

# ERA 5 calibration to Elexon power

S. Gomez<sup>1</sup>

<sup>1</sup>School of Mathematics, University of Edinburgh

2025-12-19

# Table of contents I

- 1 Overview
- 2 Calibration of generic power curve estimate
- 3 Power curve modelling
- 4 Appendix

# Overview

# Updates

## New

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

## Next steps

- Combine PC model with calibration
- Compare model against benchmarks: Quantile mapping, GAMs
- Calibration spatiotemporal model

# Data sources

## Wind speed

- ERA5 at wind farms
  - Hourly data
  - Spatial resolution  $0.25^\circ \times 0.25^\circ$
  - 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:

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

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

# Calibration

## 4. Calibration of generic power curve estimate

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

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

where  $s_i$  and  $u_t$  represent spatial and temporal effects.

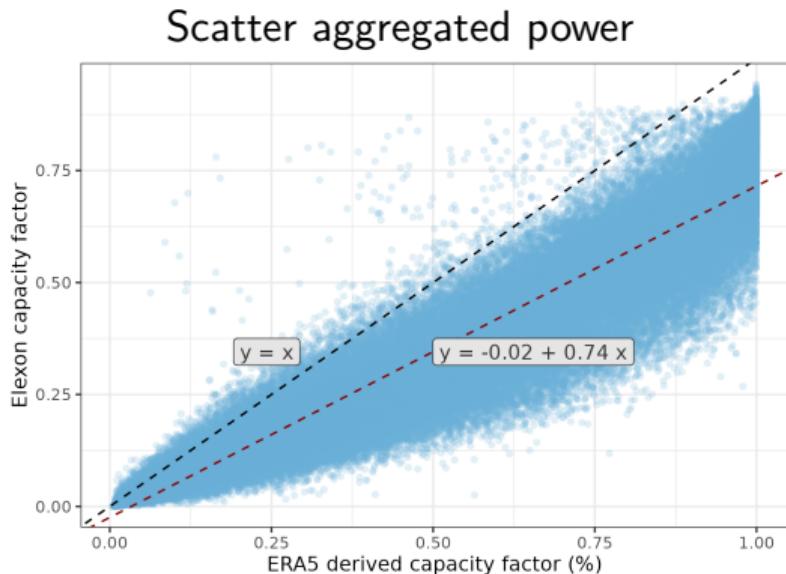
## Calibration of generic power curve estimate

