Challenging predictions in energy forecasting

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Data Science Seminar, University of Bristol
5 February 2020

University of Strathclyde Glasgow

Heilbronn Institute for Mathematical Research

Engineering and Physical Sciences Research Council

Innovation Fellowship EP/R023484/1

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- Motivation and use-cases
- High-dimensional and hierarchical energy systems

Part 2: Leveraging all of that SCADA data operators have been studiously archiving…

- Overview of methodology
- Case study and results

Part 3: Help! Some problems it would be nice to solve… and perhaps you already have

- Bounded variables
- Events vs Time series

Part 1: Introducing Energy Forecasting

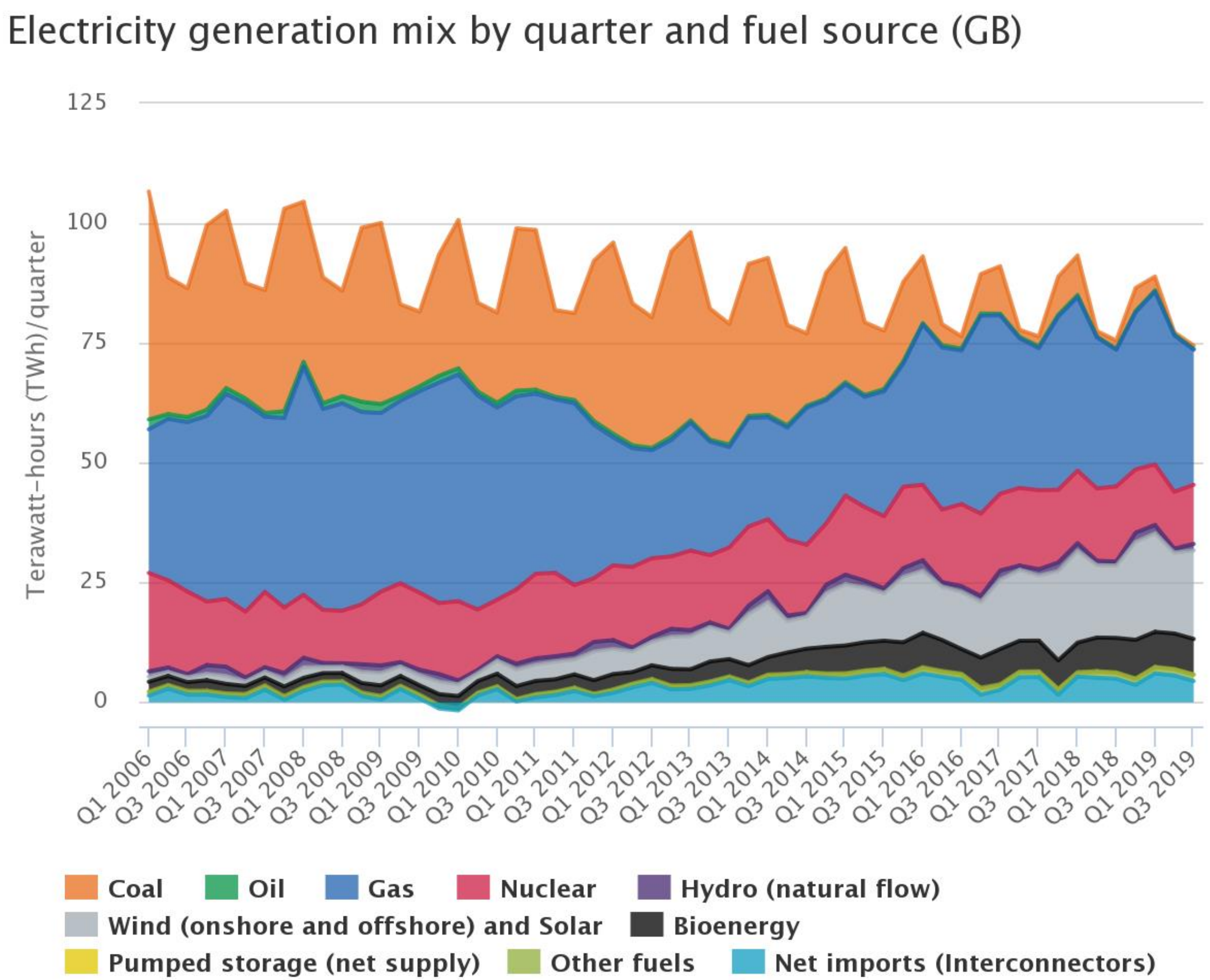
Energy Forecasting

- Management of resources and infrastructure is planned in advance:
  - Scheduling large power stations and industrial processes
  - Storing fuel (coal/biomass, petrol/diesel, natural gas, water…)
  - Flows in space and between *"energy vectors"* is constrained

One big (stochastic) optimisation problem!

Too big to solve…

Energy Forecasting



It is getting much harder to manage!

25% Wind + Solar in Q3-2019!!!

https://www.ofgem.gov.uk/data-portal/electricity-generation-mix-quarter-and-fuel-source-gb

Energy Forecasting

- Then:
  - Day-ahead demand forecast error: <2%
  - Schedule generation to meet demand
- Now:
  - Day-ahead *net-demand* forecast error: >2%
    - Especially on sunny days!
  - National wind forecast error: 4%
    - of installed capacity
    - Some days can be much higher!!!
  - Schedule generation met meet *net-demand*…
  - …and provide flexibility to manage forecast errors and ramps

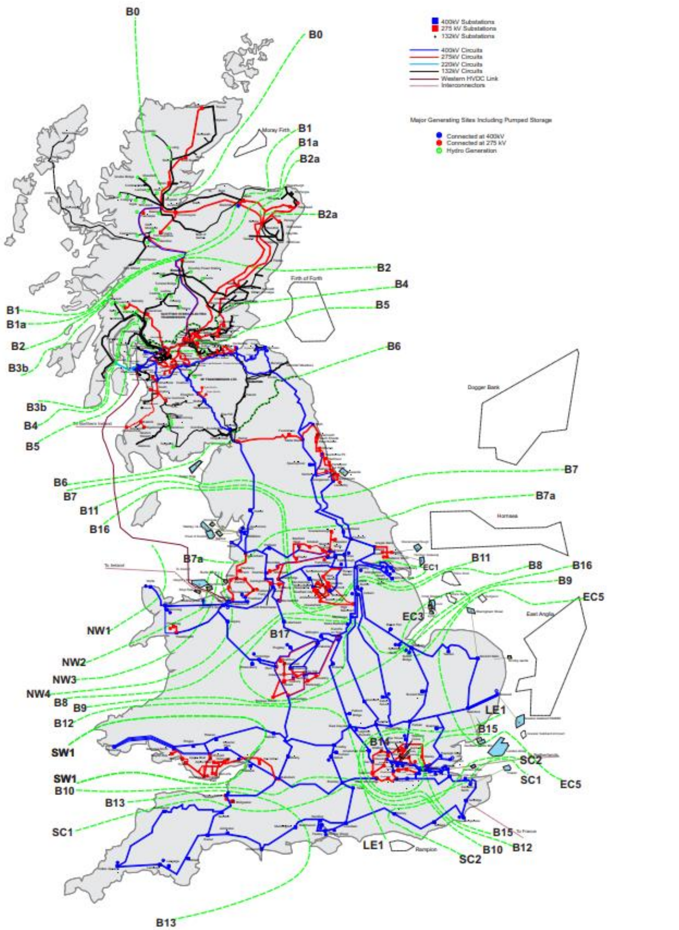
End-use: Power System Operation

Supply and demand must balance second-by-second!

Subject to:

- Network constraints
- Security criterion
  - Total reserve
  - Regional reserve
  - Angle and voltage stability
  - …

NB: Today only managed at transmission level, will be managed at distribution level in the future



End-use: Markets

Energy must be bought and sold ahead of time:

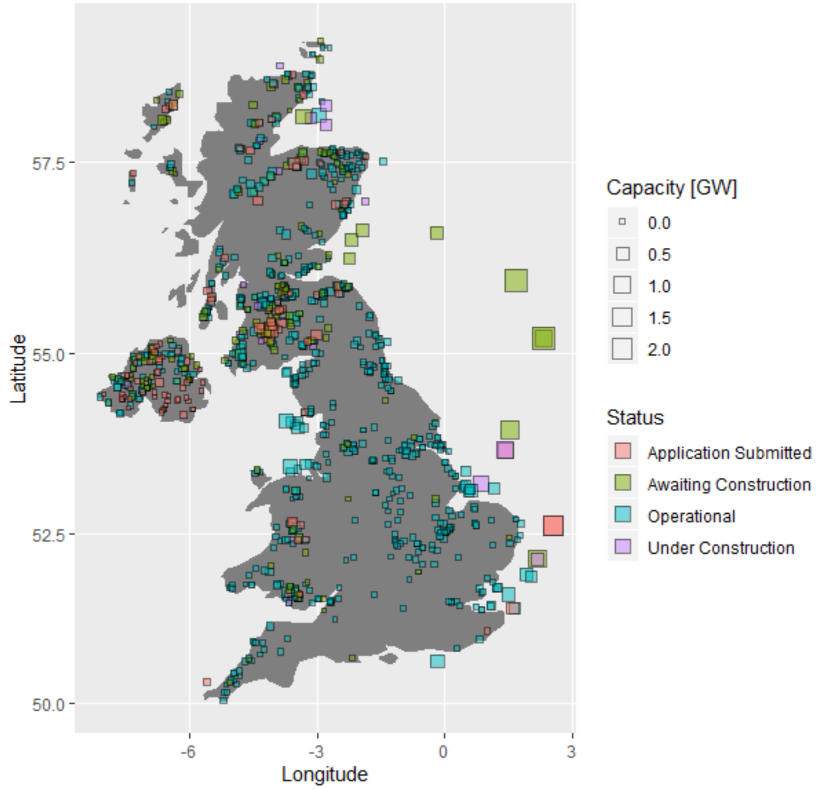
- Generation and supply ***portfolio*** effects
- Offering ***flexibility services*** as well as energy
- Uncertainty in price ***and*** volume
- ***Risk*** preferences

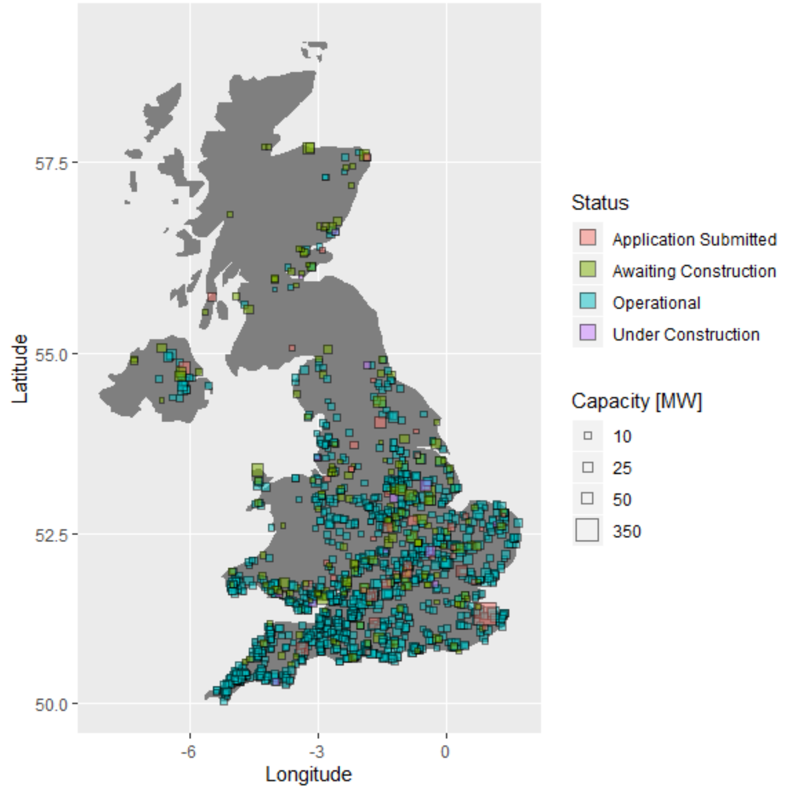
NB: This could apply at the local level in the future too!

