ERA 5 calibration to Elexon power

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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° 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 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.

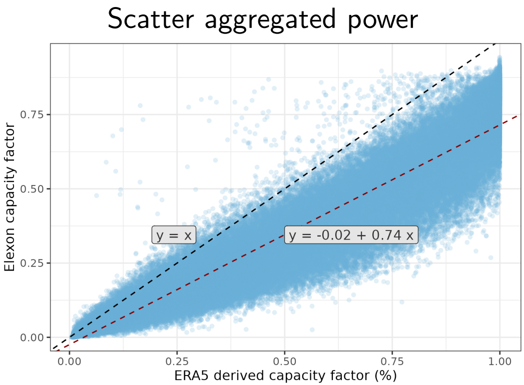
Calibration of generic power curve estimate

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 persits but dispersion is lower now

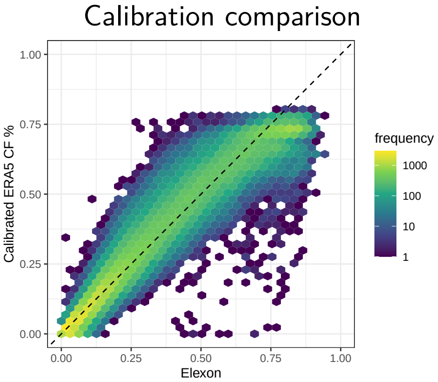


Initial linear model

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

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

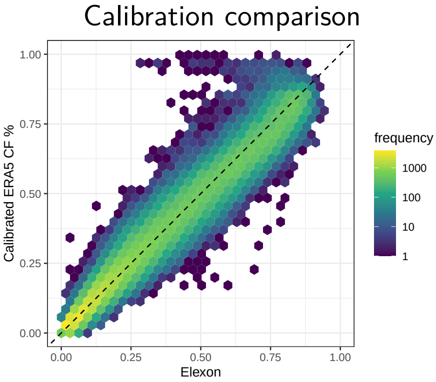
where $\alpha_{k,m}$ and $\beta_{k,m}$ represent the intercept and slope, varying by type and month



Updated linear model

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

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

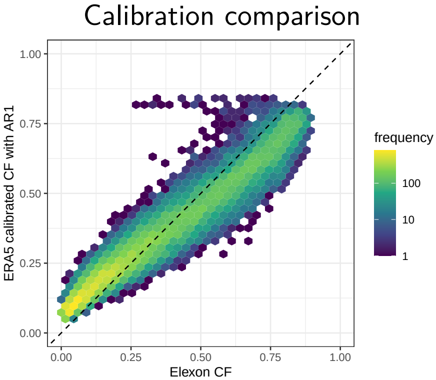


Autoregressive error

- 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).



Power curve modelling

Power curve modelling

Components

- Power curve estimate from data
- Probability of zero generation
- Penalisation to make power curve resemble manufaturer'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)

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

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

Positive–output model (Beta)

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

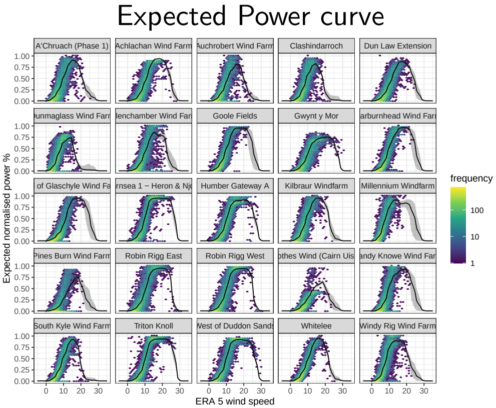
$$P_i^{\text{obs}} \mid \eta_i^{(\beta)} \sim \text{Beta}(\mu_i, \phi), \qquad \mu_i = \text{logit}^{-1}\left(\eta_i^{(\beta)}\right) , \tag{4}$$

Pseudo–likelihood model (Gaussian)

