

ERA 5 calibration to Elexon power

S. Gomez¹

¹School 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

- Power curve modelling
- Calibration comparison
- Spatial correlation check

Next steps

- Wind speed Cut-off estimation (pooling data)
- Wind direction effects on power curve
- Out-of-sample validation
- 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.

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

where C_i is the capacity at location i

Overview of power conversion

3. Potential generation

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

- Curtailement 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}

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

where s_i and u_t represent spatial and temporal effects.

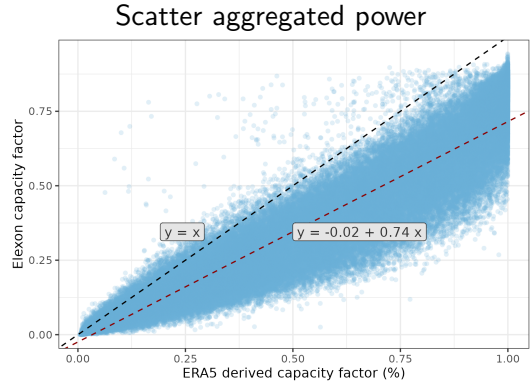
Calibration of generic power curve estimate

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

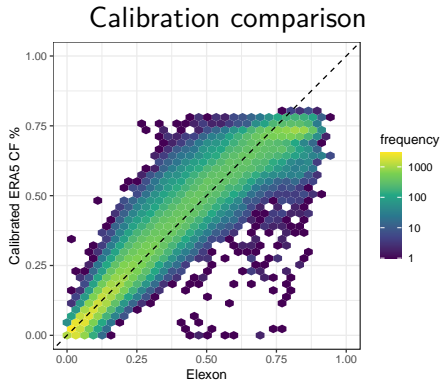
- Features of importance:

- m : month

- k : Type (offshore / onshore)

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

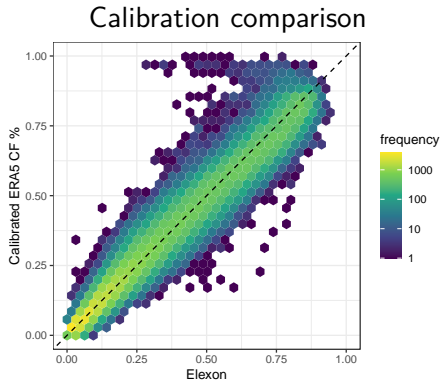
where $\alpha_{k,m}$ and $\beta_{k,m}$ represent the intercept and slope, varying by type and month



Updated linear model

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

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

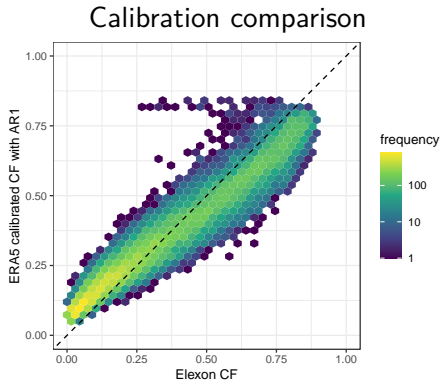


Autoregressive error

- 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 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).



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)

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

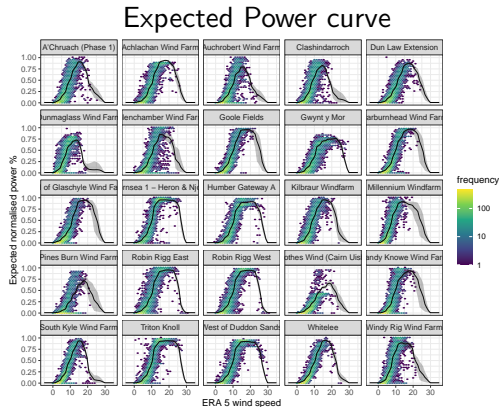
$$P_i^{\text{obs}} \mid \eta_i^{(\beta)} \sim \text{Beta}(\mu_i, \phi), \quad \mu_i = \text{logit}^{-1}(\eta_i^{(\beta)}), \quad (4)$$

Pseudo-likelihood model (Gaussian)