# 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 persists but dispersion is lower now

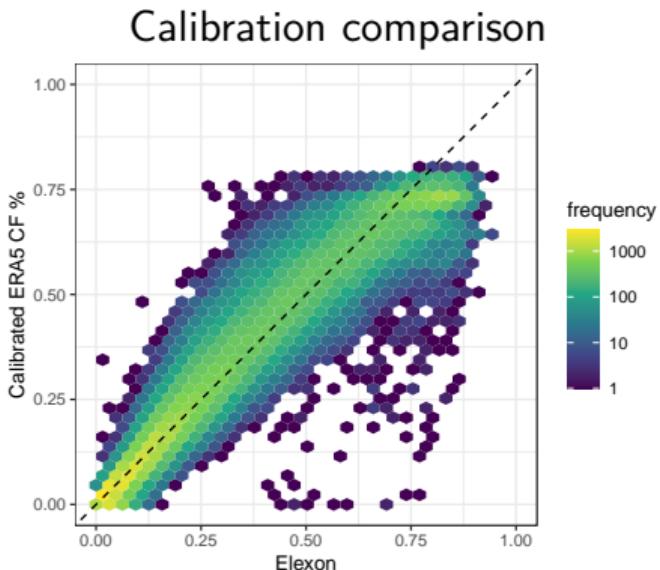


# Initial linear model

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

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

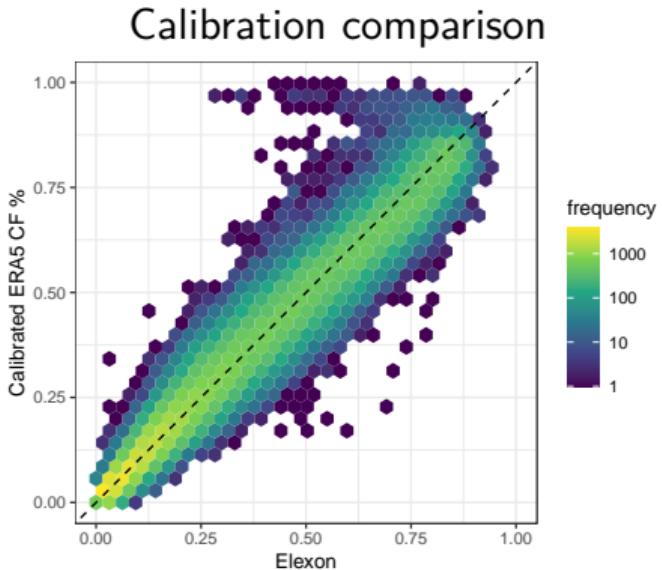
where  $\alpha_{k,m}$  and  $\beta_{k,m}$  represent the intercept and slope, varying by type and month



# Updated linear model

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

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

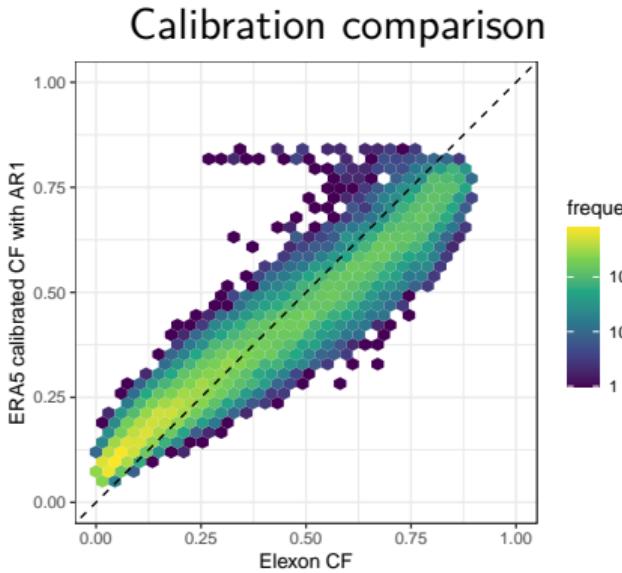


# Autoregressive error

- 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  $\alpha_0$  is the intercept, the  $\alpha_e$   $e \in k, m, h$  represent random effects (cyclic for month and hour),  $\beta_k$  is a random slope,  $f_w$  is smooth effect (RW2).



## Power curve modelling

# Power curve modelling

## Components

- Power curve estimate from data
- Probability of zero generation
- Penalisation to make power curve resemble manufacturer's PC

Using a three-likelihood approach for power curve estimation:

- **1st likelihood:** Observed power is modelled as a smooth function of wind speed
- **2nd likelihood:** Zero inflated component
- **3rd likelihood** Penalisation towards a generic PC

# Power curve model equations

Model is a Zero Inflated Beta (ZIB) with penalisation component:

## Zero-probability model (Bernoulli)

$$\eta_i^{(0)} = \alpha_{\text{bern}} + f_{\text{bern}}(w_i; \mathbf{s}(i)), \quad (1)$$

$$Z_i \mid \eta_i^{(0)} \sim \text{Bernoulli}(p_i), \quad p_i = \text{logit}^{-1}(\eta_i^{(0)}), \quad (2)$$

## Positive-output model (Beta)

$$\eta_i^{(\beta)} = \alpha_{\text{pc}} + f_{\text{pc}}(w_i; \mathbf{s}(i)), \quad (3)$$

$$P_i^{\text{obs}} \mid \eta_i^{(\beta)} \sim \text{Beta}(\mu_i, \phi), \quad \mu_i = \text{logit}^{-1}(\eta_i^{(\beta)}), \quad (4)$$