Weather-dependent Generation

As of Dec 2019:

- 987 Wind Farms
- 1379 Solar Farms (+domestic PV)





https://www.gov.uk/government/publications/renewable-energy-planning-database-monthly-extract

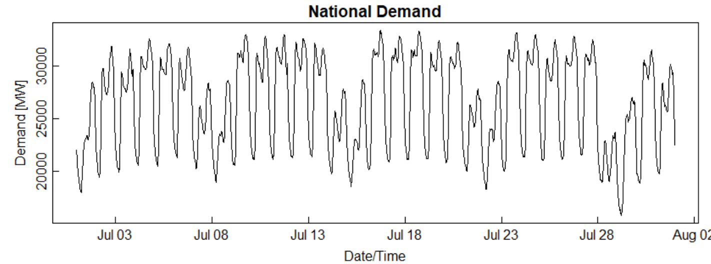
Demand Hierarchy (GB)

1 Transmission System	•Smooth profile •Significant impact of embedded generation	Net-demand, interconnectors, pump-storage (10s GW)
14 Regions	•Smooth profile •Penetration of embedded generation varies	Large regions (GW)
>350 Grid Supply Points	•Variable characteristics •Some diversity of connected loads •Some dominated by large loads or embedded generation	Homes and businesses, wind and solar (10s-100s MW)
>400,000 Primary and Secondary Substations	•Variable characteristics •Some diversity of connected loads •Some dominated by large loads or embedded generation	Homes and businesses, wind and solar (<1-100s MW)
>40,000,000 (Smart) Meters	•Highly volatile and diverse characteristics •Many states/profiles, even individual meter	Dommestic or business demand less domestic solar and micro wind (kW)

Demand Hierarchy (GB)

1 Transmission System

- Smooth profile
- Significant impact of embedded generation



14 Regions

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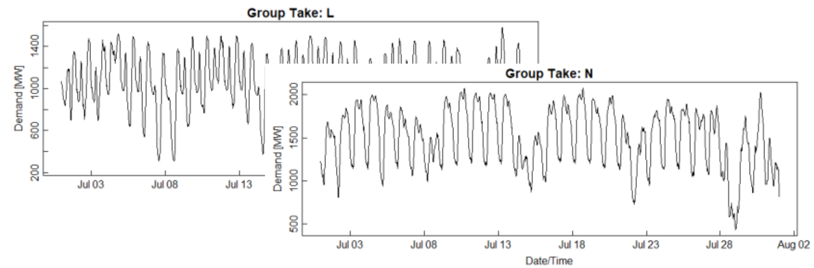

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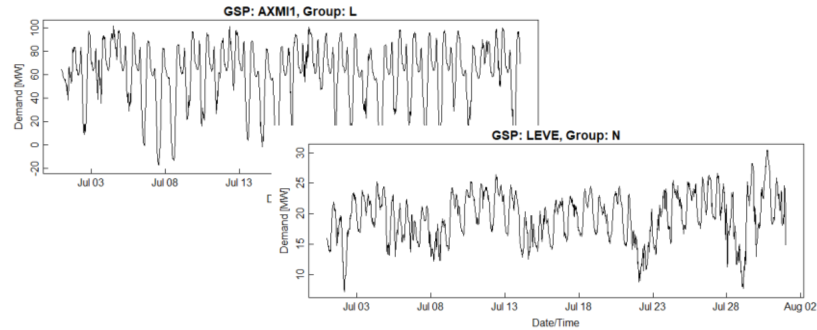

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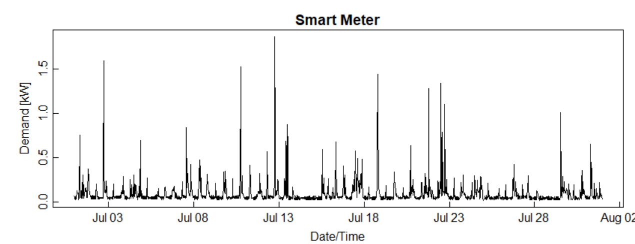
- Variable characteristics
- Some diversity of connected loads
- Some dominated by large loads or embedded generation

>40,000,000 (Smart) Meters

- Highly volatile and diverse characteristics
- Many states/profiles, even individual meter



Part 2: Leveraging turbine-level data for wind power forecasting

Work with Ciaran Gilbert and David McMillan

IEEE Trans. Sustainable Energy
https://doi.org/10.1109/TSTE.2019.2920085

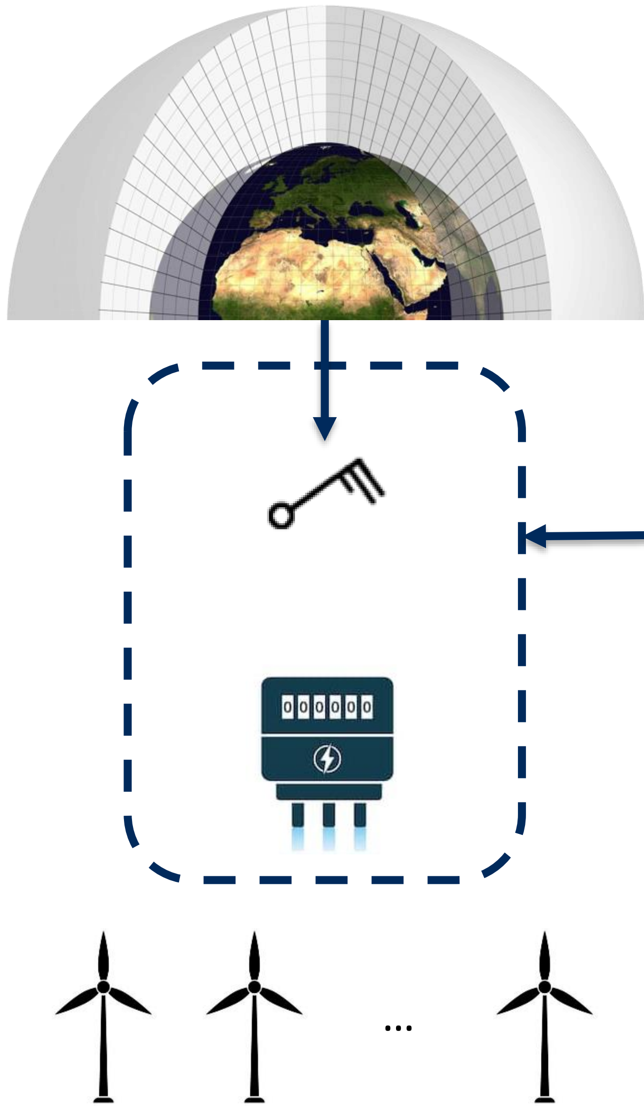
Status Quo

4D Grid of Weather Predictions

"Site" Wind Speed and Direction Forecast

Windfarm Export Meter

Wind Turbine SCADA

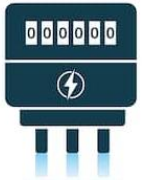


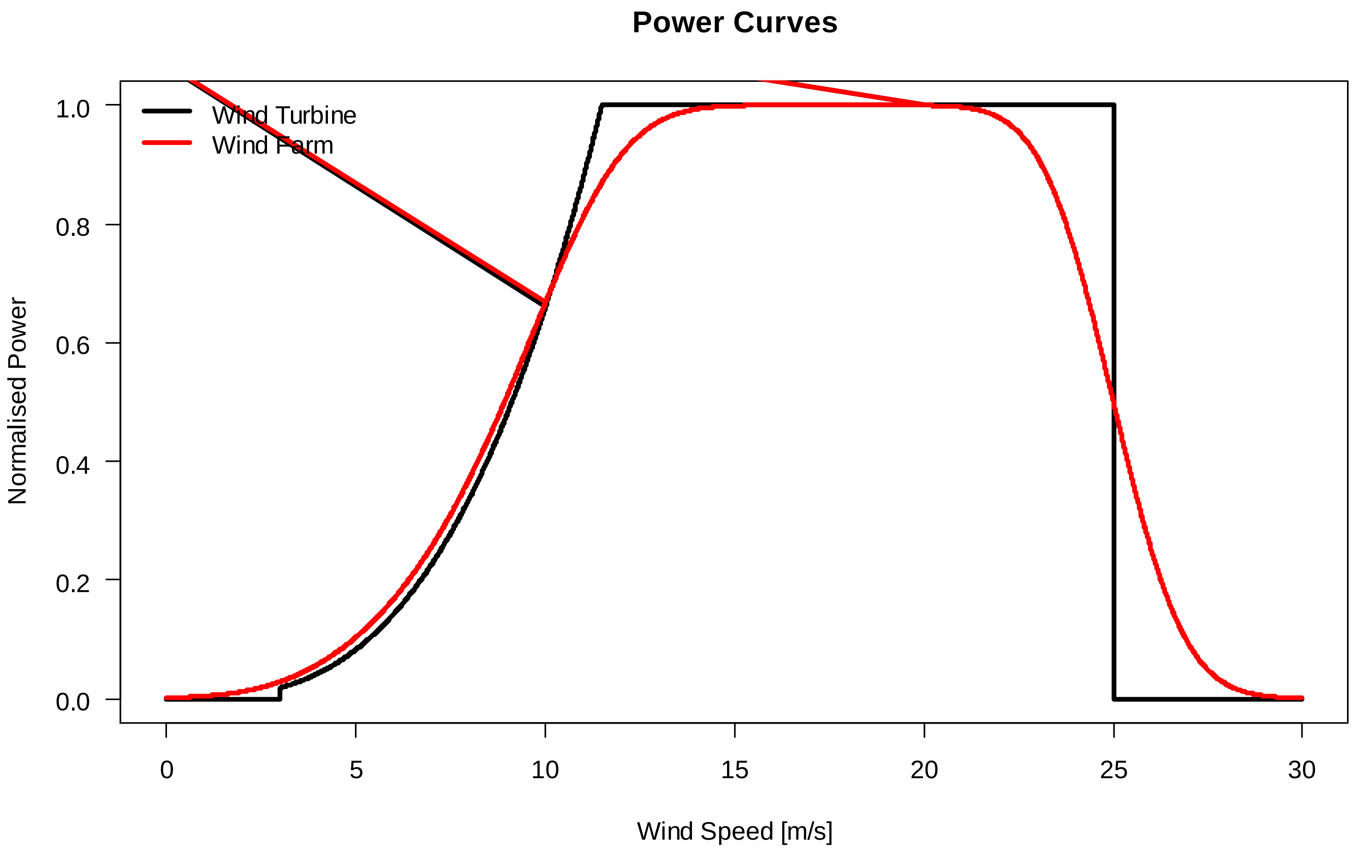
Weather-to-power relationship…

Based on farm-level power curve…

- Weather is a prediction, and therefore uncertain
- Single wind speed and direction for wind farm
- Wind farm power curve is complex and uncertain

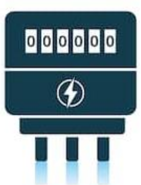
Status Quo





Power Curves
Wind Turbine
Wind Farm
Normalised Power
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
20
25
30
Wind Speed [m/s]

