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A specialist energy consultancy

# Using probabilistic forecasting in electricity transmission system operation

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25/05/2022

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# Summary

Findings from an NGESO Network Innovation Allowance project, completed by TNEI in collaboration with the University of Strathclyde and the University of Edinburgh

We showed that NGESO could produce high-quality skilful forecasts using the data that it already has, and methods that are available almost off-the-shelf

We also showed that these forecasts could be valuable for operational decisions within NGESO in multiple different use-cases.

# Content

1. NGESO’s current approach to forecasts and risks
2. The forecasts produced within our project
3. How those forecasts might be used
4. Conclusions and possible next steps

# Introduction to TNEI

- TNEI is an independent specialist energy consultancy providing technical, strategic, environmental and consenting advice to organisations operating within the renewable energy sector.
  - Around 80 employees in Manchester, Newcastle, Glasgow, Cape Town and Dublin.

- For this work, we had two academic partners:
  - University of Strathclyde (led by Jethro Browell, now at University of Glasgow) provided cutting-edge expertise on probabilistic energy forecasting
  - University of Edinburgh (led by Chris Dent) provided insight about the possible use of these probabilistic forecasts for decision-support

# Introduction to NGESO

- NGESO is responsible for keeping frequency within 50±0.2Hz and managing grid constraints.
- NGESO does not buy or sell electricity, but we have several levers available to help manage frequency:
  - Re-dispatch of generators from forward market positions using bids and offers in the BM
  - Ancillary services (DM, DR, DC, FFR, etc)
  - Market notices (EMNs, CMNs, LOLP)

# How does NGESO use forecasts?

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### Long term

- Margins analysis
- Summer/winter outlook

### 48h ahead

- Energy strategy team in ENCC
- Plant scheduling
- Ancillary service procurement

### Within-day

- Operational forecasts made (0-12h ahead)
- Plant rescheduling
- Plant warming

### 4h ahead

- Energy balancing team ENCC
- Plant rescheduling
- Plant dispatch

### Real-time

- Response and reserve dispatch

# Drivers of forecast error and uncertainty

The future state of the system is uncertain and there are three main drivers behind this uncertainty...

| Weather | Market Behaviour | Consumer Behaviour |
|---|---|---|
| • Wind forecast<br>• Solar forecast<br>• Demand forecast | • Plant unreliability<br>• Plant re-scheduling<br>• Price avoidance | • Demand forecast error<br>• TV pickups<br>• Holidays and special events |

# How does NGESO manage forecast uncertainty

- Operational reserves are required to account for forecast error and uncertainty
- We currently set reserve levels twice a year using a statistical analysis of historic forecast errors
- Sizing reserves "*appropriately*" is important for secure operation of the system
  - "Appropriate" is a function of historical plant reliability, forecast errors, and NGESO's risk appetite

# How does NGESO manage forecast uncertainty

- Compile three-year historic time series of:
  - Changes to BMU PNs
  - Wind forecast errors
- Sum timeseries
- Remove outliers
- Group time series by:
  - GMT/BST
  - Day of week
  - Cardinal point
- Select 99.75% quantile as reserve level
- Add on median wind forecast error

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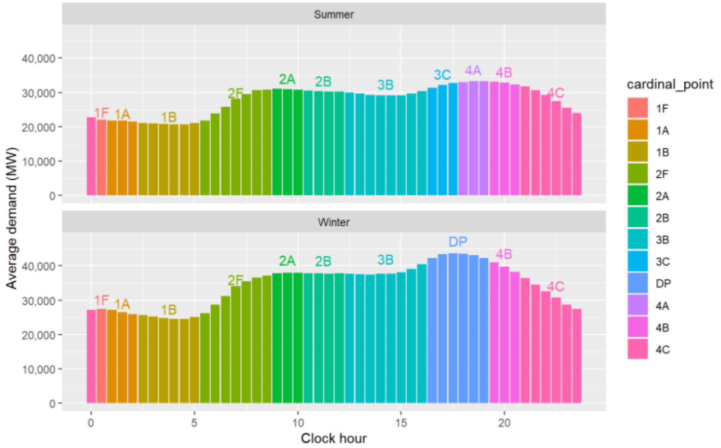
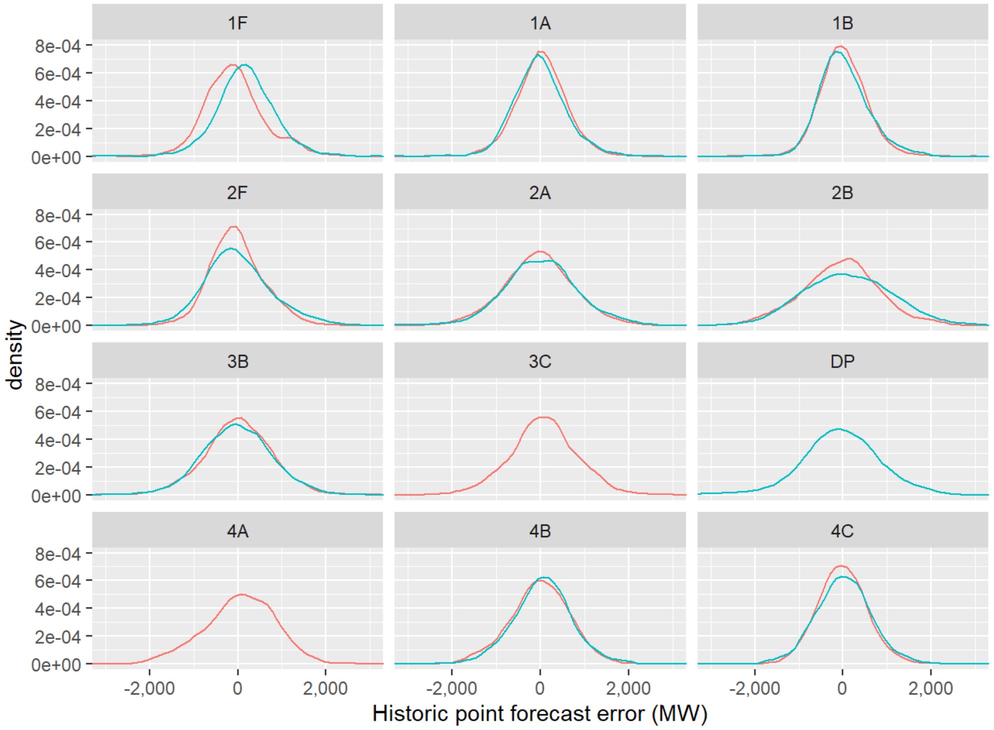
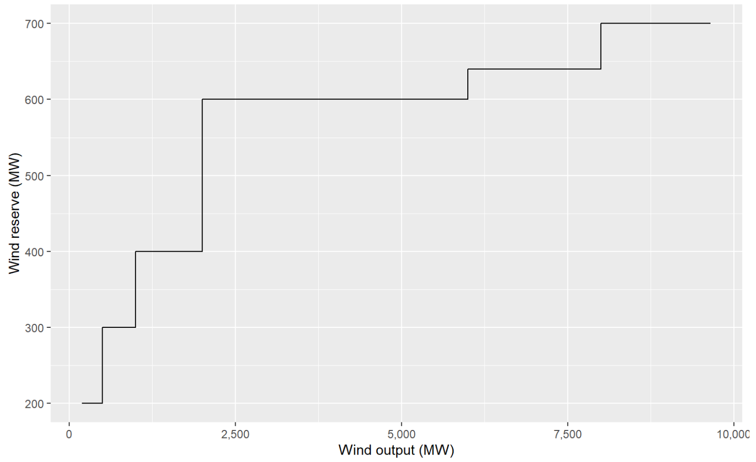