## Pseudo-likelihood model (Gaussian)

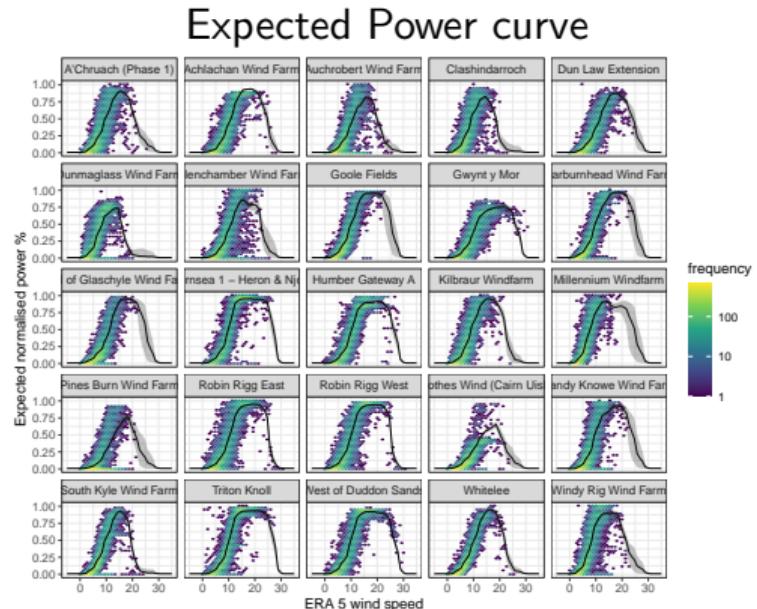
$$\tilde{P}_i \mid \eta_i^{(\beta)} \sim \mathcal{N}(\eta_i^{(\beta)}, \tau_{\text{ps}}^{-1}), \quad \tau_{\text{ps}} = \text{precision or penalisation}. \quad (5)$$

## Alternative versions

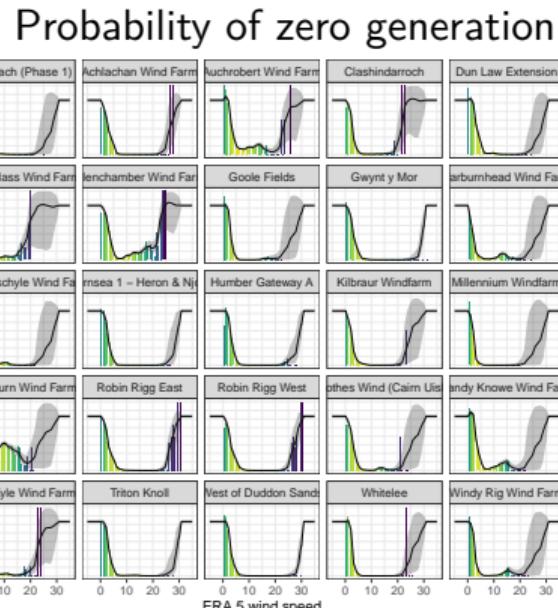
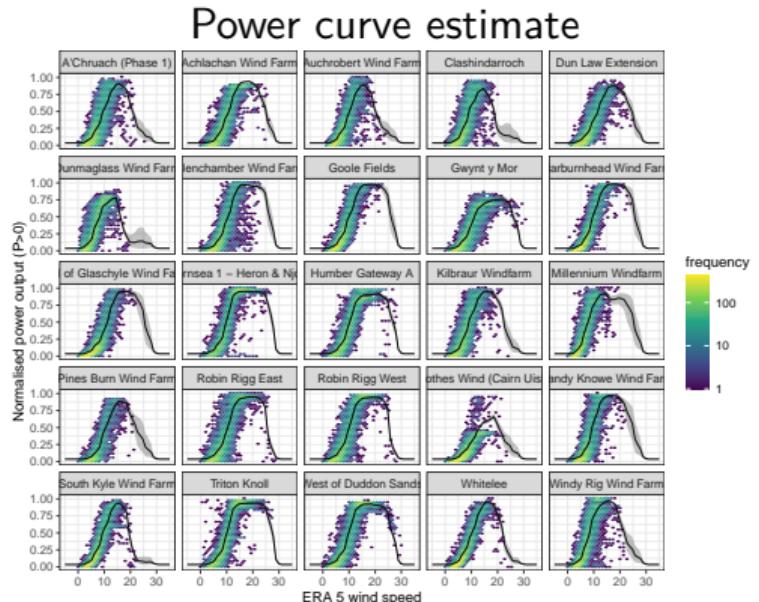
- Beta model with RW2 based power curve (B-RW2)
- Beta model with 1D SPDE based power curve (B-SPDE)
- ZIB model with 1D SPDE based power curve (ZIB-SPDE)

