# Probabilistic Wind Power Forecasting


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# Wind energy resource assessment

# Wind energy integration

Climate change requires us to integrate renewable sources to the energy system.
Wind energy can account for up to 68.3% of total generation in the UK.

- Supply cannot be controlled
- We want to predict wind energy and quantify its uncertainty
- Use this information to meet energy demand optimally

# Objective

## Objective

Generate renewable energy predictions along with their associated uncertainty for regions of interest in the short term. In addition to the point estimate, we aim to produce energy scenarios whose behaviour closely resembles observed data.

# Behaviour

Let $P(s)_t$ denote the normalised wind energy output at point $s$ and time $t$.

- Leverage spatio-temporal properties

$$\mathrm{Cov}(P(a)_t, P(b)_t)$$

$$\mathrm{Cov}\left(P(s)_t, P(s)_{t+h}\right)$$

- Smoothness and variability

$$\Delta P(s)_t = P(s)_{t+1} - P(s)_t \ , \quad \mathrm{Var}(P(s)_t)$$

- Physical constraints: installed capacity

$$0 < P(s)_t < P(s)_t^{\max}$$

# Data sources

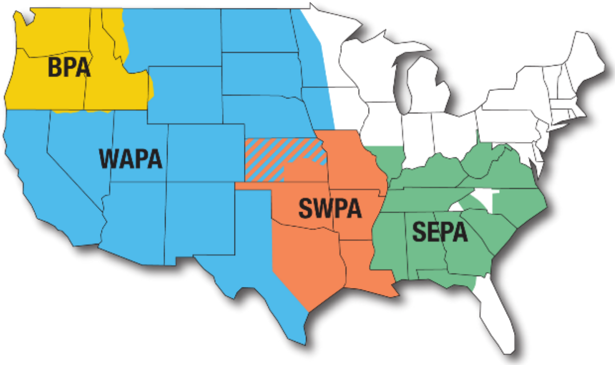
# Data

Mix of spatio-temporal data sources:

- Gridded weather data: wind speed $w(s)_t$
- Historical generation and forecast $\tilde{p}_t, \tilde{f}_t$ in MW
- Wind farm capacity $c_t$
- Normalised wind power $p_t = \tilde{p}_t / c_t$

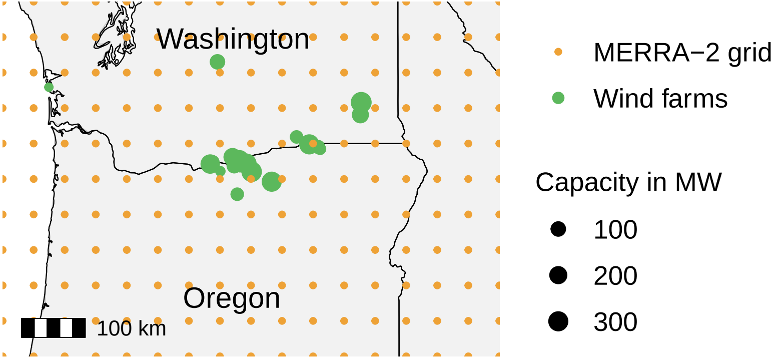
# Bonneville Power Administration US

Figure 1: US power administration coverage

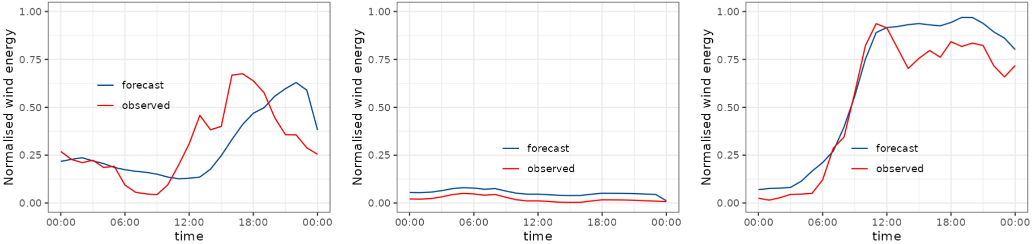


# Gridded data and wind farms locations

Figure 2: Locations of the 21 wind farms



# Wind power time series




(a) 2013-08-29 (b) 2013-10-13 (c) 2013-11-02

Figure 3: 24h forecasts for three days.