Status Quo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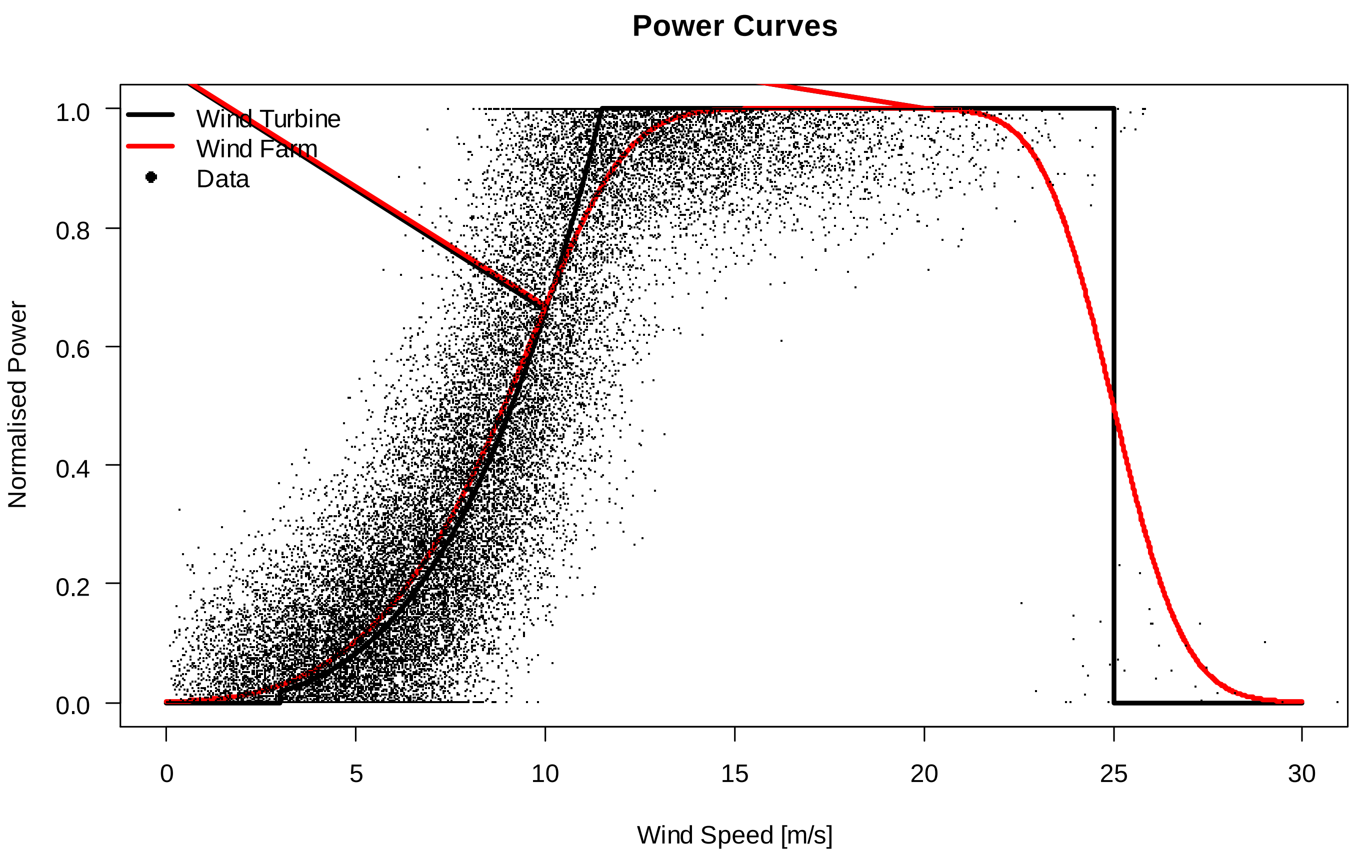
Power Curves
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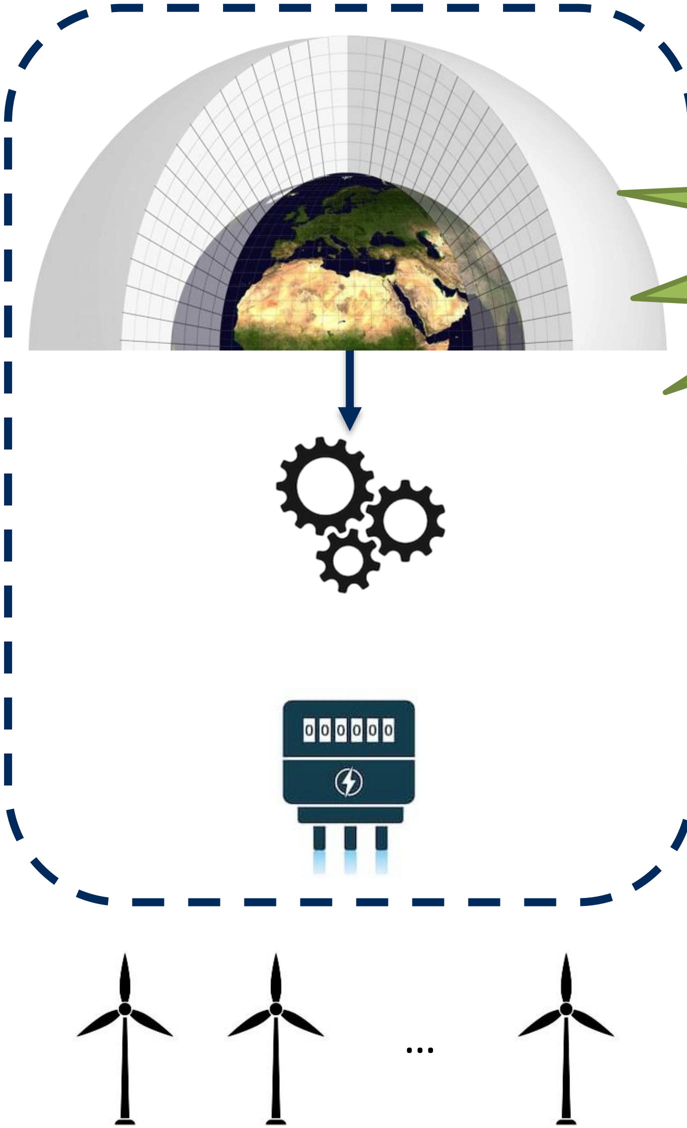
Recent evolution…

4D Grid of Weather Predictions

Feature Engineering

Windfarm Export Meter

Wind Turbine SCADA



>10% reduction in day-ahead MAE and CRPS*

Weather-to-power relationship…

Complex farm power curve…

Engineered features capture:

- common NWP biases, phase and spatial errors
- variation across large areas
- wider weather situation and indicators of uncertainty

*Andrade & Bessa (2017), doi:10.1109/TSTE.2017.2694340

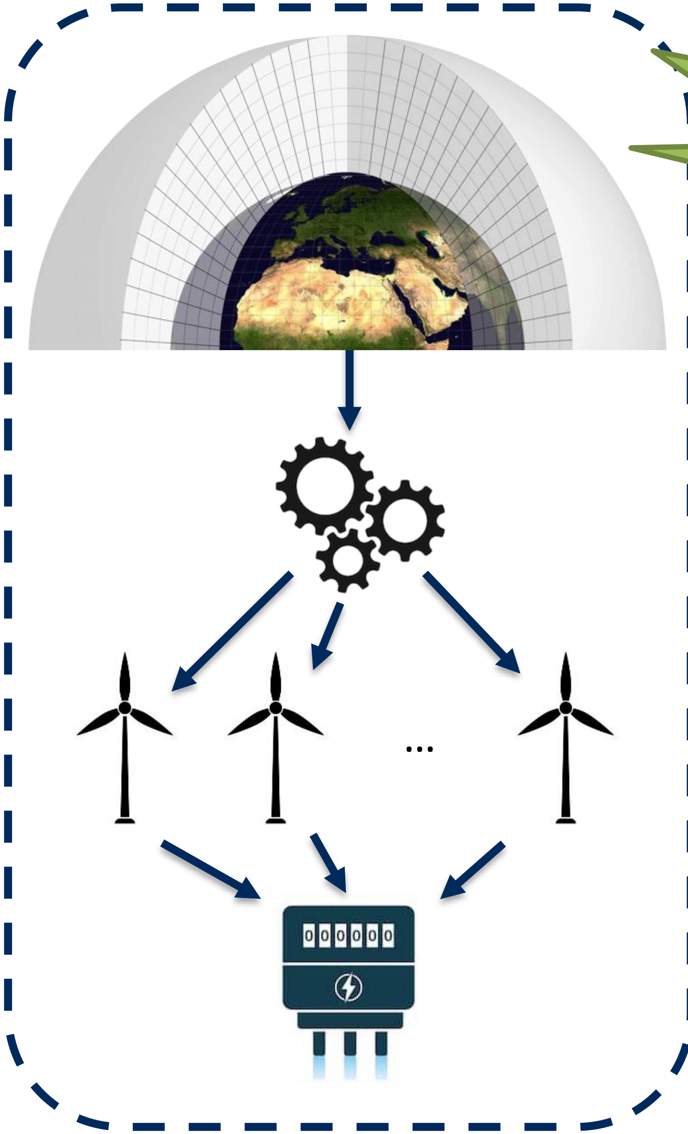
The next evolution?

4D Grid of Weather Predictions

Feature Engineering

Wind Turbine SCADA

Windfarm Export Meter



>5% reduction in day-ahead MAE and CRPS*

Weather-to-power relationship…

Complex ***turbine*** power curves…

Turbine-level data enables:

- reduction in epistemic uncertainty
- direct incorporation of availability
- advanced very short-term forecasting

*Gilbert, Browell & McMillan (2019), doi:10.1109/TSTE.2019.2920085

Hierarchies in Forecasting

Motivation:

1. Gather as much information as possible to improve forecast skill
   - Electricity network is a natural hierarchy
   - Turbine – Farm – Region – National/Zone
   - Information from other levels can improve predictive performance
2. Coherency across hierarchy
   - Some applications require that forecasts from lower level to sum to upper level, e.g. market settlement

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Hierarchies in Forecasting

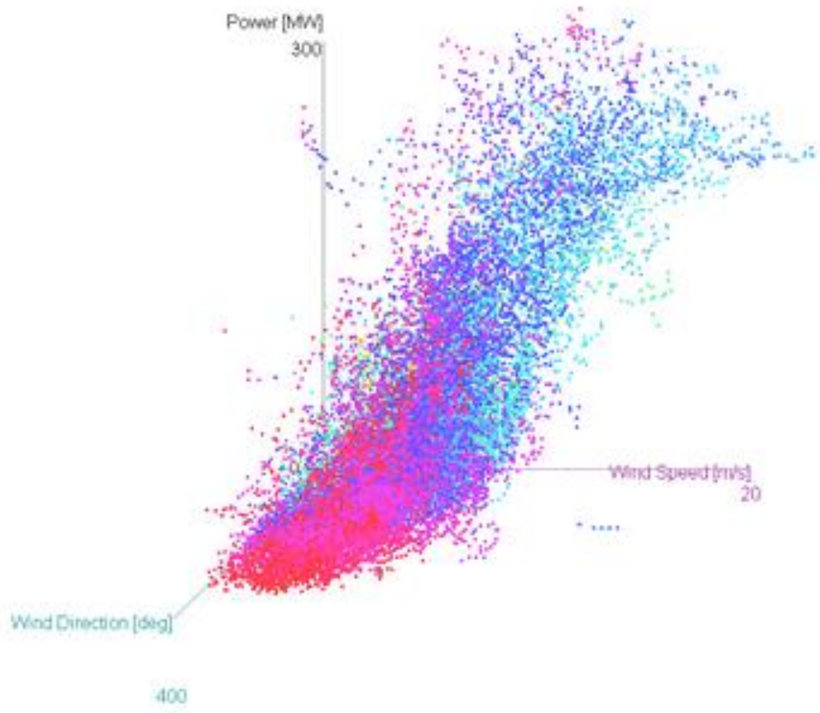
University of Strathclyde Glasgow

- Wind farm power curve is complicated by many factors: layout, terrain, interactions
- It is difficult to distinguish between random variation and true processes…

Smoothing vs Training Error

- …can looking at individual turbine behaviours can help extract more signal from the noise?