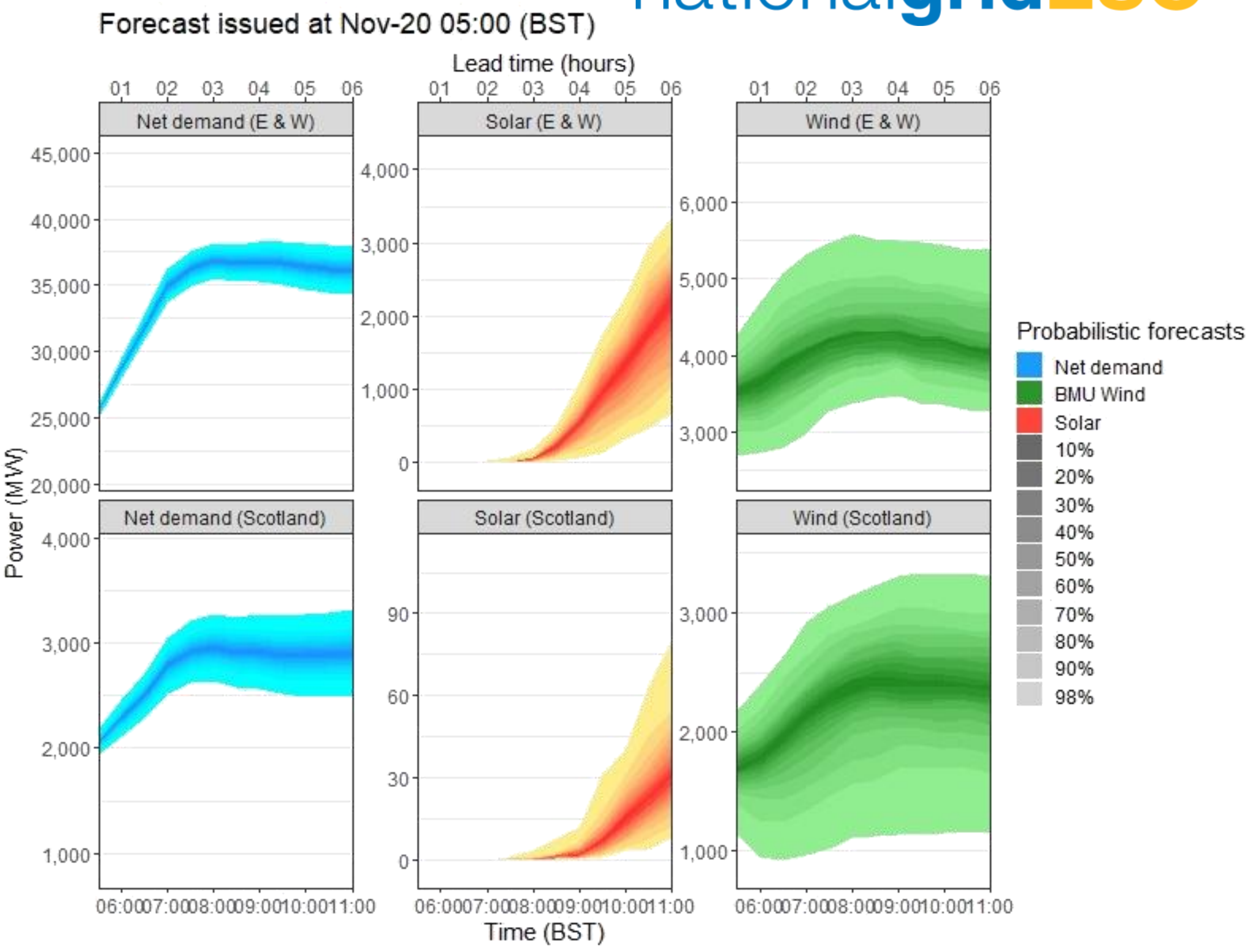



# Univariate forecasts

Our first task was to produce separate *univariate* forecasts for all the individual quantities we are interested in.

Different types of demand and renewable generation, at various lead-times, and levels of spatial granularity.



# Data-driven forecast models

*Time of the year*

*Time of the day*

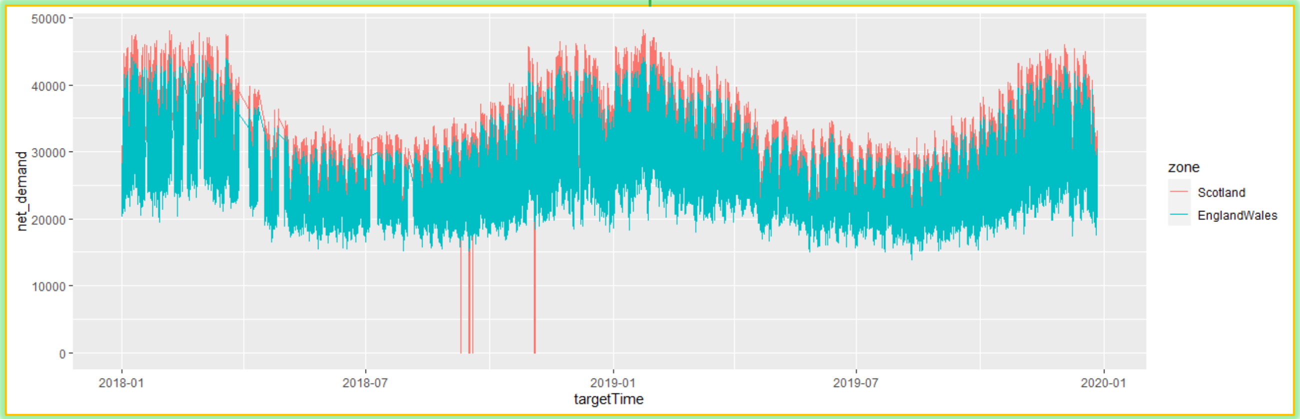
*Weather forecasts*

*Weekends*

*Holidays*

Forecasting model

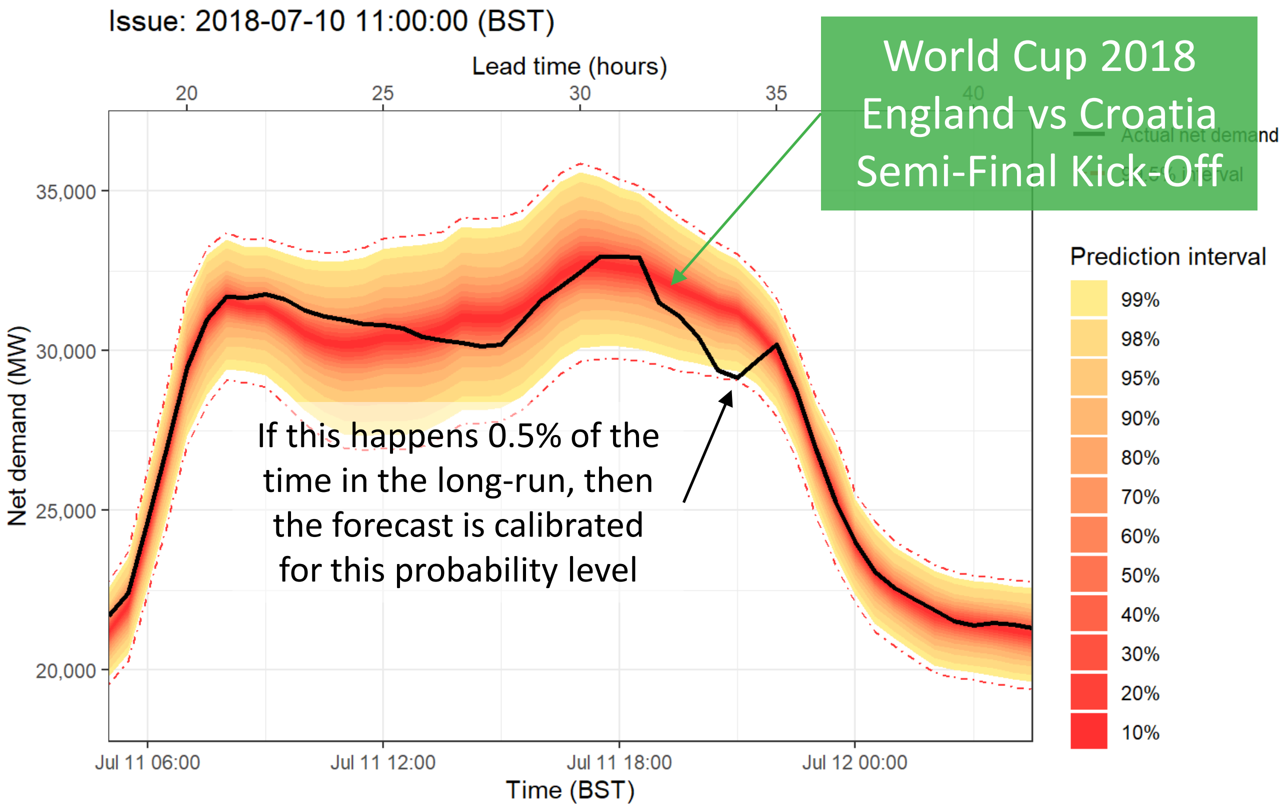
*Statistics and machine learning methods to train the model.*