# Power curve model estimates

- Starting models with
  - 1Y of data (2024)
  - 25 wind farms
  - Hourly data
  - Excluding outages listed in REMIT



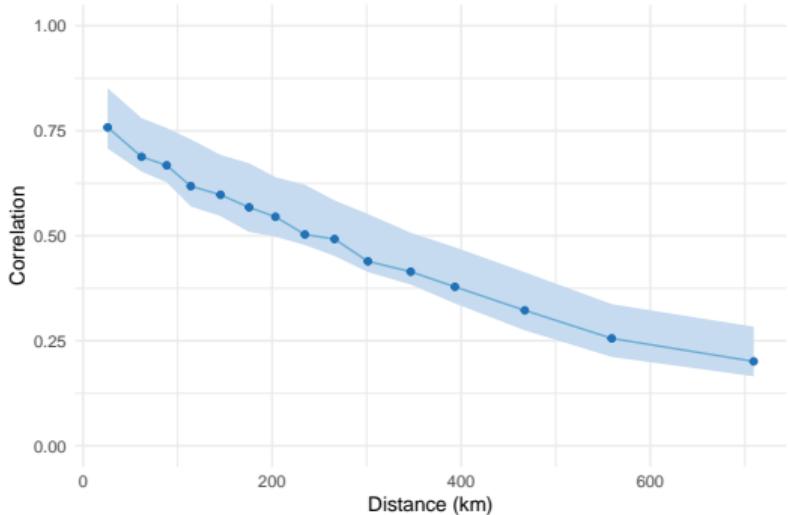
# Power curve model estimates



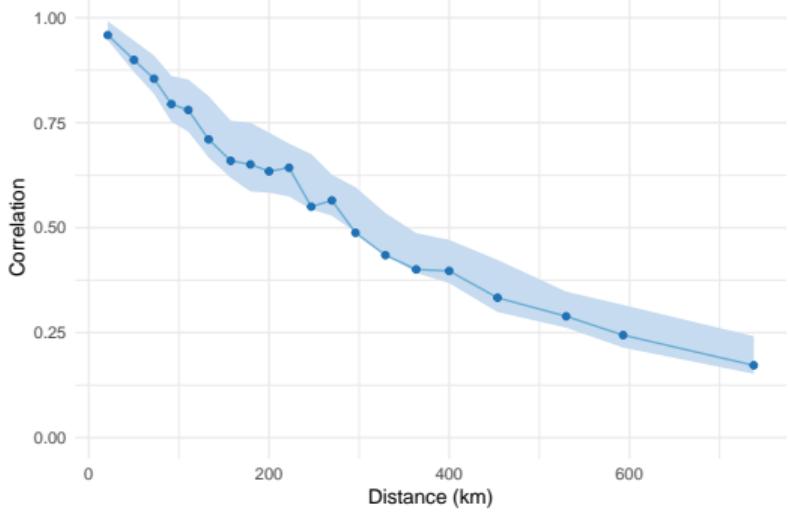
## Spatial correlation

# Spatial correlation

Correlation for Elexon generation



Correlation for ERA5 uncalibrated estimate



## Next Steps

- Combine updated power curve model with calibration
- Benefits of including spatial correlation
- Model validation against benchmarks