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

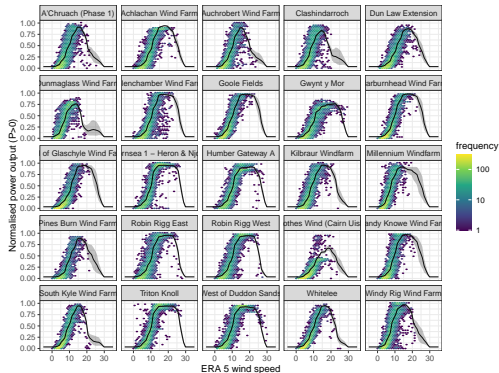
Power curve model estimates

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

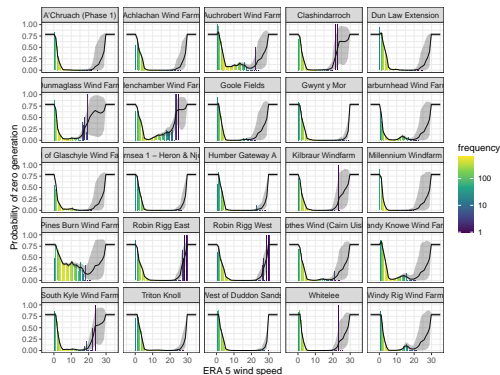


Power curve model estimates

Power curve estimate



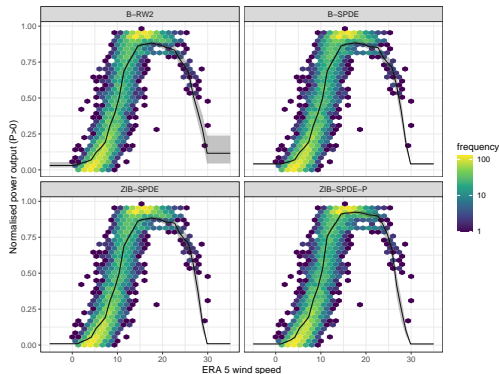
Probability of zero generation



Alternative versions

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

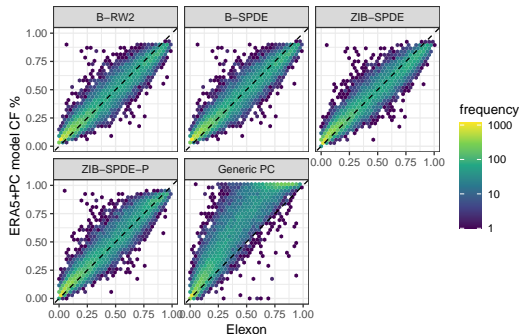
Power curve estimates under different models



ZIB model vs observed data

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

Power curve models vs observed data



Error metrics

model	RMSE	MAE	Bias
B-RW2	0.0647	0.0508	0.0142
B-SPDE	0.0647	0.0508	0.0143
ZIB-SPDE	0.0627	0.0476	0.0061
ZIB-SPDE-P	0.0668	0.0486	0.0235
Generic PC	0.1961	0.1535	0.1504

Next Steps

- Combine updated power curve model with calibration
- Wind speed Cut-off estimation (pooling data)
- Wind direction effects on power curve
- Out-of-sample validation
- Compare model against benchmarks: Quantile mapping, GAMs
- Calibration spatiotemporal model

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

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

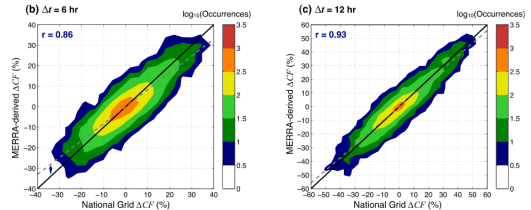
where: A and D are the upper and lower asymptotes, C is the inflection point, B the slope at inflection point, and G controls the asymmetry.

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

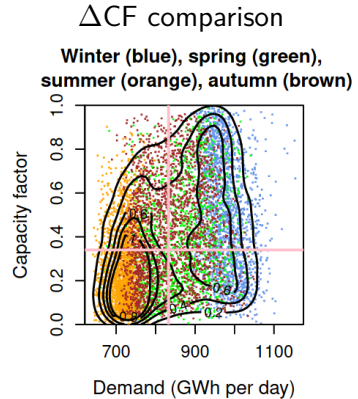
ΔCF comparison



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

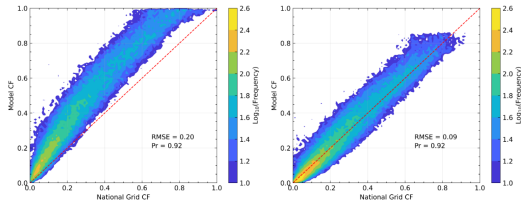


Analysis of extreme wind droughts

Panit Potisomporn, C. Vogel (2024) perform an 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



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>.