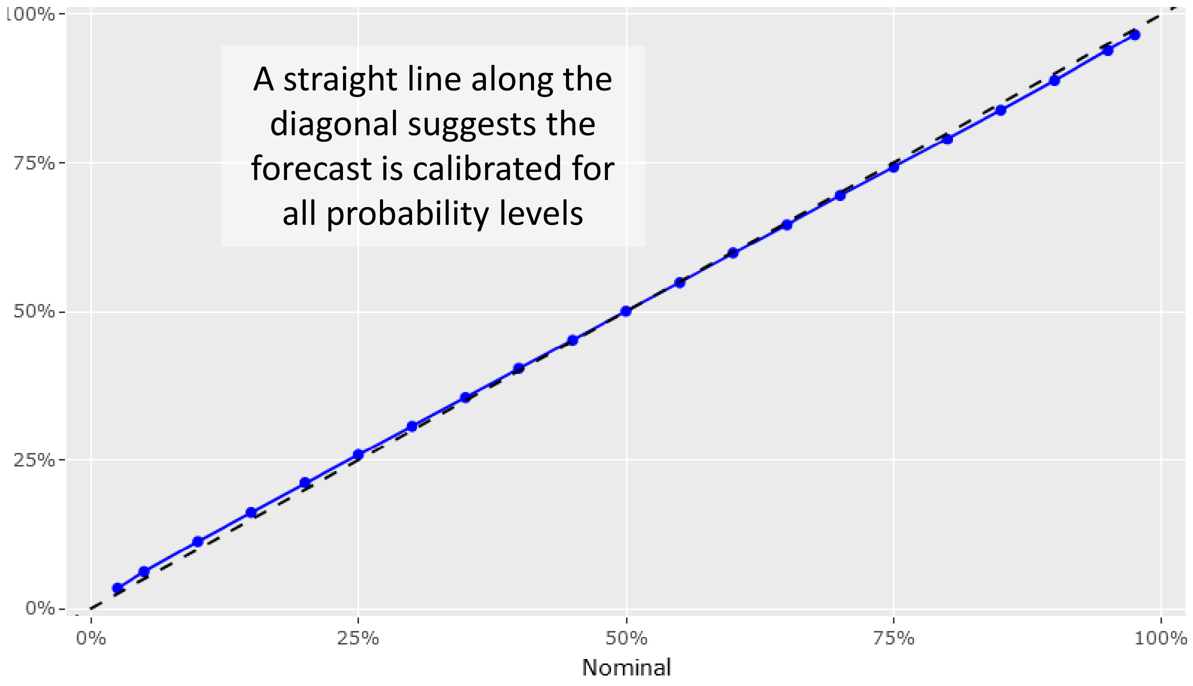



*Historic demand and generation data*

**We only use comparable forecasts to those available within NGESO – e.g., no individual NWP ensemble members**

# Forecast calibration

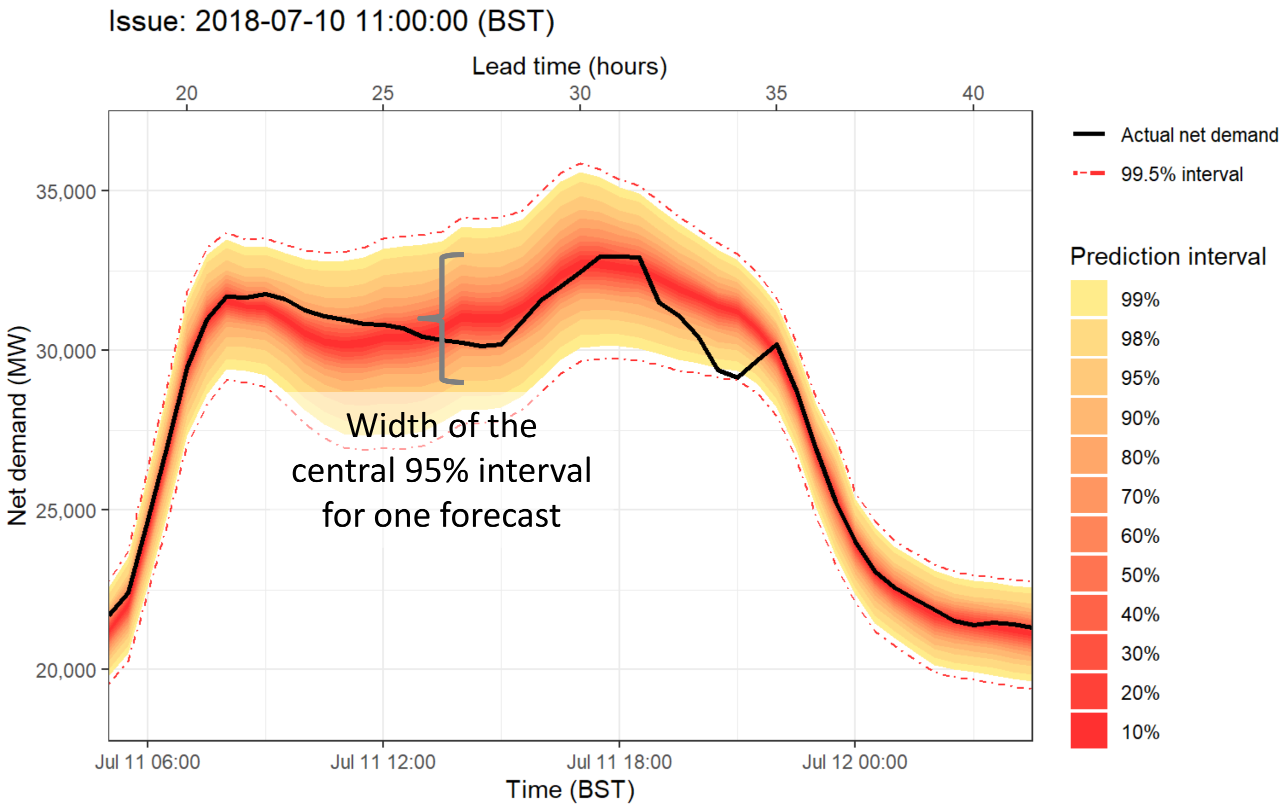


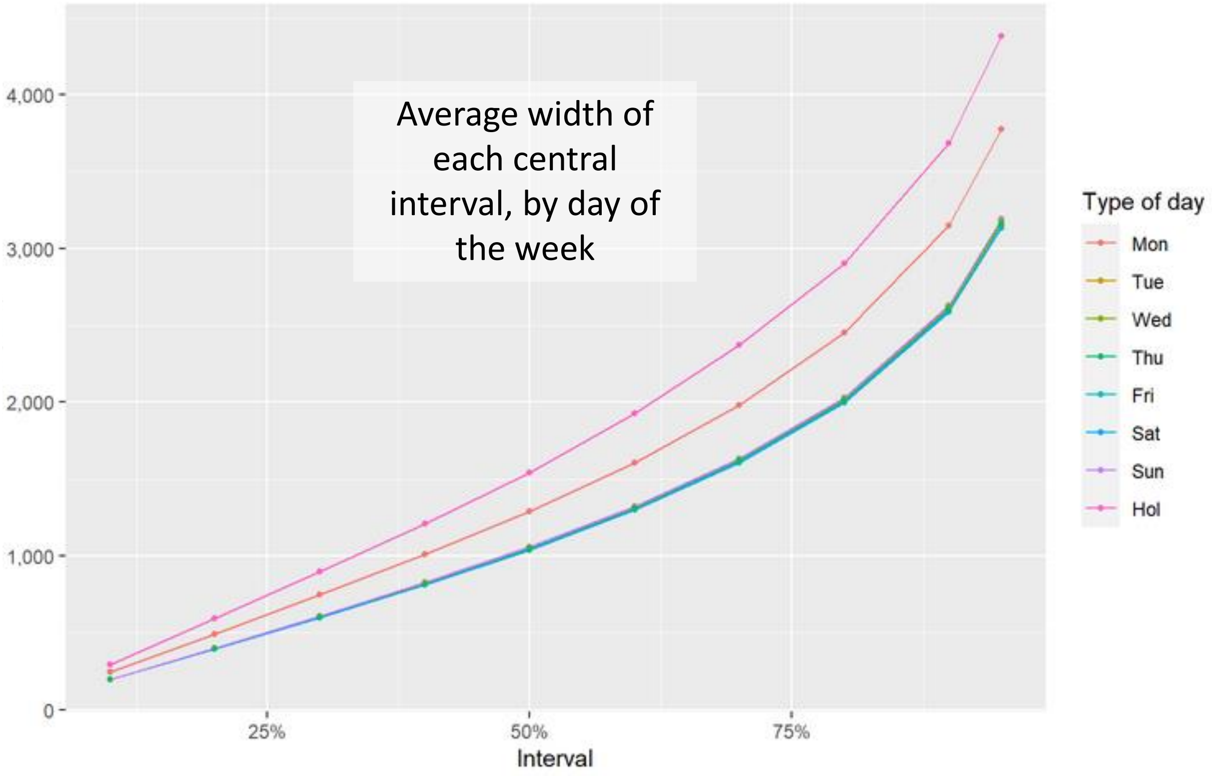




Calibrated (or reliable) forecasts are ones that are consistent with true outcomes.

In other words, how often is the true outcome (black line) lower than each quantile value?