# Objective

## Project goal

Leverage historical point forecasts and additional data sources to produce probabilistic forecasting.

- Uncertainty quantification (UQ) around wind power point forecasts.
- Integrate extra information: weather, time, constraints, etc.
- Obtain short-term probabilistic scenarios
- Match behaviour of the wind energy process

# Model framework

# Model framework

- Bayesian modelling estimated using Integrated Nested Laplace Approximation (INLA)
- Beta distribution: wind power $P_t \in (0, 1)$
- Power ramp effect
- Autoregressive components: AR(p)
- Nonlinear effects
- Regime switching

# Hierarchical Bayesian Model

Normalised Power with Beta likelihood model (NPB):

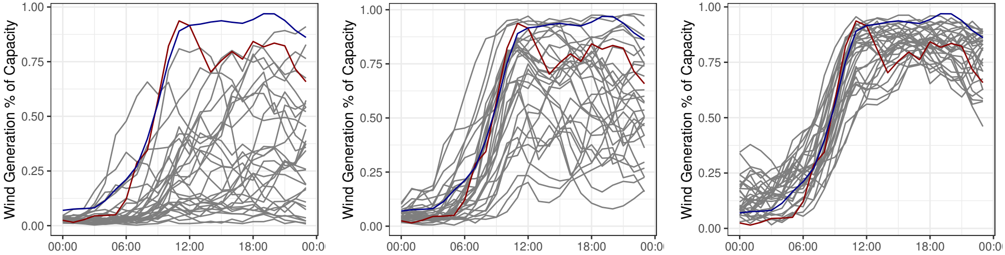
$$
\begin{aligned}
P_t &\sim \text{Beta}\left(\mu_t\phi,\ \phi(1-\mu_t)\right), \\
E[P_t|\mathbf{x}_t] = \mu_t &= g^{-1}(\eta_t + \beta\Delta\eta_t), \\
\eta_t &= \alpha + s_f(f_t) + s_w(w_t) + s_m(m_t) + s_h(h_t) + u_t, \\
u_t &= \rho_1 u_{t-1} + \rho_2 u_{t-2} + \epsilon_t, \quad \epsilon_t \sim N(0, \tau_u^{-1}),
\end{aligned}
\tag{1}
$$

where $g$ is the logit function, $\Delta^2 s_k \sim N(0, \tau_k)$, i.e. a random walk of order 2.

$P_t$ : Normalised power at $t$
$\mu_t$ : expected wind power
$\phi$ : dispersion
$\eta_t$ : linear predictor
$\beta$ : power ramp sens.
$w_t$ : wind speed
$f_t$ : day-ahead power forecast
$\alpha$ : Intercept
$s_f$ : forecast regime correction
$s_w$ : wind regime correction
$s_m, s_h$ : month, hour effects
$u_t$ : autocorrelation term

# Results

# Posterior samples




(a) Base model (b) + power ramp (PR) (c) + regime switch (RS)

Figure 4: Posterior samples on 2013-11-02.

# Scoring

Comparing NPB model vs. the Nonparametric density estimation method of Staid et. al.(2017).

Table 1: Model Scoring

| Model | CRPS | Energy | Variogram | | |
|---|---|---|---|---|---|
| | | | $p = 0.5$ | $p = 1$ | $p = 2$ |
| NPB | 0.064 | 0.387 | 0.455 | 0.318 | 0.122 |
| PR-NPB | 0.052 | 0.315 | 0.345 | 0.234 | 0.085 |
| RS-PR-NPB | **0.045** | **0.274** | **0.313** | **0.208** | **0.081** |
| Nonparametric | **0.045** | 0.288 | 0.368 | 0.226 | 0.086 |

# Power Ramp behaviour

Method represents better the distribution of large ramp events, but it is not as smooth as the data in the low end.