Hierarchies in Forecasting



Methodology Overview

Objective

- Extend forecasting methodologies to incorporate turbine-level information
- Produce improved probabilistic (density) forecasts

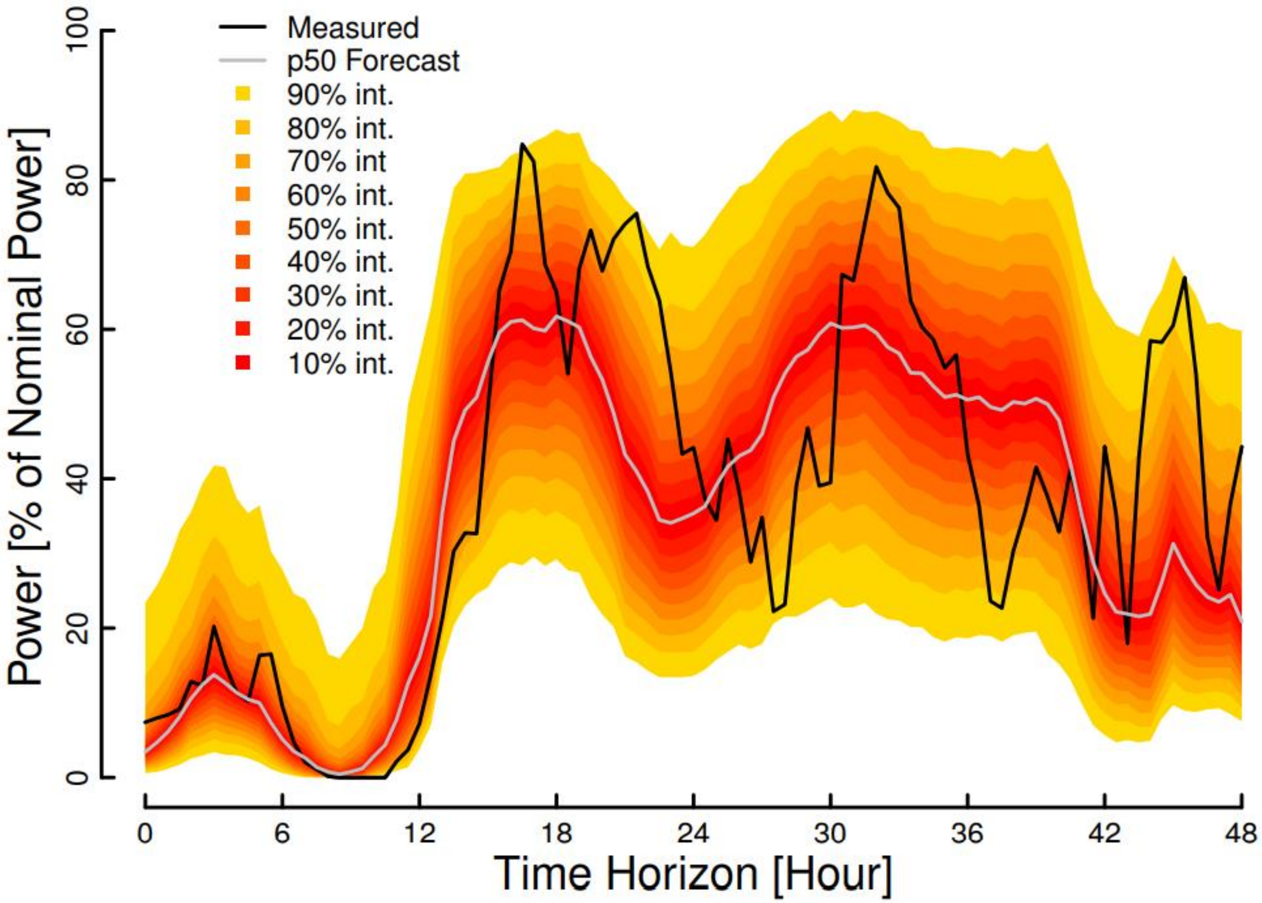
New Approaches

1. Bottom-up: predict energy production for individual turbines and use as additional explanatory information
2. Spatial Dependency: predict the full joint distribution of energy production from all turbines in a wind farm

Benchmarks (using NWP and windfarm data only)

1. Analog Ensemble (*k*NN) – super robust and competitive
2. GBM/quantile regression – leading machine learning algorithm

Objective: Density Forecasts



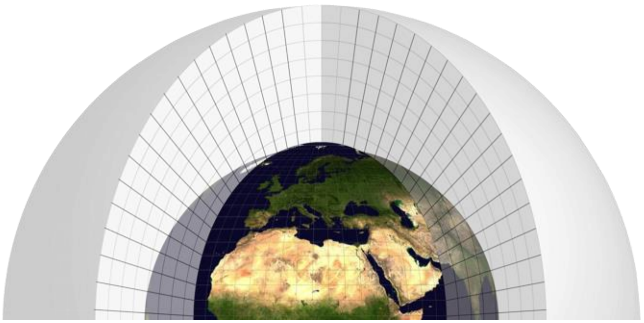
Benchmark

GBM

- Gradient Boosted Decision Tree – a powerful non-linear function approximator
- Quantile regression: one model per quantile: 5,…,95
- Inputs: features derived from NWP
- Target: Windfarm power

Density forecast for wind farm

$$q^{\alpha} = f^{\alpha}_{\mathrm{GBM}}(\boldsymbol{x}_{\mathrm{NWP}})$$



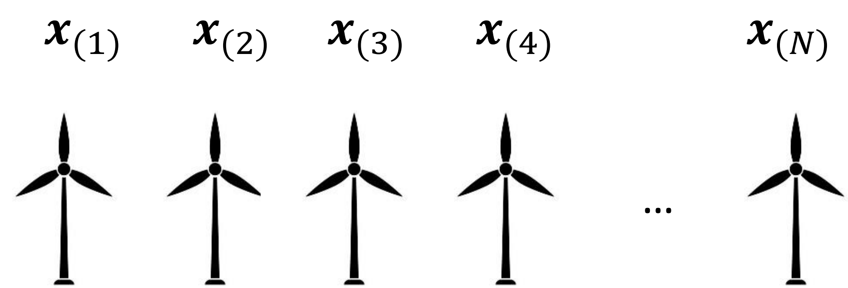
Bottom-up Approach

Bottom-up

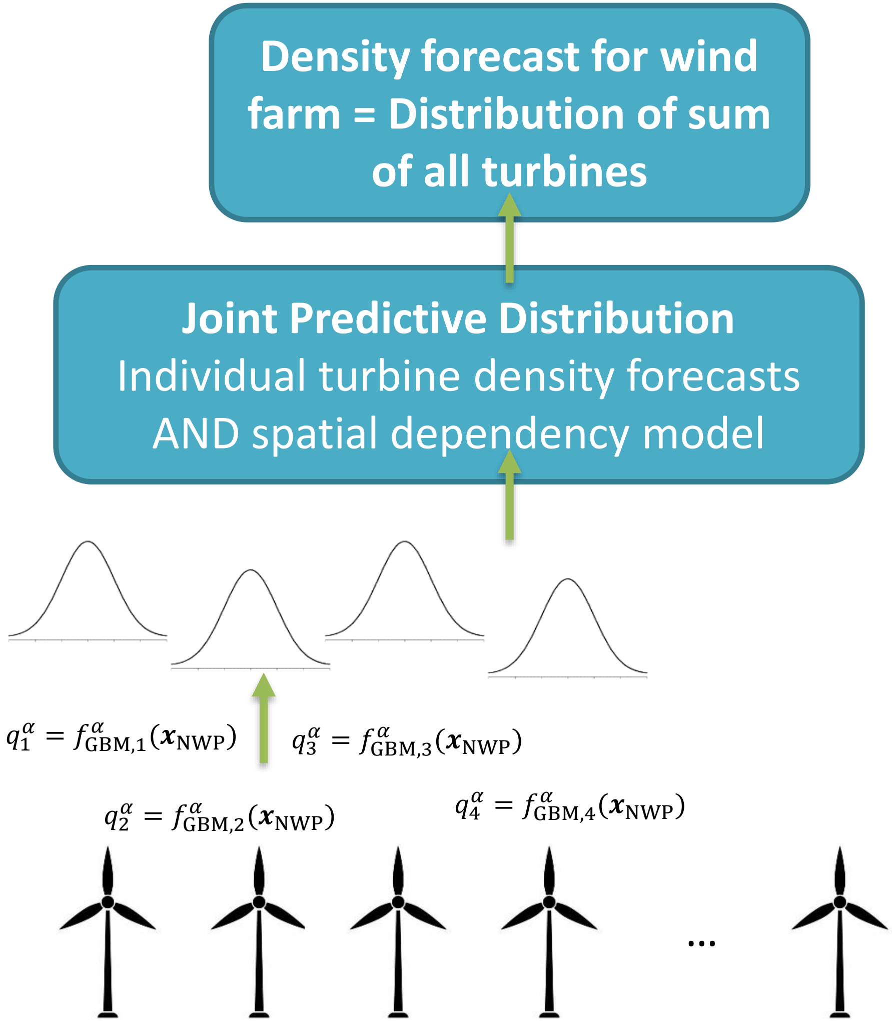
1. Produce deterministic forecasts for each individual turbine
2. Use these as ***additional features*** in a windfarm power forecasting model

Density forecast for wind farm

$$q^{\alpha} = f^{\alpha}_{\mathrm{GBM}}(\boldsymbol{x}_{\mathrm{NWP}}, \boldsymbol{x}_1, \dots, \boldsymbol{x}_N)$$



Spatial Dependency Approach



Spatial Dependency Approach

1. Produce density forecast for each turbine
2. Model spatial dependency using Gaussian copula with parametric covariance
3. Sample and sum turbine power prediction
4. Construct wind farm density forecast from samples

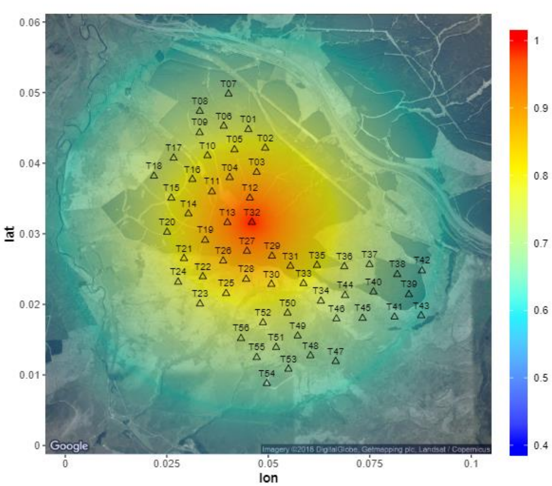
Additional Benchmarks:

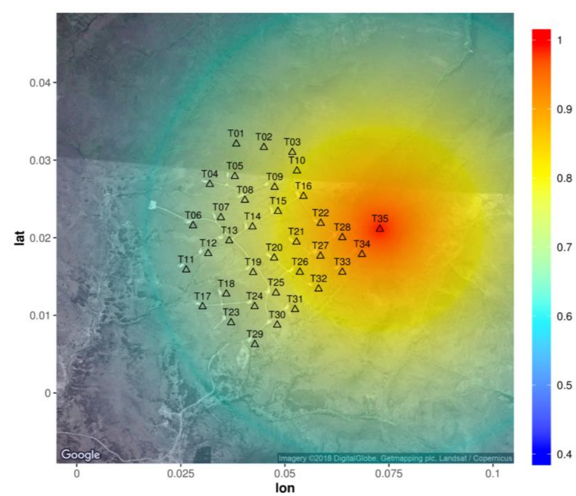
1. Empirical Covariance (training data)
2. Vine Copula (facilitates more complex spatial structure)

Case Study

Set up

- 2 Wind Farms with 56 and 35 turbines
- NWP inputs plus ***engineered features***
- 30 minute wind farm production
- 30 minute wind turbine production
- Produce probabilistic (density) forecasts up to 48h ahead