# Forecast sharpness

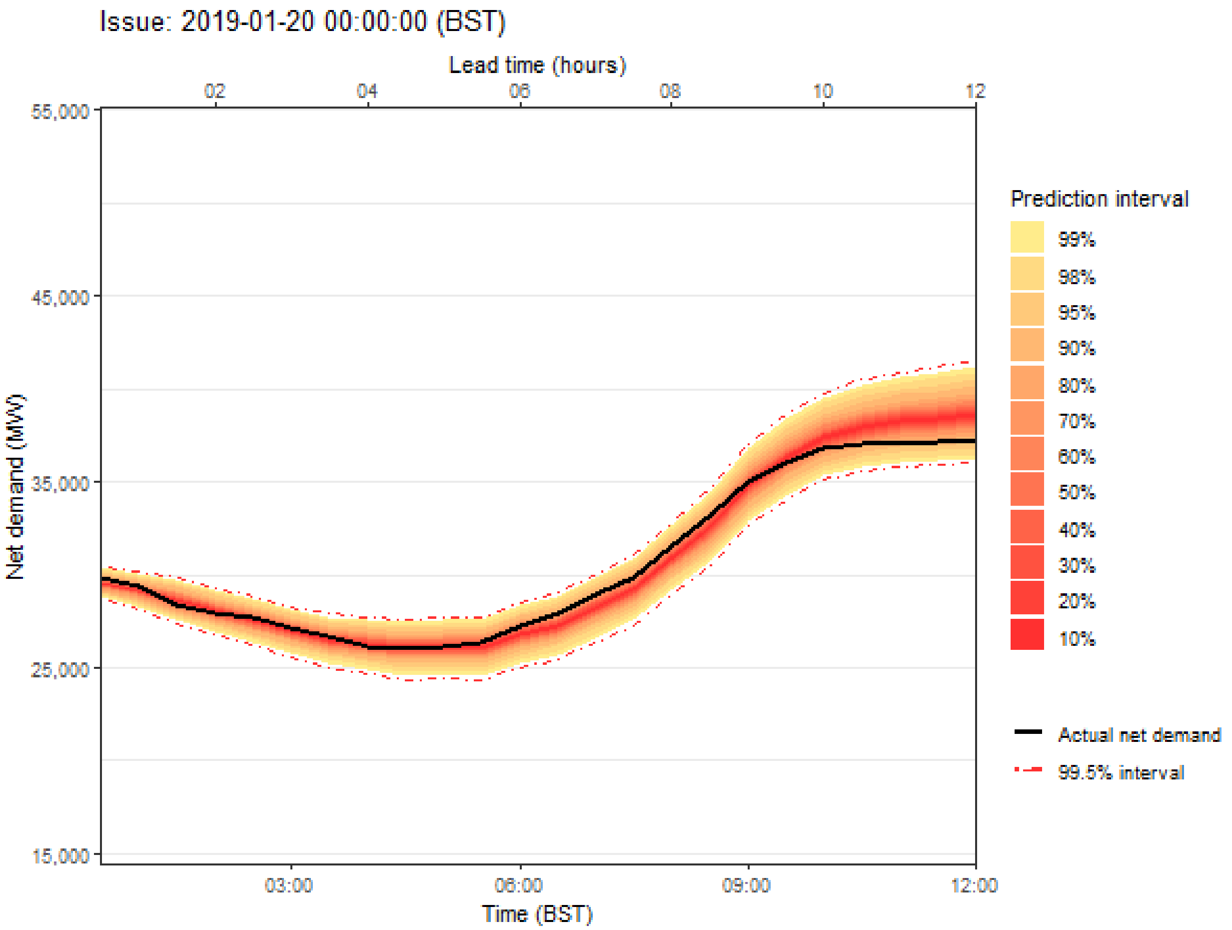


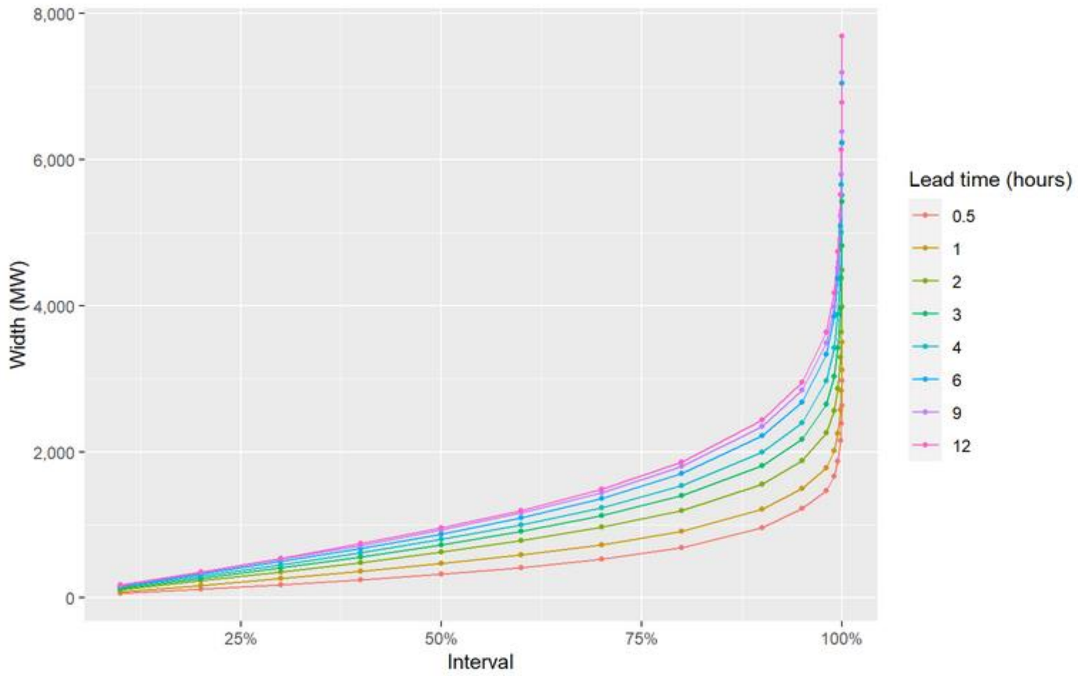




Sharp probabilistic forecasts have narrow probability intervals (and therefore lower uncertainty)

We choose forecast models that minimise sharpness, subject to calibration.

# Short-term forecasts

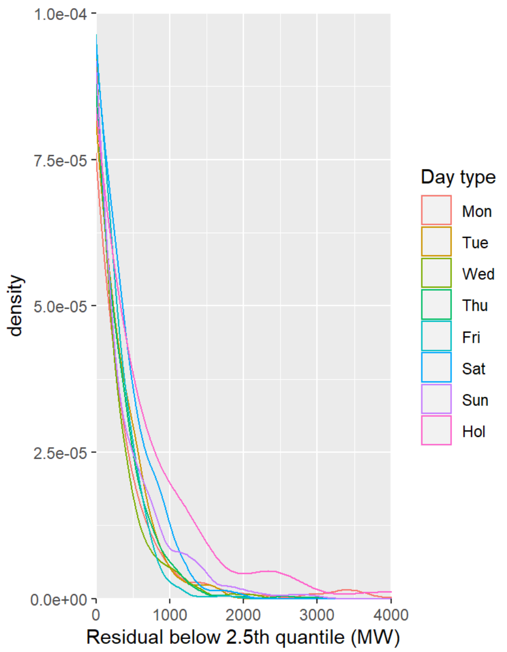


