

ERA 5 calibration to Elexon power

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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.

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

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.

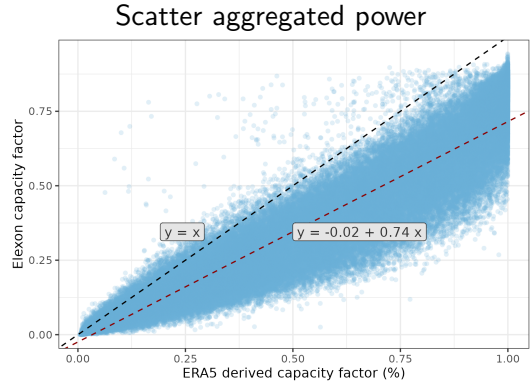
Calibration of generic power curve estimate

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

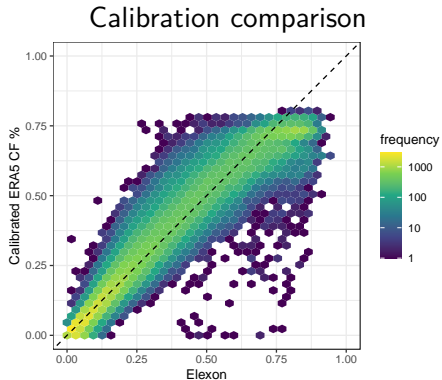
- Features of importance:

- m : month

- k : Type (offshore / onshore)

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

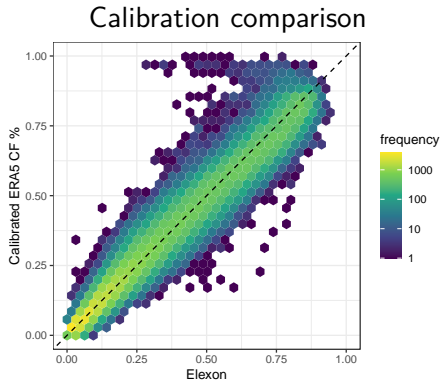
where $\alpha_{k,m}$ and $\beta_{k,m}$ represent the intercept and slope, varying by type and month



Updated linear model

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

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

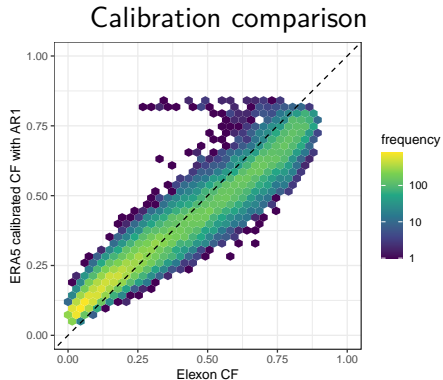


Autoregressive error

- 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)

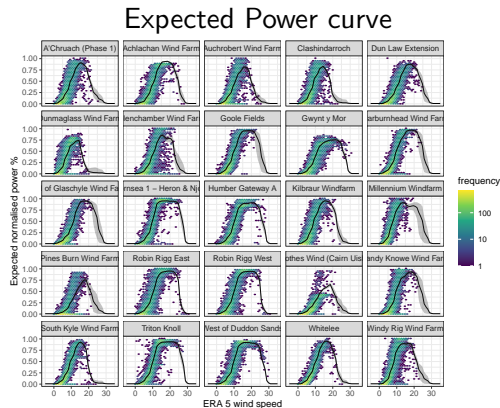
$$\tilde{P}_i \mid \eta_i^{(\beta)} \sim \mathcal{N}(\eta_i^{(\beta)}, \tau_{\text{ps}}^{-1}), \quad \tau_{\text{ps}} = \text{precision or penalisation}. \quad (5)$$

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)