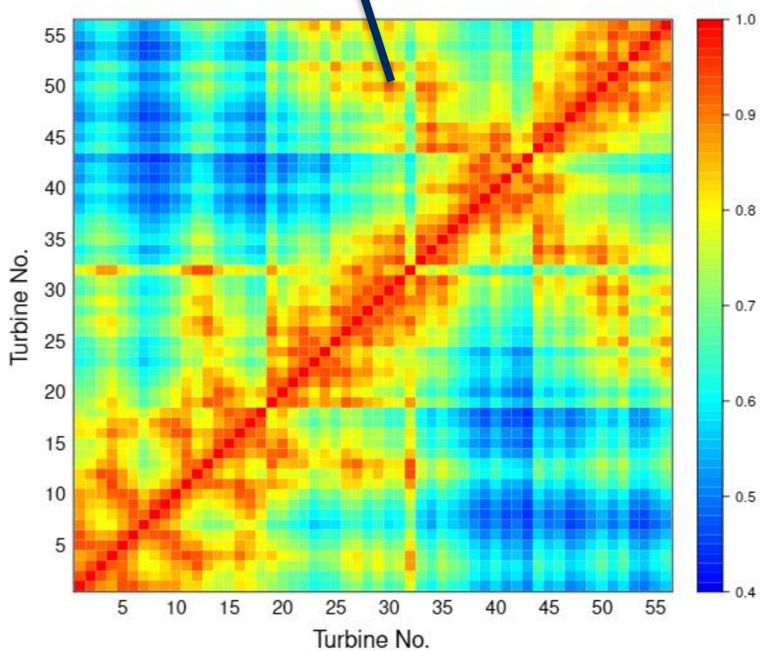


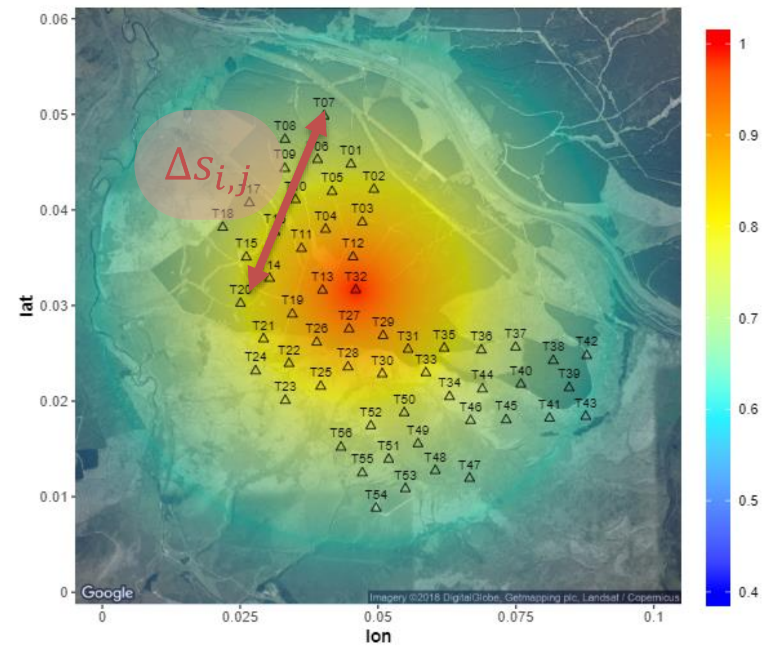


Spatial Structure at WF-A

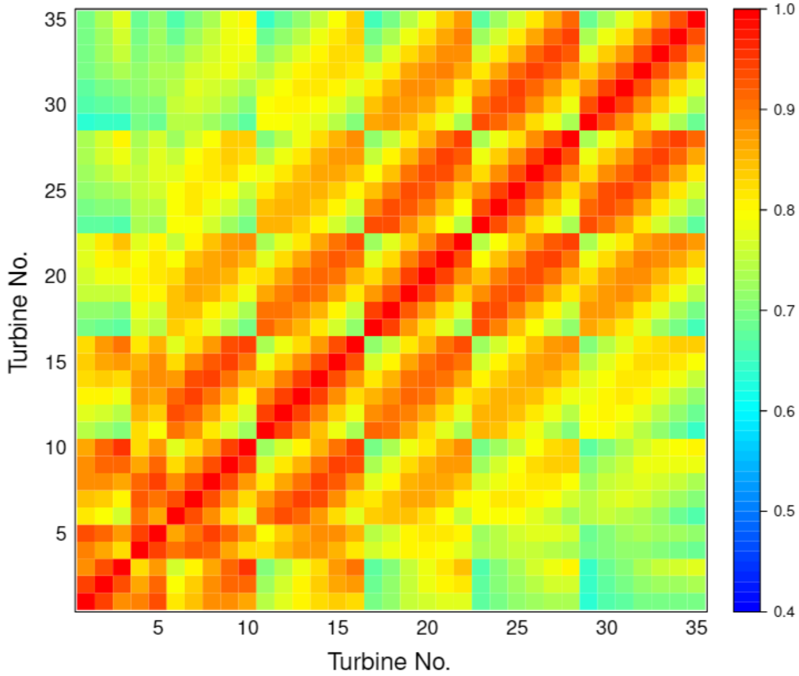
$$\Sigma_{i,j} = \exp\left(-\frac{\Delta s_{i,j}}{\eta}\right)$$

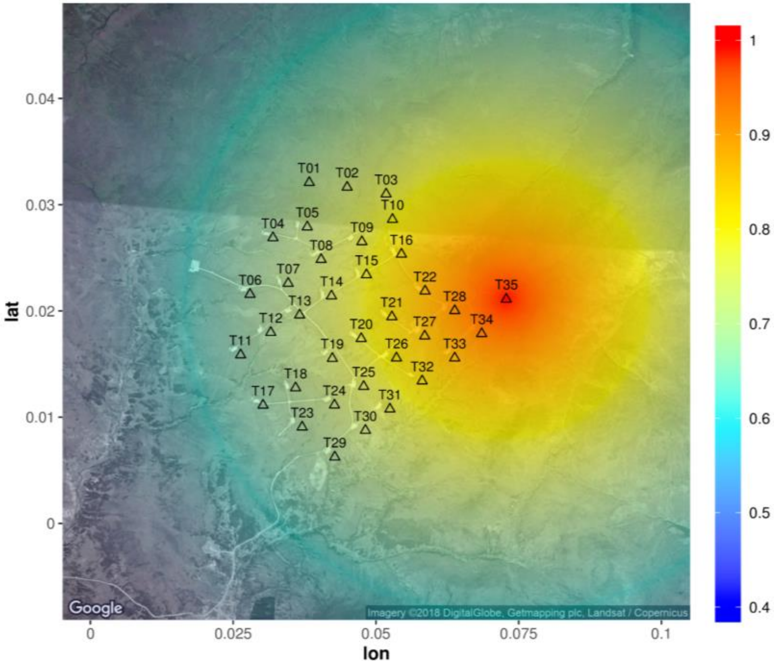
Only one parameter to estimate



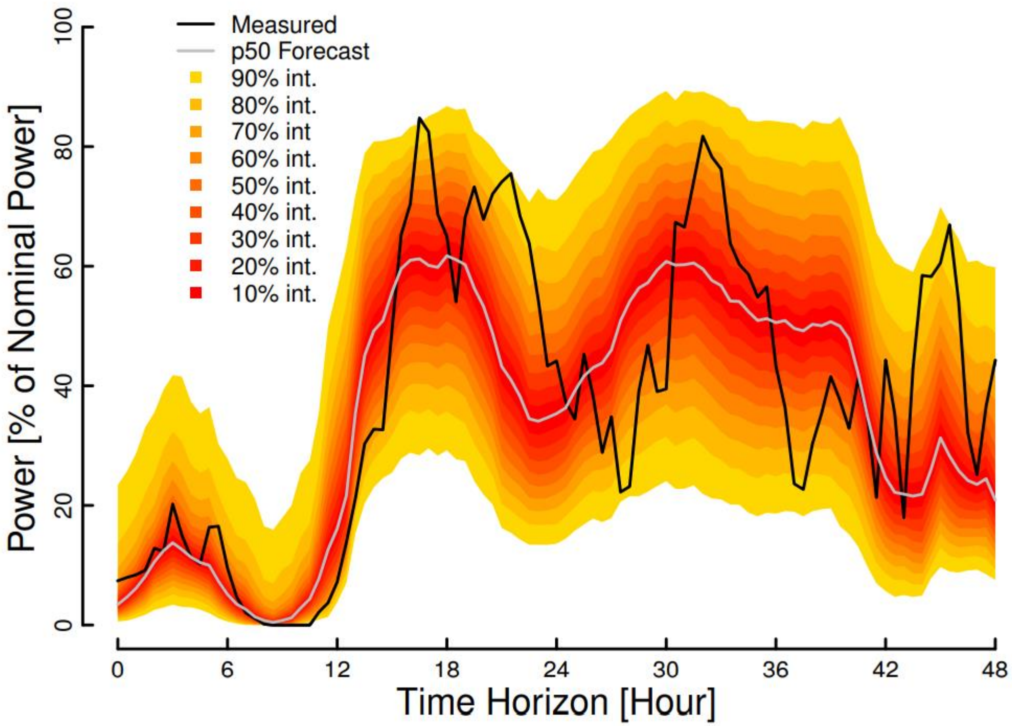


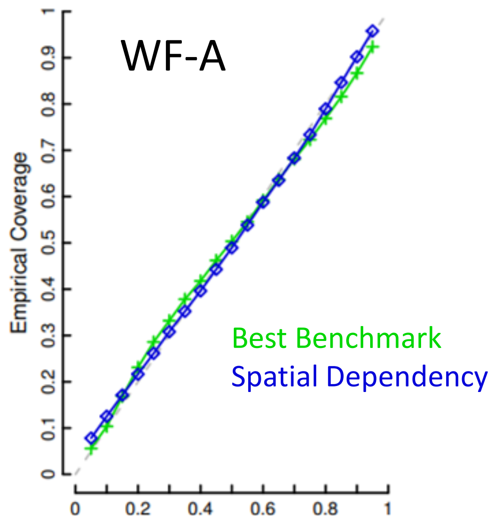
Spatial Structure at WF-B

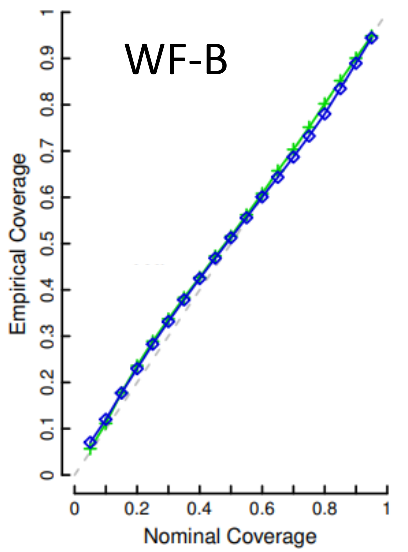




Results: Reliability

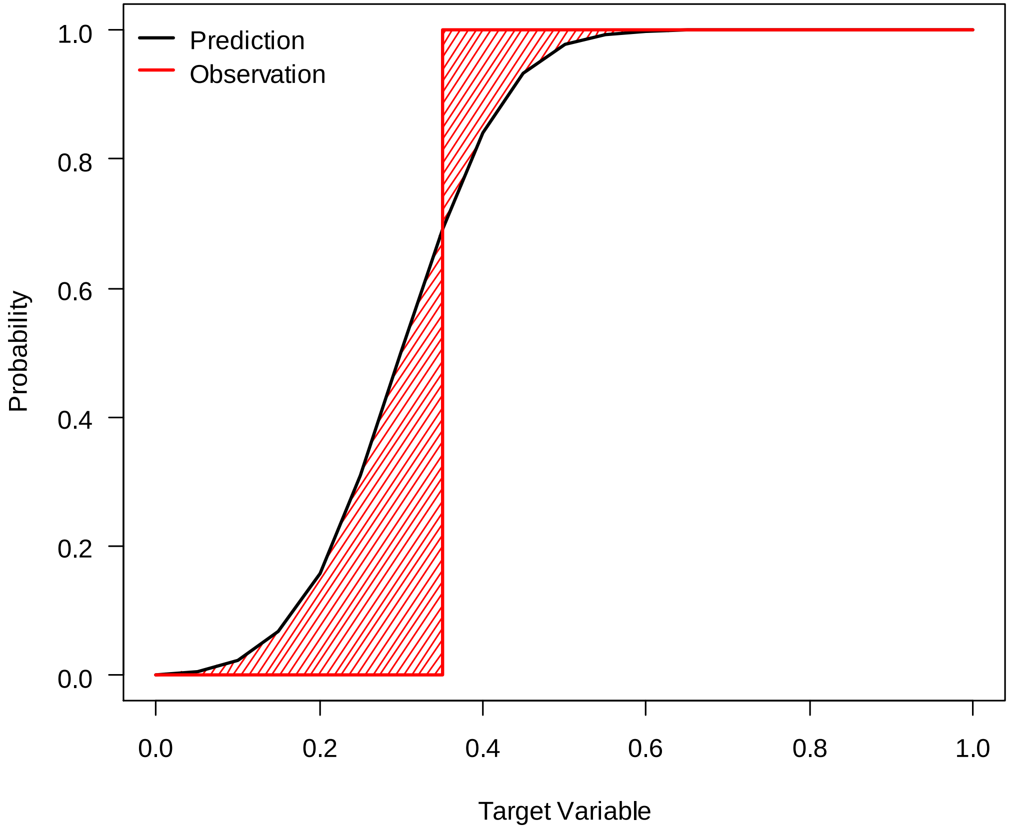






Results: CRPS

Continuous Ranked Probability Score



Rewards both sharpness and reliability

Continuous form of quantile loss

Results: Scores

Windfarm	Score	Best Benchmark	Bottom-up	Full Spatial Model
WF-A	**MAE**	9.69	9.27	***9.11*** *(6%)*
	CRPS	7.02	6.74	***6.66*** *(5%)*
WF-B	**MAE**	11.39	***11.21*** *(2%)*	11.26
	CRPS	8.10	***8.00*** *(1%)*	8.02