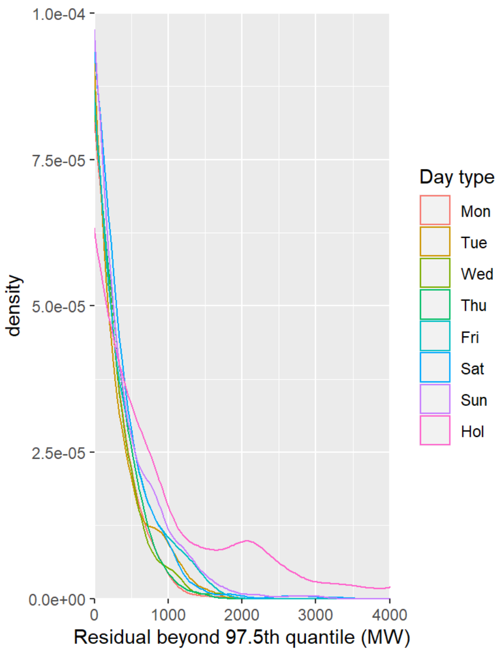



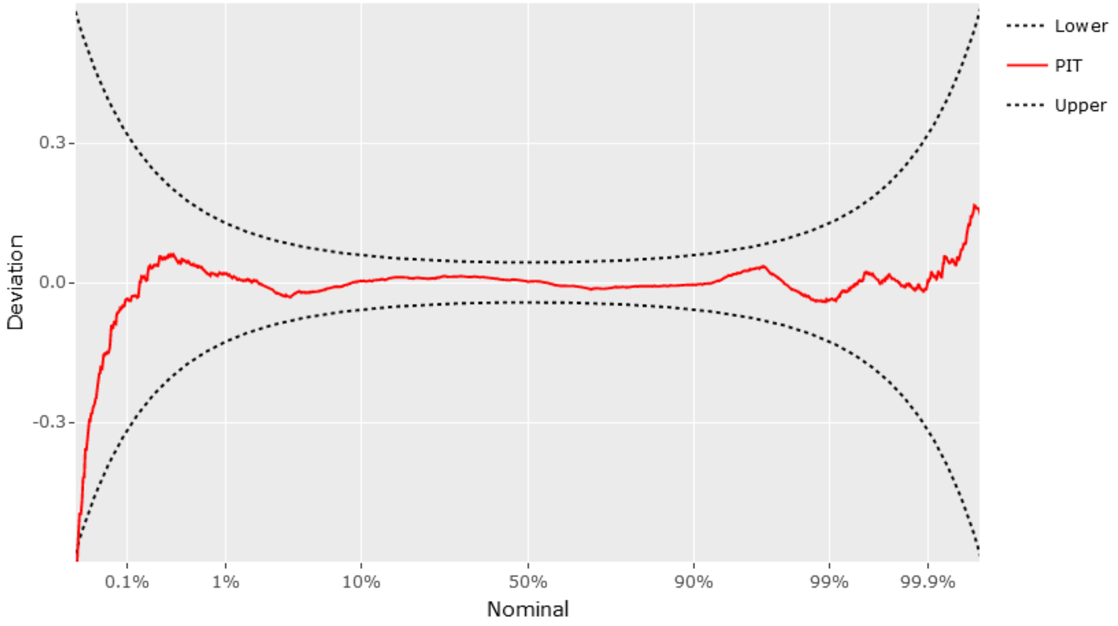

We use a non-linear moving-average approach for very-short term forecasts, from 12 hours- to 30 minutes-ahead.

# Extreme values

We used conditional extreme value distributions to model the tails of the forecasts. The shapes of these extreme value distributions vary dynamically.