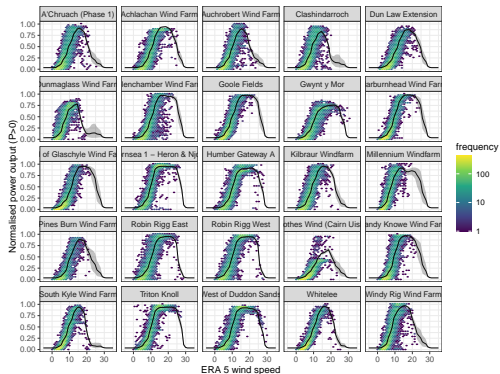
Power curve model estimates

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

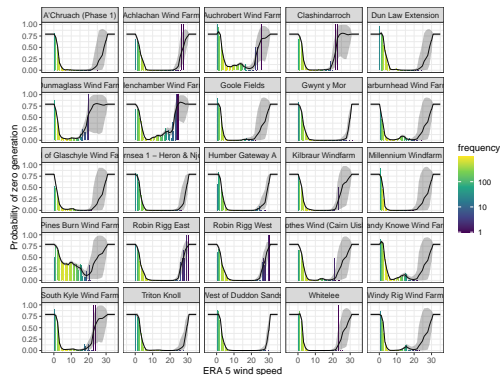


Power curve model estimates

Power curve estimate



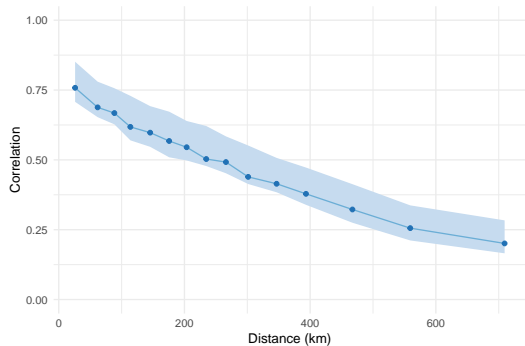
Probability of zero generation



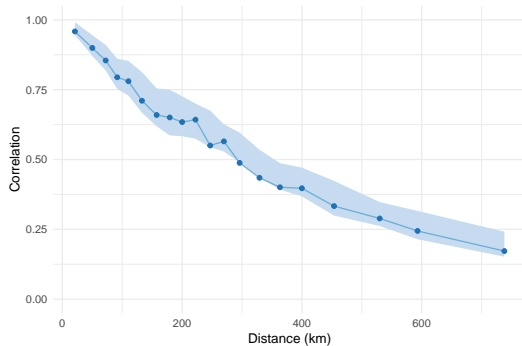
Spatial correlation

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 τ controls the transition.

Power curve modelling

5 parameter curve

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

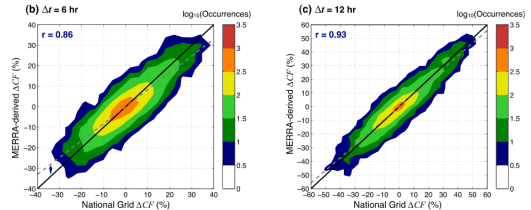
where: A and D are the upper and lower asymptotes, C is the inflection point, B the slope at inflection point, and G controls the asymmetry.

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

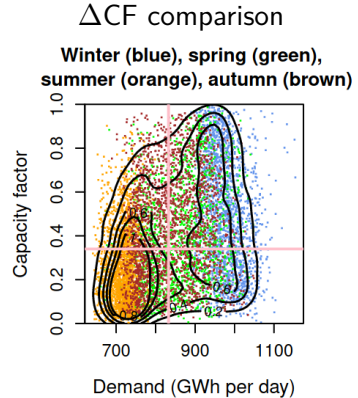
ΔCF comparison



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

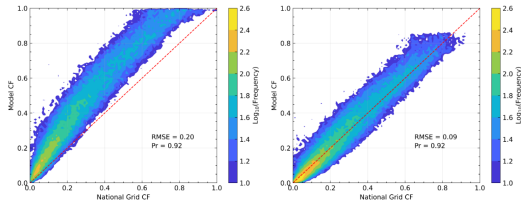


Analysis of extreme wind droughts

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

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<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.
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