Additional benchmarks…

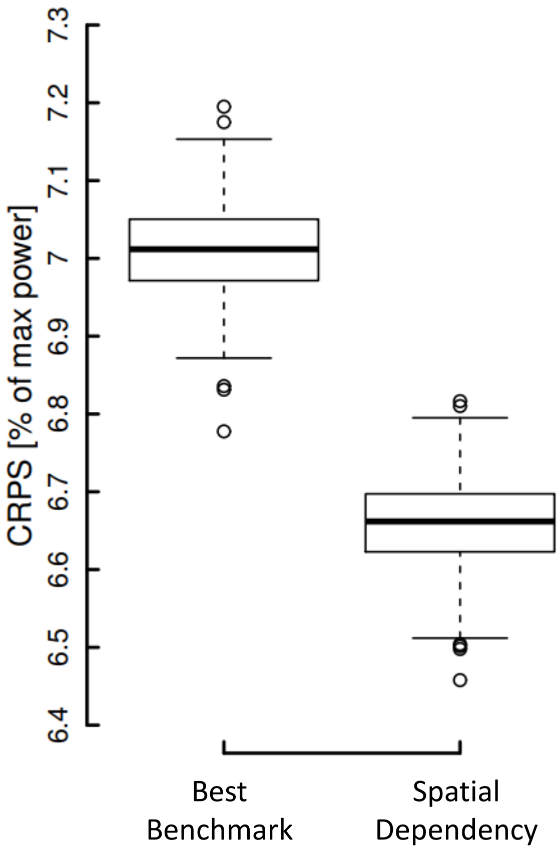
Empirical Covariance and Vine Copula

…performance a little worse than parametric covariance model.

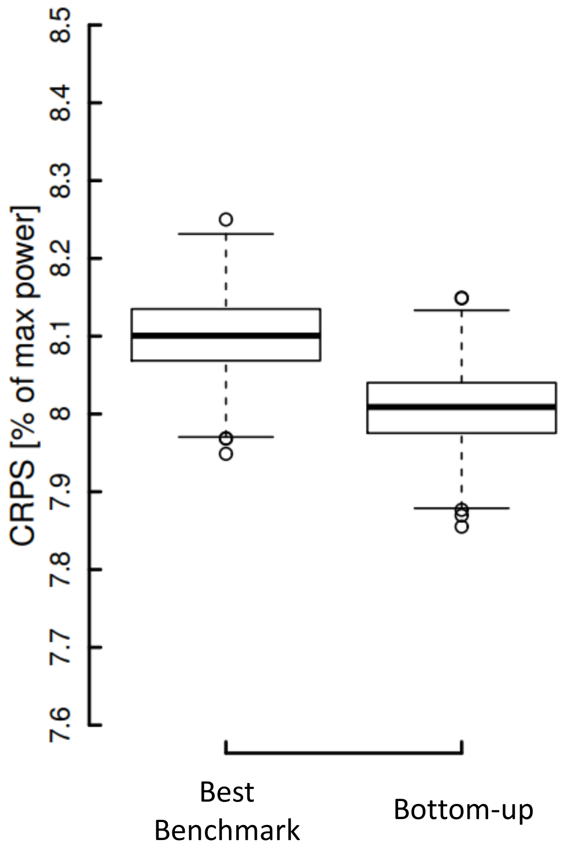
Results: Scores

Significance of improvement: sampling variation

WF-A



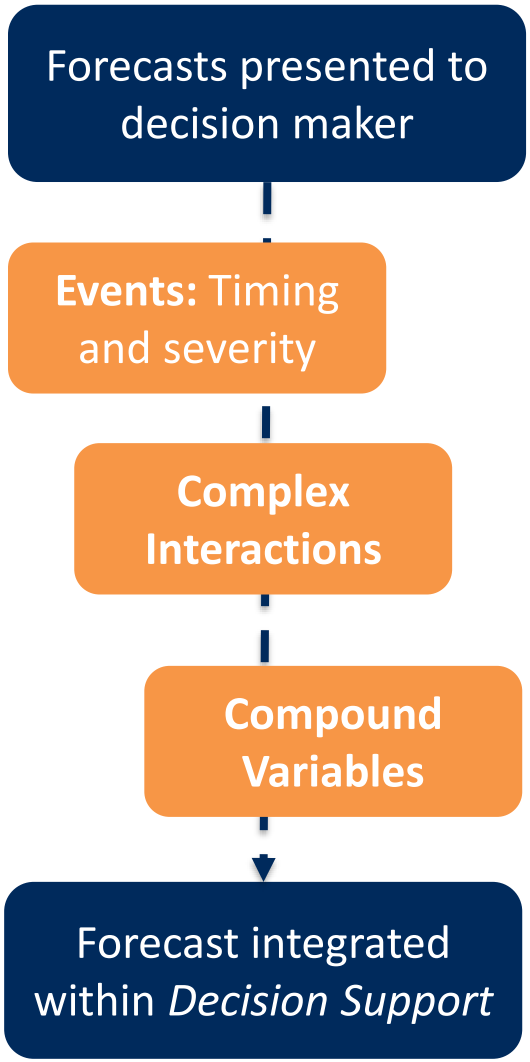
WF-B



Recommended Practice (coming up next!) & Forthcoming paper in *Wind Energy* by IEA Task Members

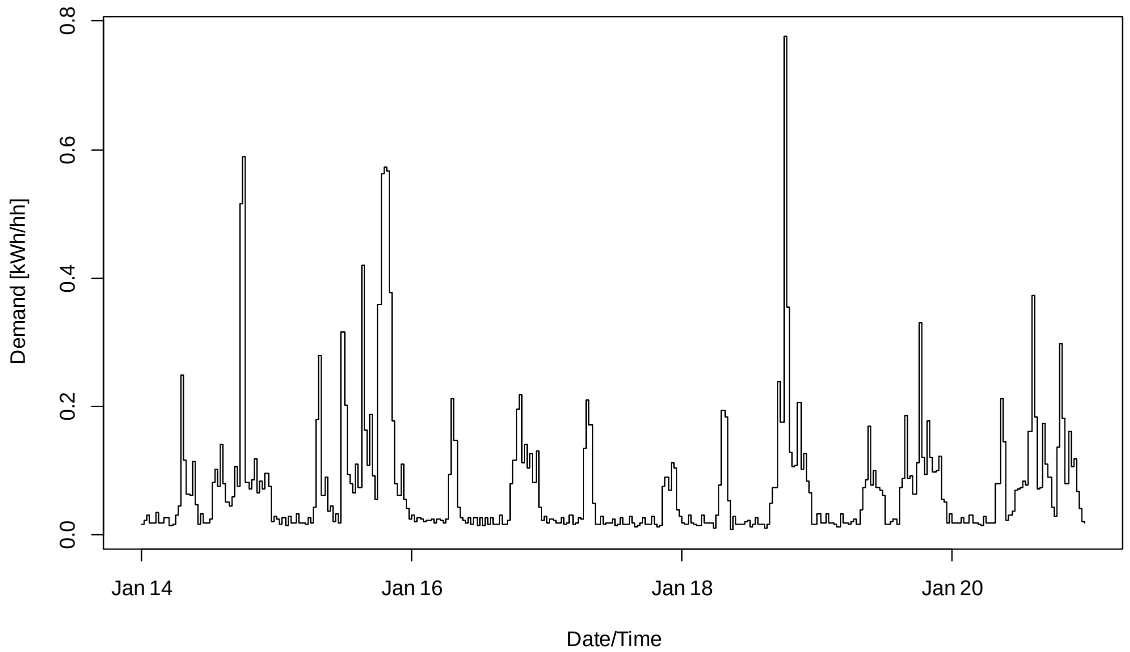
Part 3: Some challenges in energy forecasting

What do we want to predict anyway?



- **Energy:** Blocks of energy for trading and scheduling
- **Power:** ramps for system operation; instantaneous power for ancillary service provision
- **Interdependency with markets:** risk management**,** algorithmic trading
- **Network flows/constraints:** constraint management and regional balancing

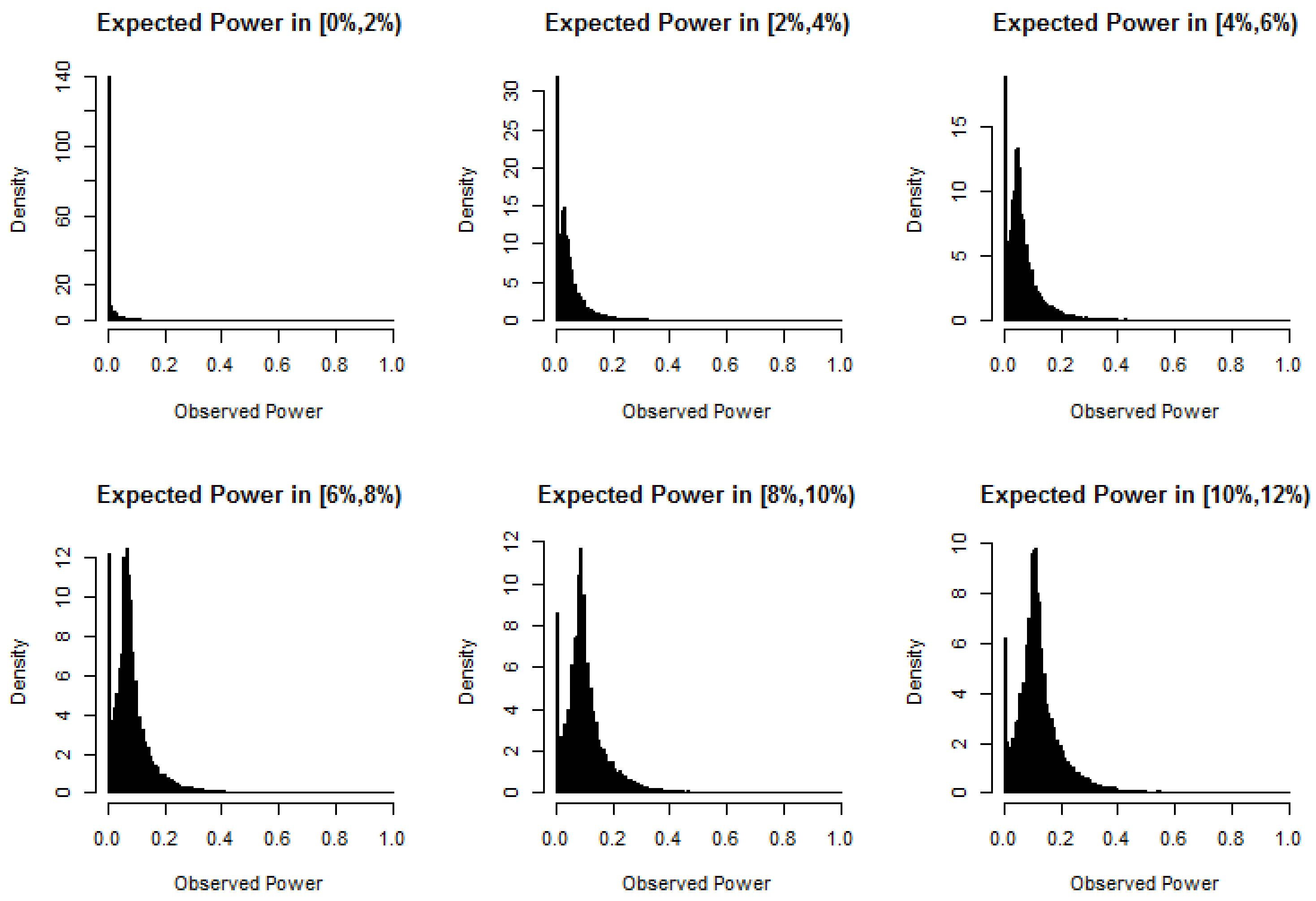
What do we want to predict anyway?