## 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  $\tau$  controls the transition.

# Power curve modelling

5 parameter curve

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

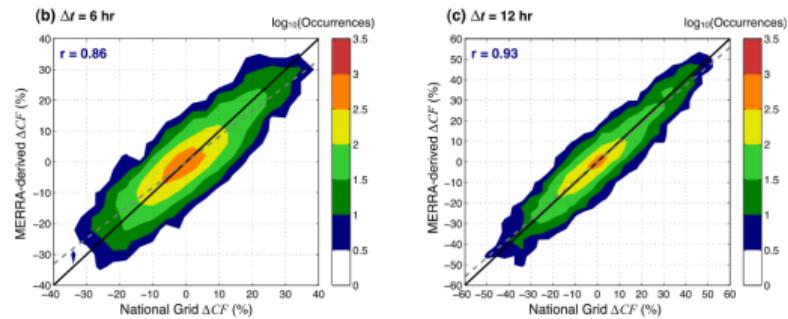
where:  $A$  and  $D$  are the upper and lower asymptotes,  $C$  is the inflection point,  $B$  the slope at inflection point, and  $G$  controls the asymmetry.

# 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 analyse extreme low and high levels, and ramps

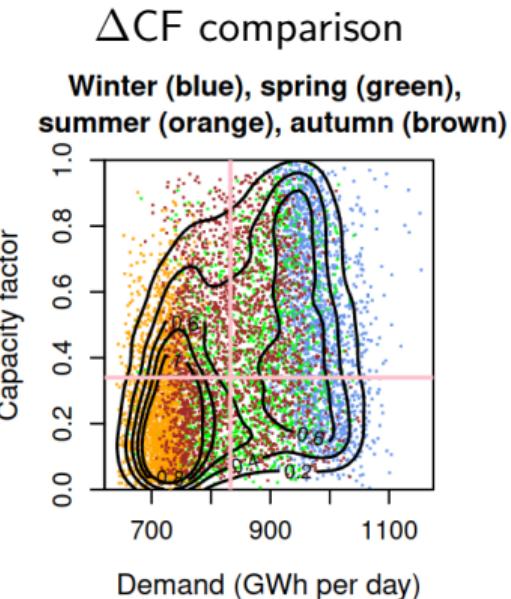
## $\Delta CF$ comparison



# Balancing energy

H. Thornton, D. Brayshaw (2020) analyse the relationship between weather, energy demand, and wind power.

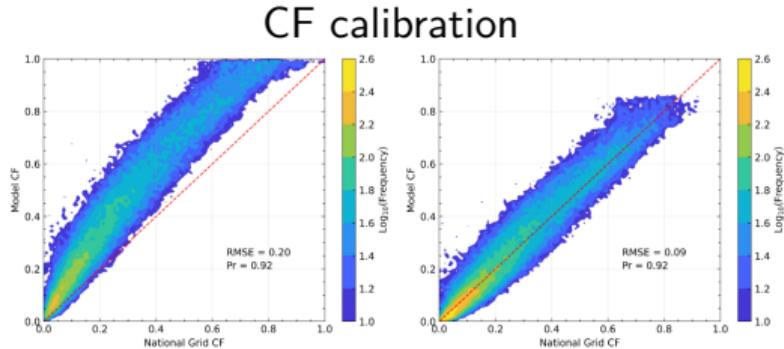
- ERA Interim wind speed
- Cubic power curve with air density correction
- CF compared with GB average from other studies
- Seasonal effects on Demand and



# 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.



## References

- Cannon, D. J., D. J. Brayshaw, J. Methven, P. J. Coker, and D. Lenaghan. 2015. "Using Reanalysis Data to Quantify Extreme Wind Power Generation Statistics: A 33 Year Case Study in Great Britain." *Renewable Energy* 75 (March): 767–78. <https://centaur.reading.ac.uk/38448/>.
- Potisomporn, P. 2024. "Spatiotemporal Variability of Extreme Low Wind Power Events in Great Britain - ORA - Oxford University Research Archive." [Http://purl.org/dc/dcmitype/Text](http://purl.org/dc/dcmitype/Text). <https://ora.ox.ac.uk/objects/uuid:de37bee2-1813-42e5-a69c-9b15f038d096>.
- Thornton, Hazel E. 2020. "Atmospheric Circulation, Seasonal Predictability and Britain's Energy System." PhD thesis, University of Reading. <https://doi.org/10.48683/1926.00095832>.