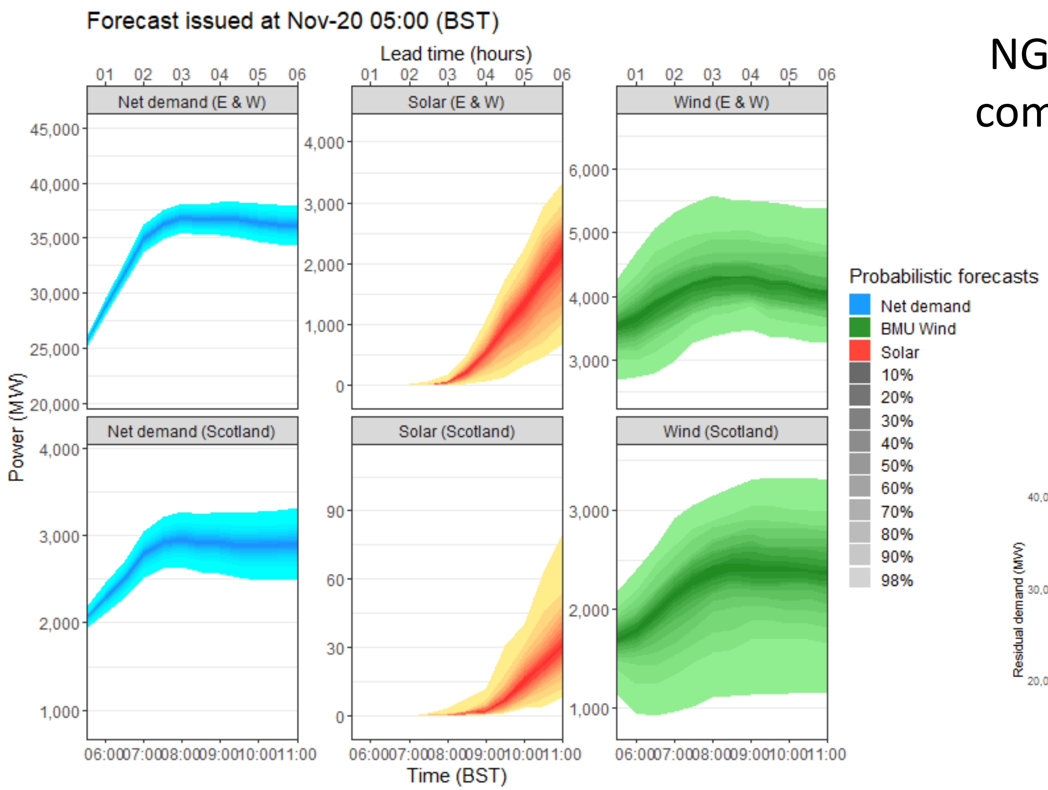



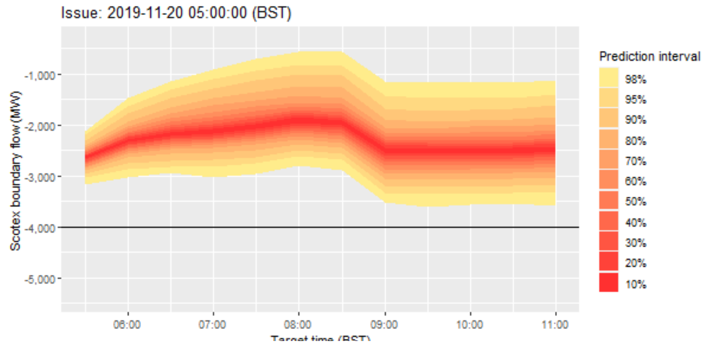

NGESO has a very low risk appetite when operating the system, so these extreme predictions matter.

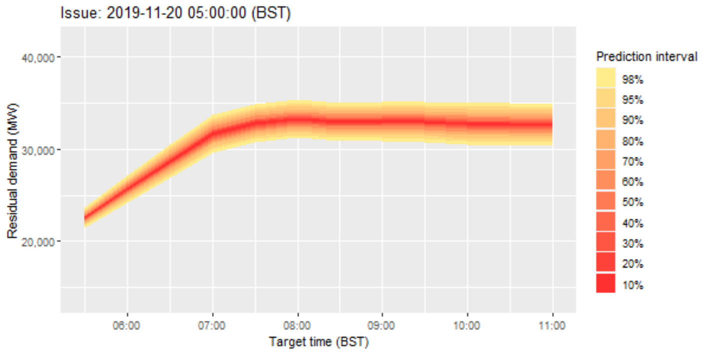
The forecasts are consistent with being well-calibrated even out to some very extreme quantiles.

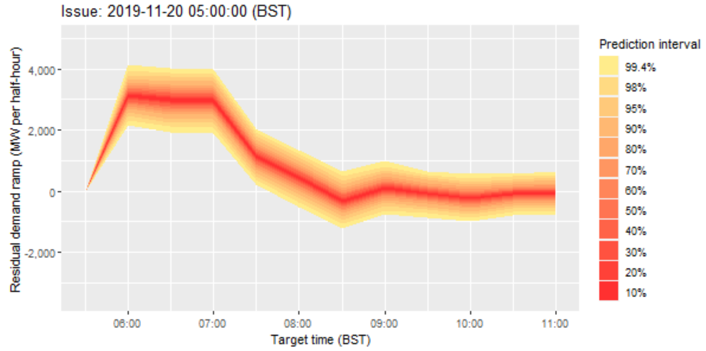
# Combining forecasts




NGESO needs to consider how combinations of these variables might affect operability.




These quantities *could* be forecast directly, but it aids interpretation to have a coherent set of individual components.

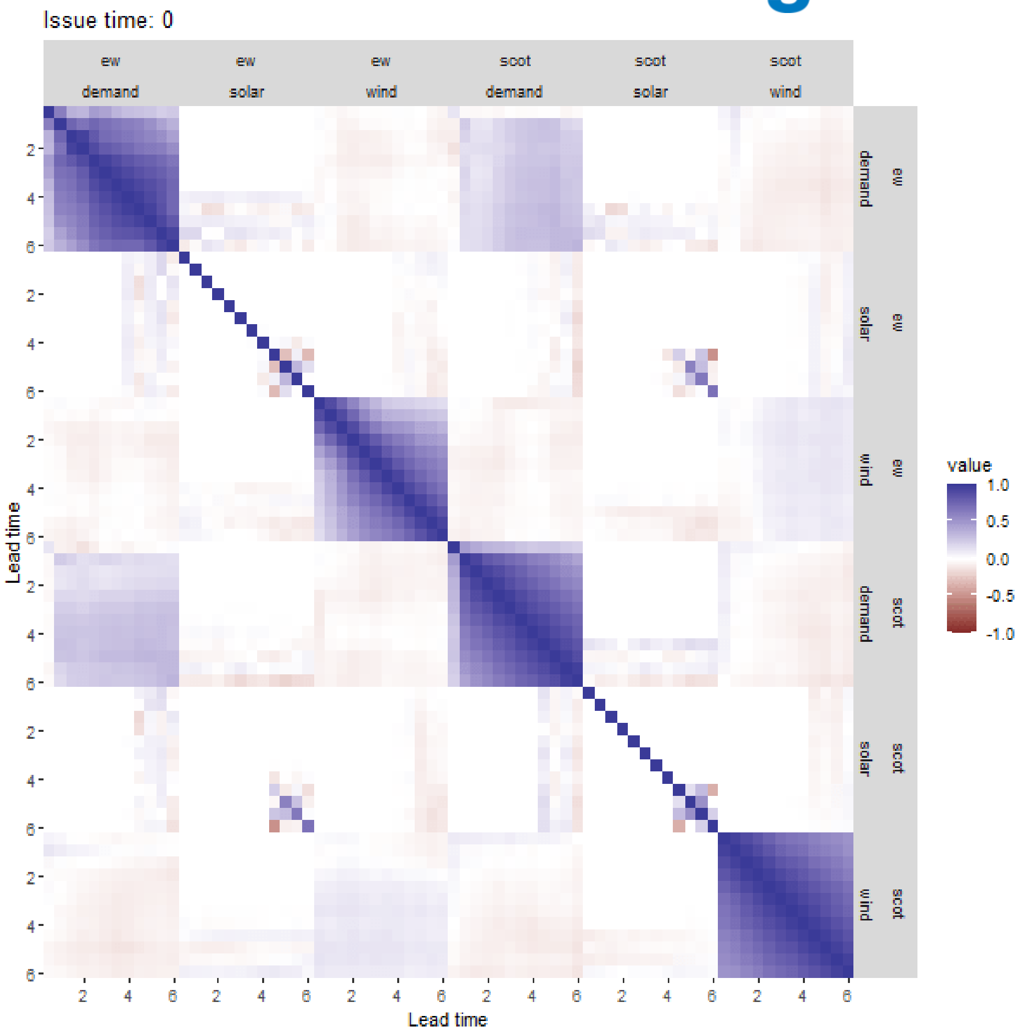
# Dependency structures

We have modelled dependencies using a spatio - temporal copula.