Table 2: Percentage of hourly ramp events falling within threshold

| Model | Power ramp threshold | | | | |
|---|---|---|---|---|---|
| | $\leq$1% | $\leq$2% | $\leq$5% | $\leq$10% | $\leq$20% |
| Actuals | 36.1 | 51.6 | 76.7 | 93.2 | 99.3 |
| RS-PR-NPB | 27.4 | 47.5 | **77.3** | **93.3** | **99.6** |
| Nonparametric | **37.5** | **54.2** | 83.5 | 98.1 | 99.9 |

# Conclusions

- Method extends point estimates to probabilistic forecasts
- Framework contemplates
  - Capacity constraints
  - Autoregressive properties
  - Power ramp behaviour

# Next steps

- Spatial disaggregation
- Extreme behaviour matching
- Extension to solar energy

Thanks!

# References


Bonneville Power Administration (BPA). 2024. "Wind Generation and Load Data." https://transmission.bpa.gov/Business/Operations/Wind/default.aspx.

Gómez-Rubio, Virgilio. 2020. *Bayesian Inference with INLA*. Chapman; Hall/CRC.

Rue, Håvard, Sara Martino, and Nicholas Chopin. 2009. "Approximate Bayesian Inference for Latent Gaussian Models Using Integrated Nested Laplace Approximations (with Discussion)." *Journal of the Royal Statistical Society B* 71: 319–92.

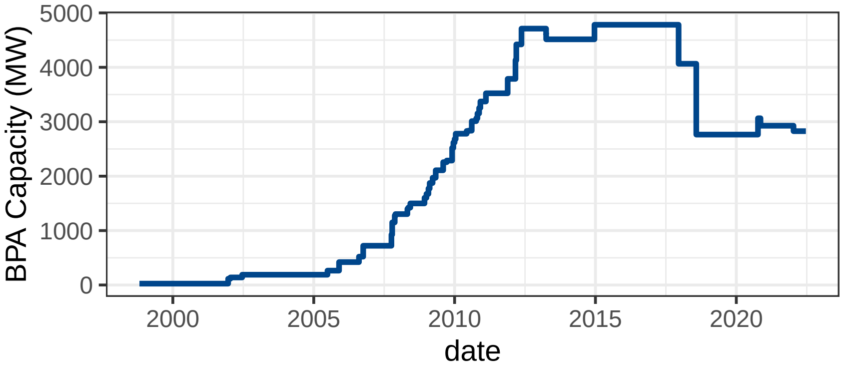
Staid, Andrea, Jean-Paul Watson, Roger J.-B. Wets, and David L. Woodruff. 2017. "Generating Short-Term Probabilistic Wind Power Scenarios via Nonparametric Forecast Error Density Estimators." *Wind Energy* 20 (12): 1911–25.

Woodruff, David L., Julio Deride, Andrea Staid, Jean-Paul Watson, Gerrit Slevogt, and César Silva-Monroy. 2018. "Constructing Probabilistic Scenarios for Wide-Area Solar Power Generation." *Solar Energy* 160 (January): 153–67.

# Appendix

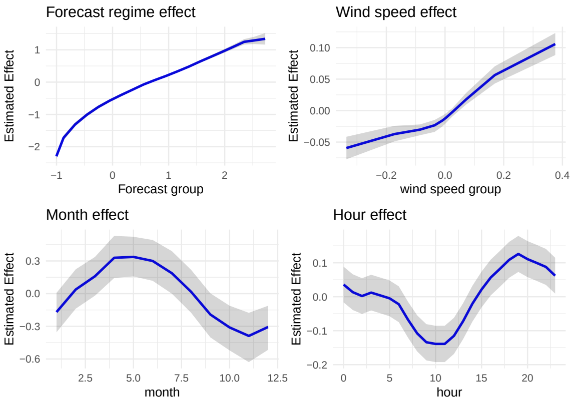
# BPA capacity through time

Figure 5: Installed capacity through time



# Inference on model terms

Figure 6: Estimated effects from the model



# Posterior density of hyper parameters

Figure 7: Hyperparameters of the model