- **Value:** reducing peak demand to avoid need for network reinforcements
- **Driver:** Individual peaks and group diversity
- **Prediction:** Auto-regression/OLS not appropriate! Possibly some sort of generative model?
- **Evaluation:** Event-based? Reproduction of characteristics/statistics?

Very short-term

Challenge: AR with bounded process



Very short-term

Challenge: AR with bounded process

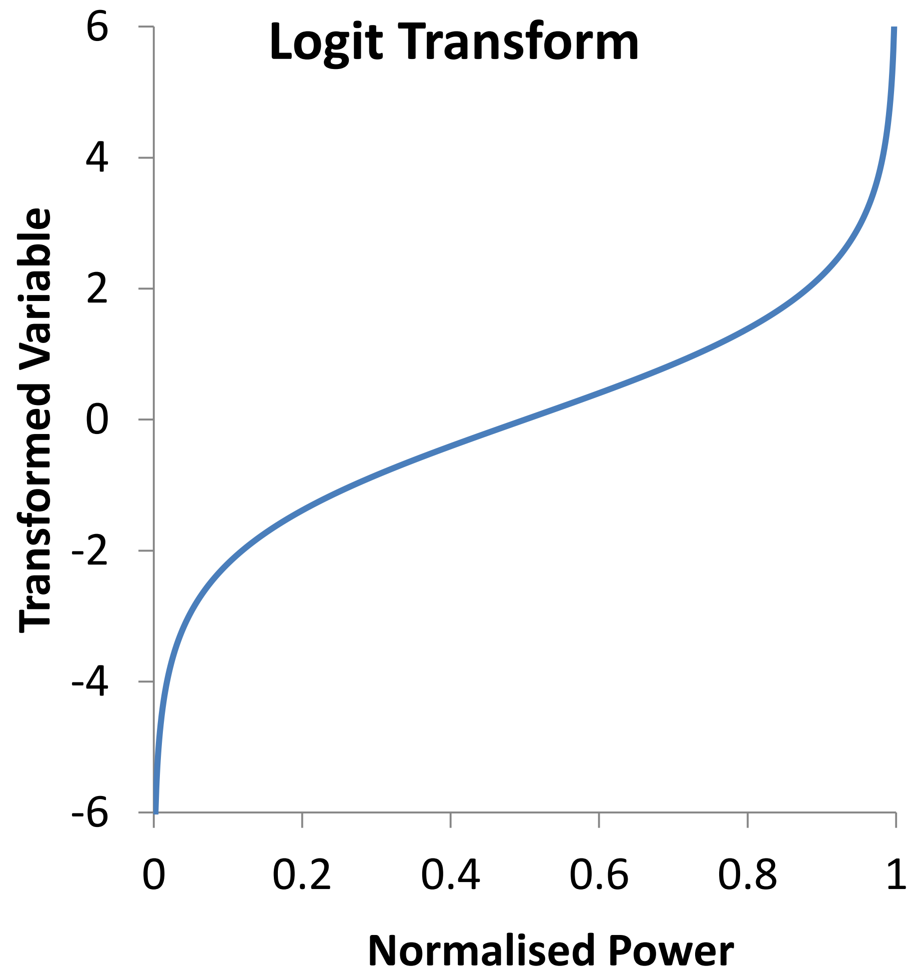
Censored Distributions

- Censored Normal

Transformation

- Copula
- Logarithmic

$$y = \ln\left(\frac{x}{1-x}\right), x \in (0,1)$$



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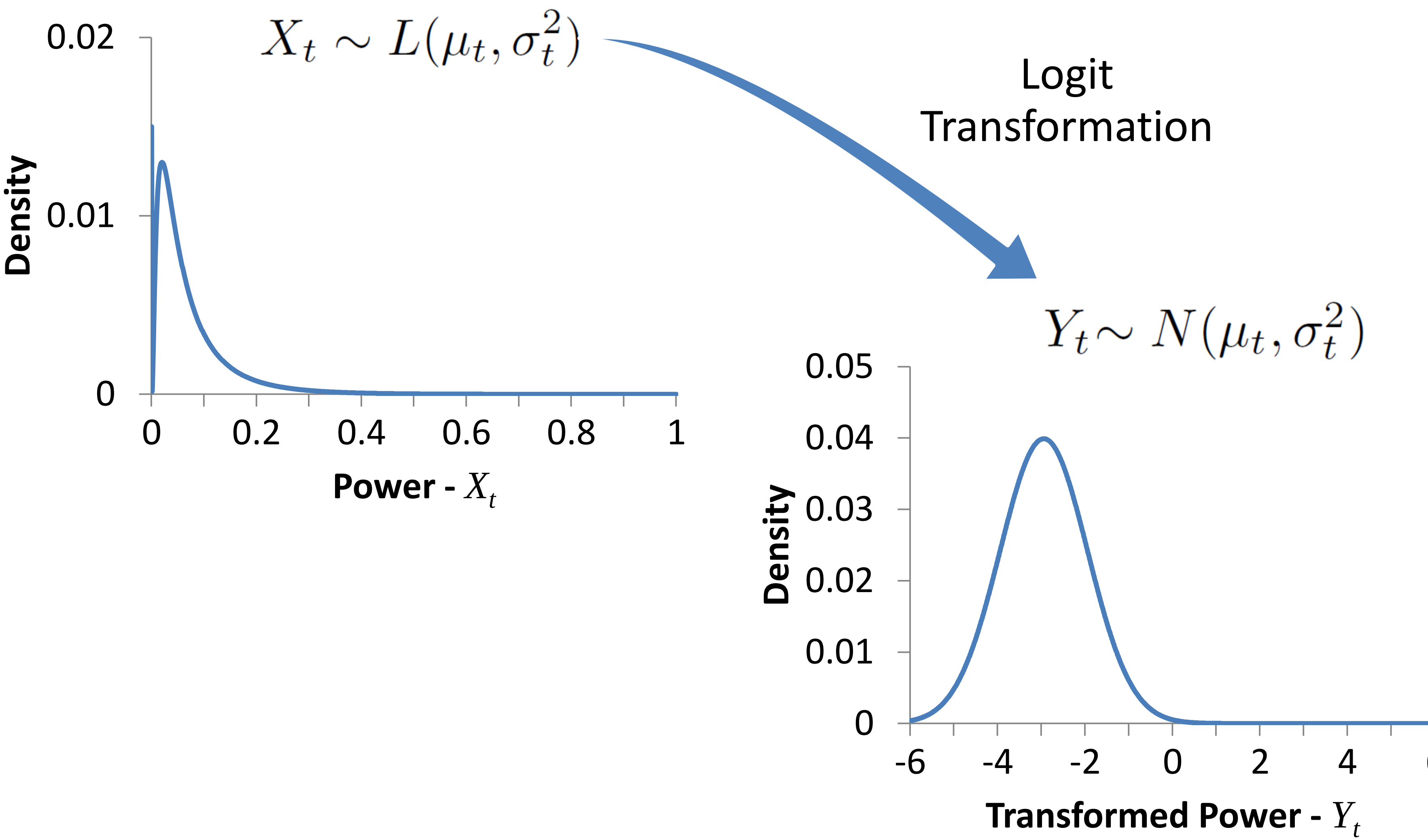

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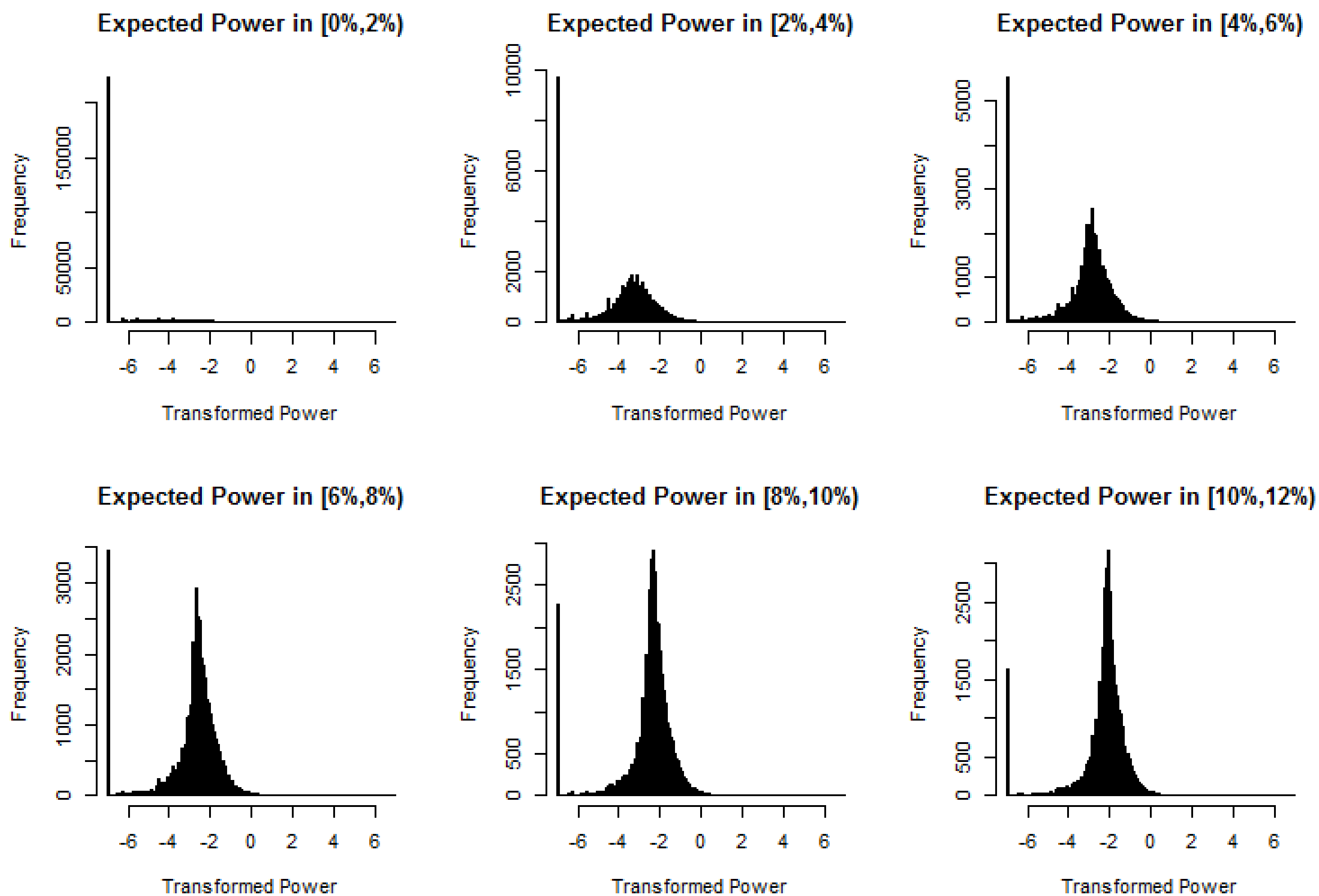