This is complex, and requires some strong assumptions to be made.

This a relatively nascent area of research.

But, the combinations we are interested in from these joint forecasts are still well calibrated.



# Use cases for probabilistic forecasts

*Scheduling , commitment, and dispatch of generation in the control-room.*

*Day-ahead prediction of tomorrow's reserve requirements*

*Early days-ahead notice of insufficient margin in generation capacity.*

# Reserve sizing from probabilistic forecasts

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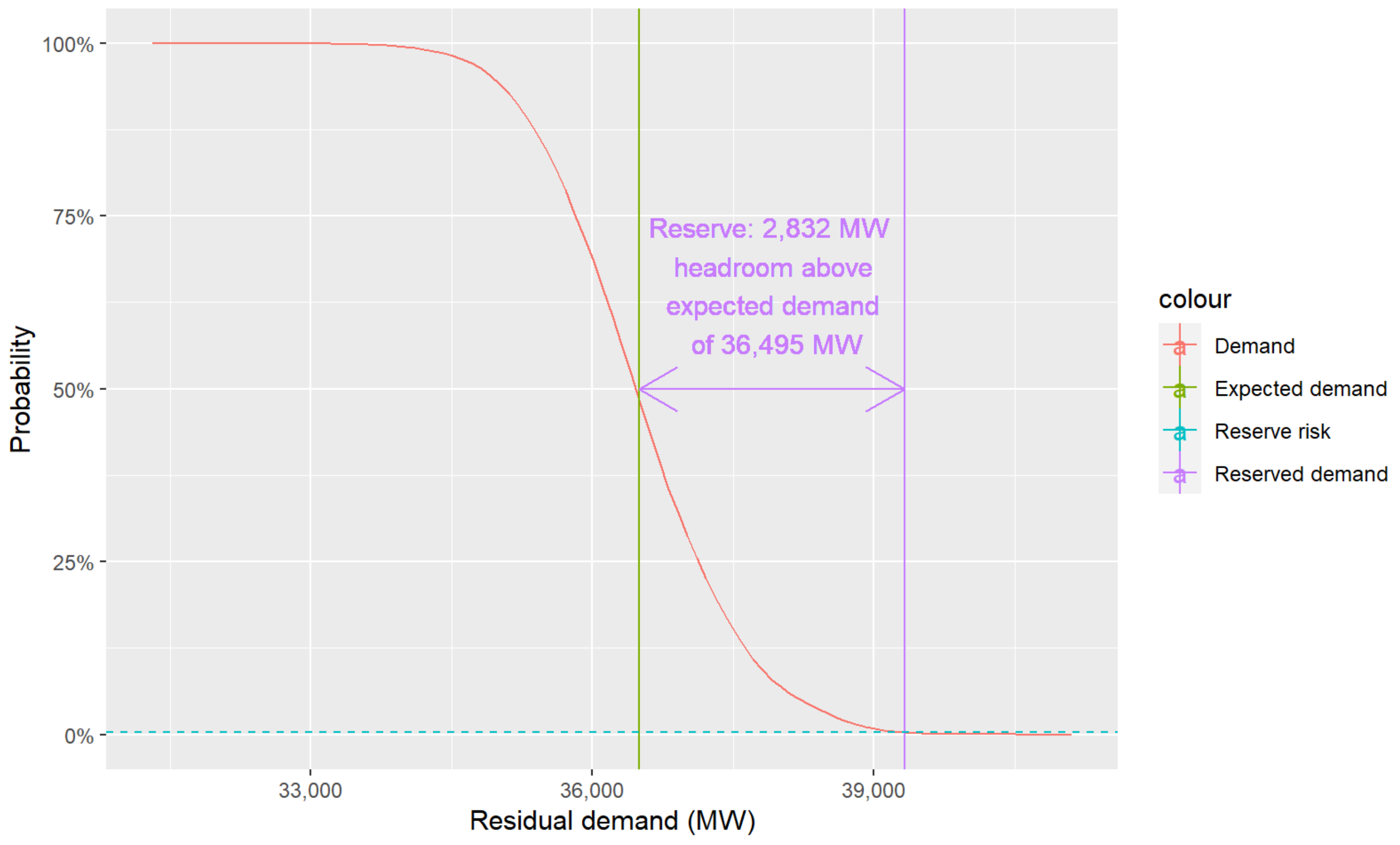
We used our four-hour ahead forecasts to consider NGESO's decisions about committing regulating reserve.

We sized this by considering the 99.7th percentile of the residual demand distribution for each half-hour forecast.

We compared this to an approximation of NGESO's current reserve-sizing approach, based on long-run errors.

