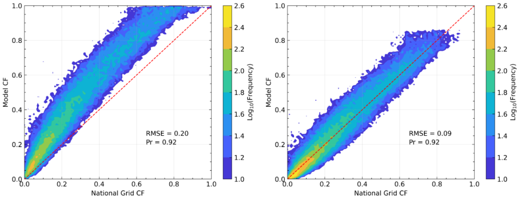


Analysis of extreme wind droughts

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



Next Steps

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