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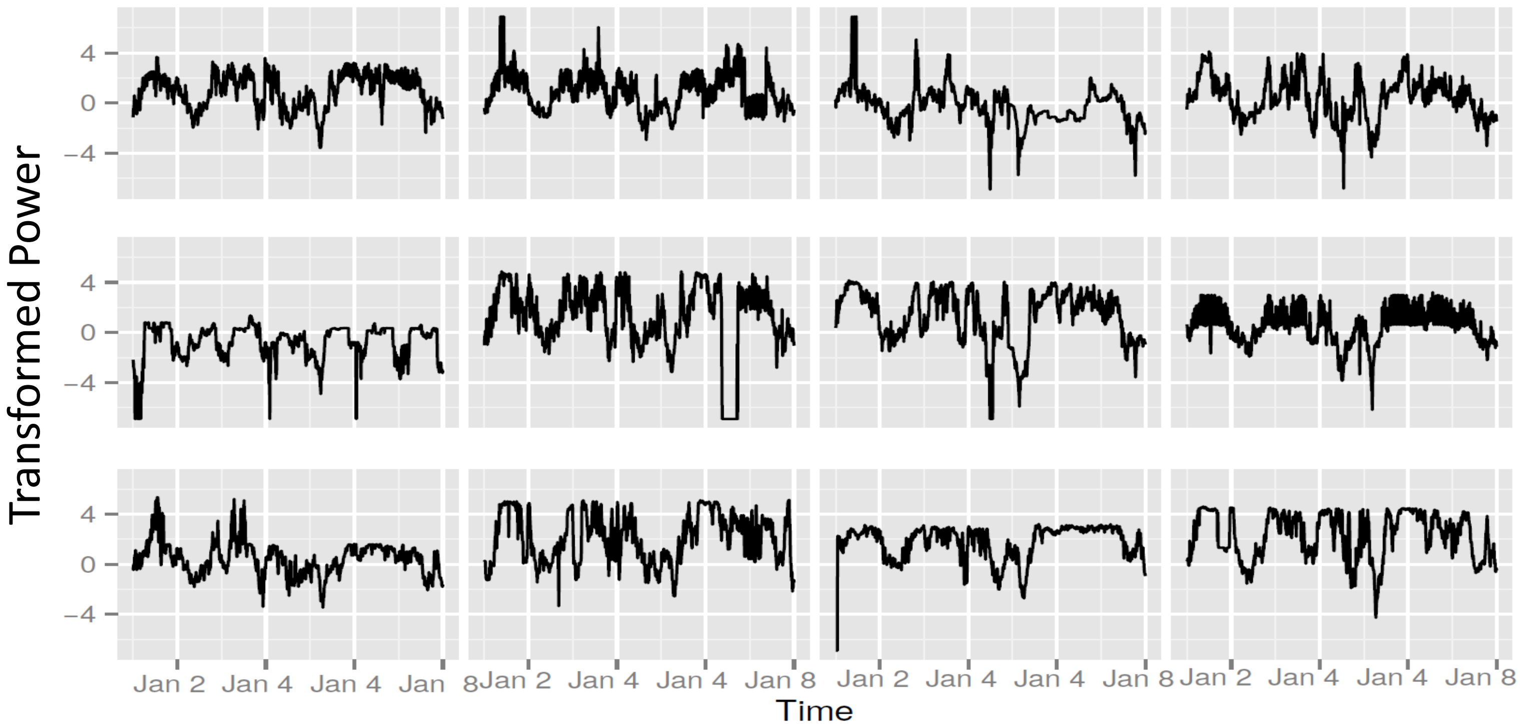

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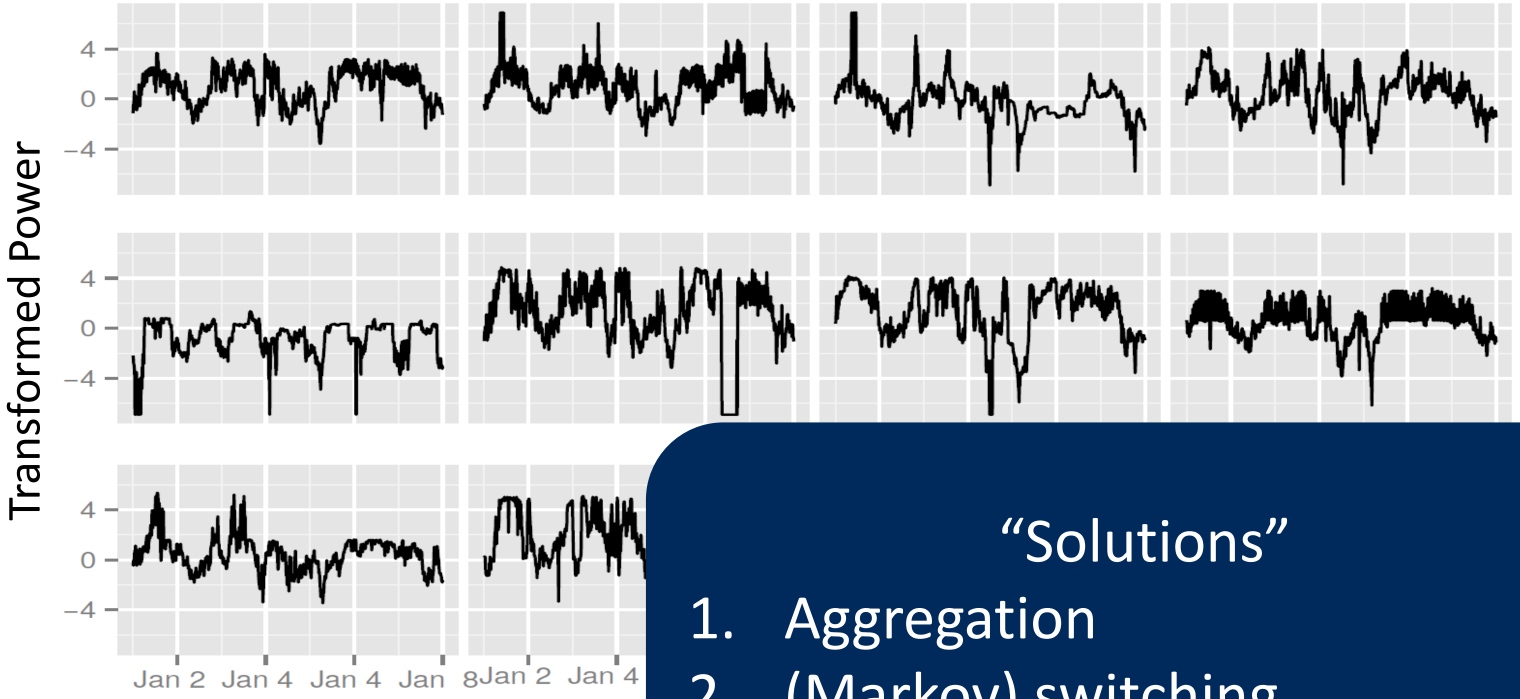
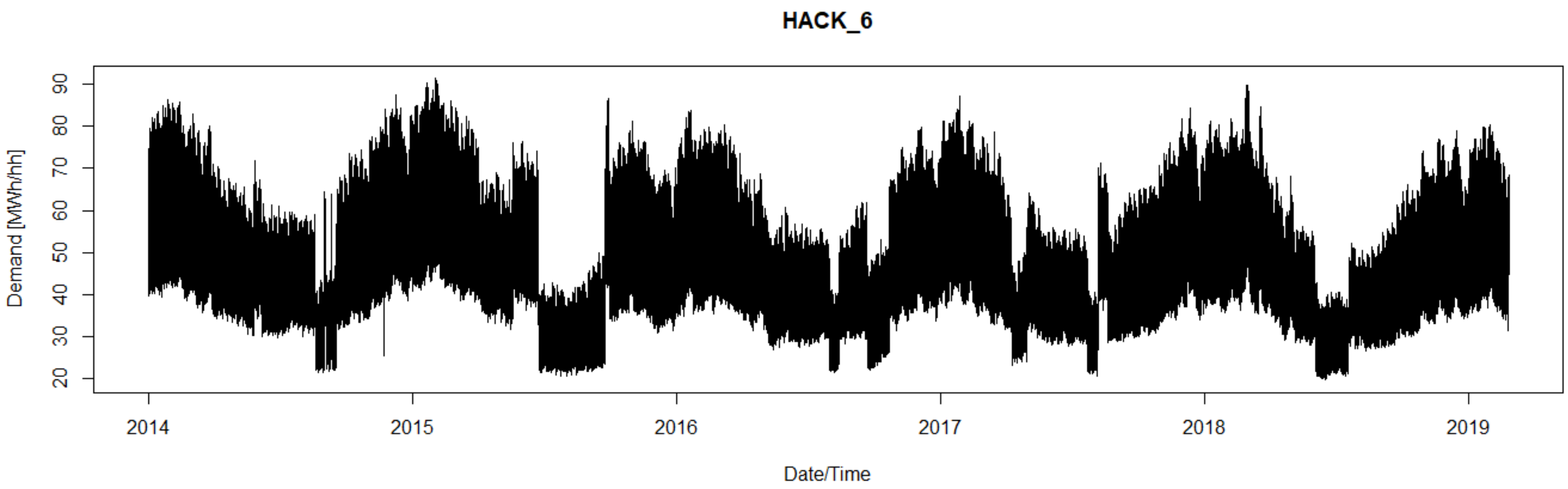


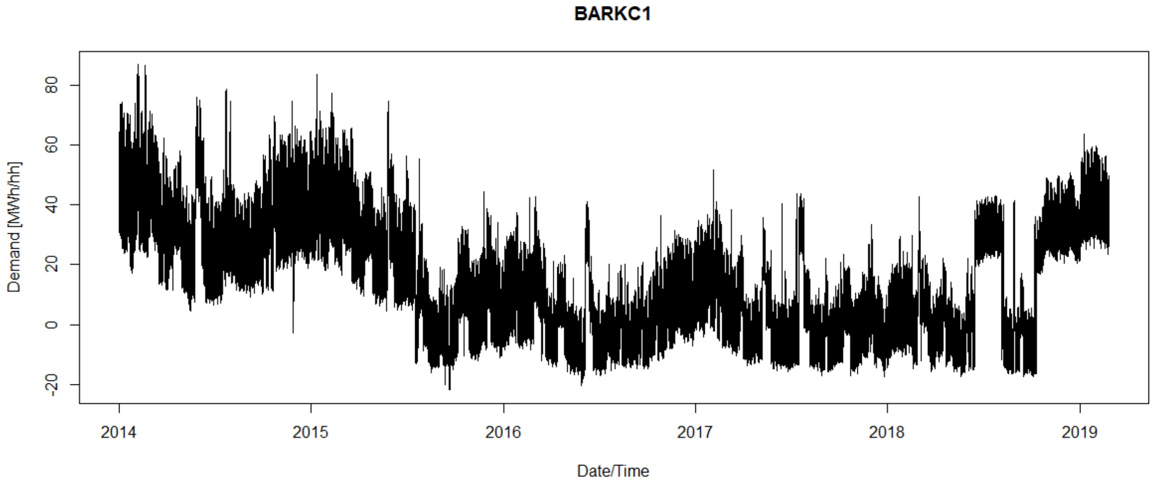
"Solutions"

1. Aggregation
2. (Markov) switching
3. Censoring

Change Points

For model training and operational forecasting





Summary

- Energy forecasting is in increasing demand, both practice and end-use is evolving rapidly
  - Data-science driving innovation
  - Forecasts should get a little better
  - Potentially more ***value*** will come from improving the way we use forecast information in the future…

- We can leverage existing sources of data to improve wind power forecast with software alone!

- Forecasting needs to be better connected to use-cases:
  - **Events** are often more important than time series (which can be misleading)
  - **Decision-support** for spatially-constrained problems: regional balancing, network constraints

Thanks!

Papers and more at jethrobrowell.com

University of Strathclyde Glasgow