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

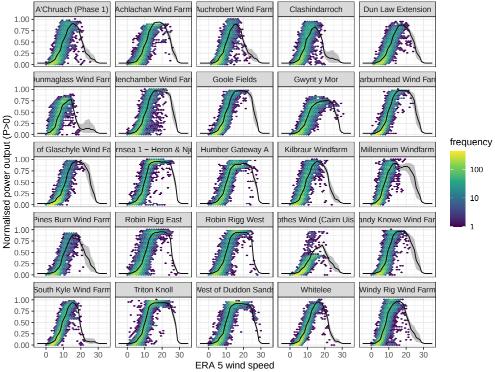
Power curve model estimates

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

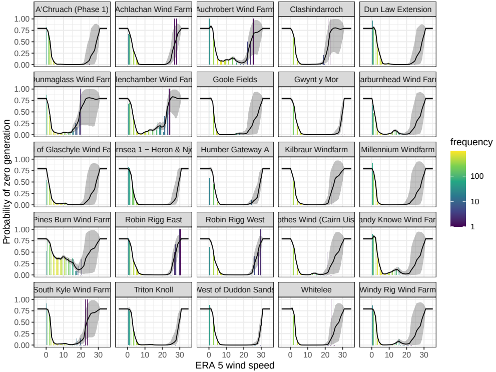


Power curve model estimates

Power curve estimate



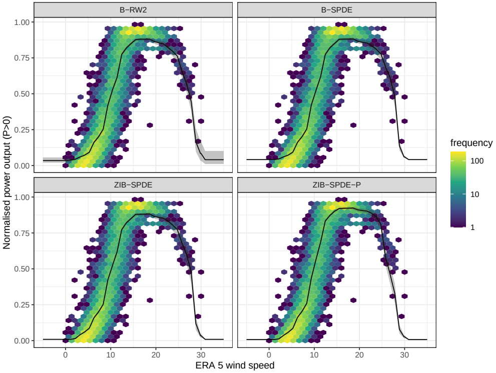
Probability of zero generation



Alternative versions

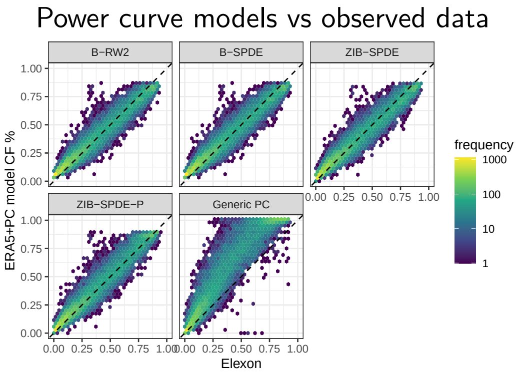
- Beta model with RW2 power curve (B-RW2)
- Beta model with 1D SPDE power curve (B-SPDE)
- ZIB model with 1D SPDE power curve (ZIB-SPDE)
- ZIB model with 1D SPDE power curve penalised (ZIB-SPDE-P)

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)



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
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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

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

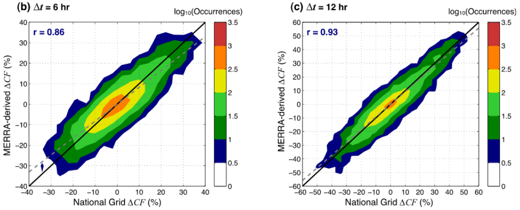
where: A and D are the upper and lower asymptotes, C is the inflection point, B the slope at inflection point, adn G controls the asymmetry.

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

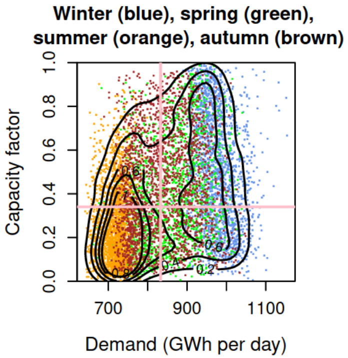


Balancing energy

H. Thornton, D. Brayshaw (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

ΔCF comparison

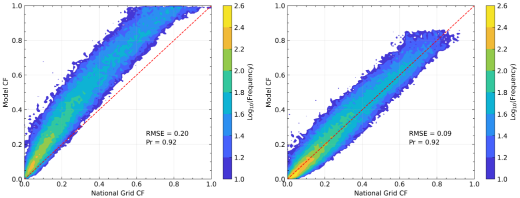


Analysis of extreme wind droughts

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



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