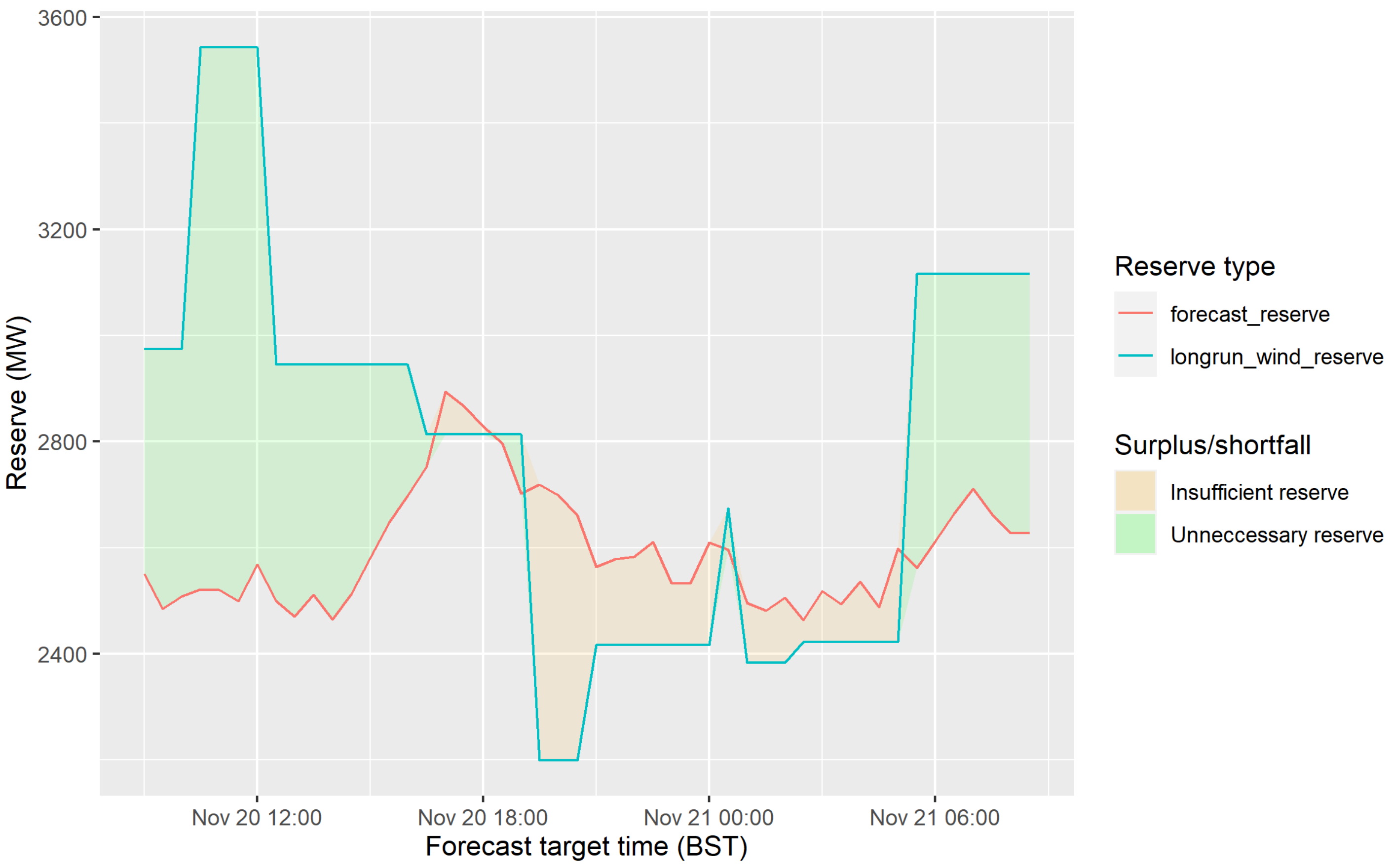


# Long-run and forecast reserves

Our approach keeps the risk exposure constant at 0.3%, which results in more dynamic variation in the amount of reserve.

The existing approach has less variation in the amount of reserve, but much more variation in the system's risk exposure.

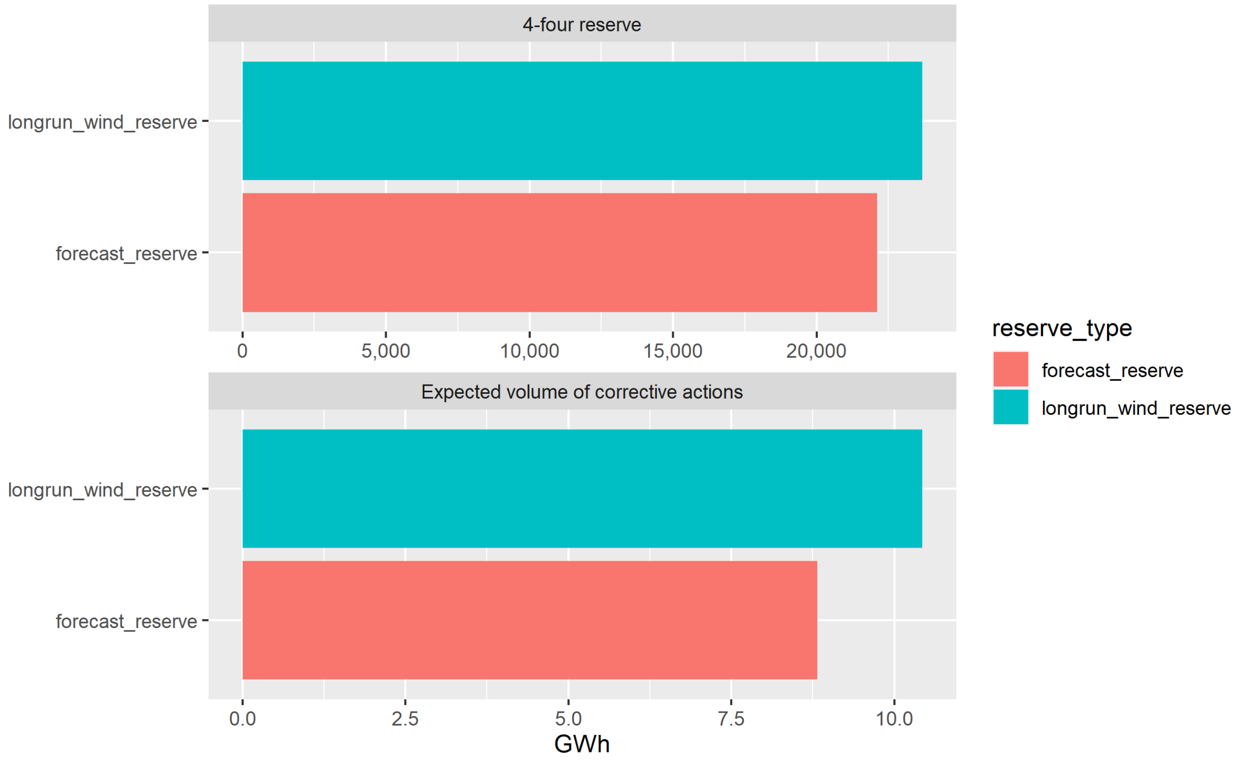
Sometimes, this results in more reserve than needed, and sometimes less than needed.



# Benefits of using probabilistic forecasts in reserve commitment

We evaluated this over two historic years and found that the reserves from the forecast reduced both:

1. The total volume of reserve committed in the year.
2. The expected volume of "corrective" action after 4-hours, when there is insufficient reserve.




With a reserve cost of £50 / MWh, this would represent an average saving of £75m per year.

# Further research needs

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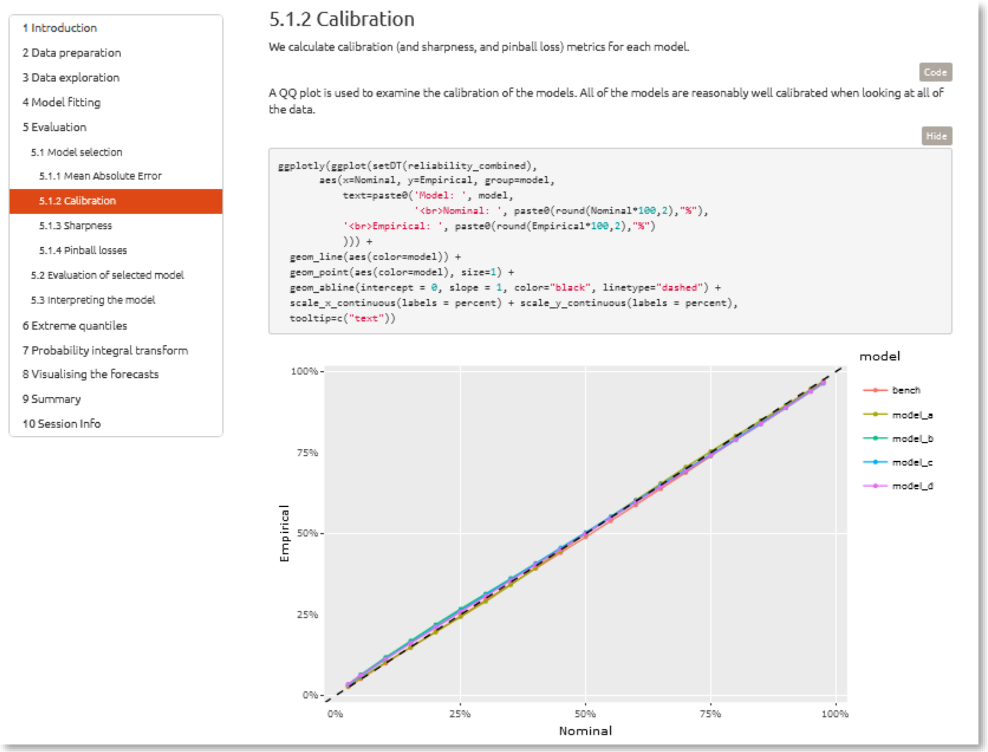
- Modelling of dynamic dependencies
- Forecasting extreme outcomes
- “What if” scenario forecasting with ensembles
- More sophisticated cost-optimal decision-support

# Next steps

- NGESO is going to try and duplicate the work carried out during this NIA project internally.
- To do this, NGESO will use the excellent workbooks delivered as an output of this project.
- Hoping to publish some outputs soon.



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# Thank you!

# Unused slides

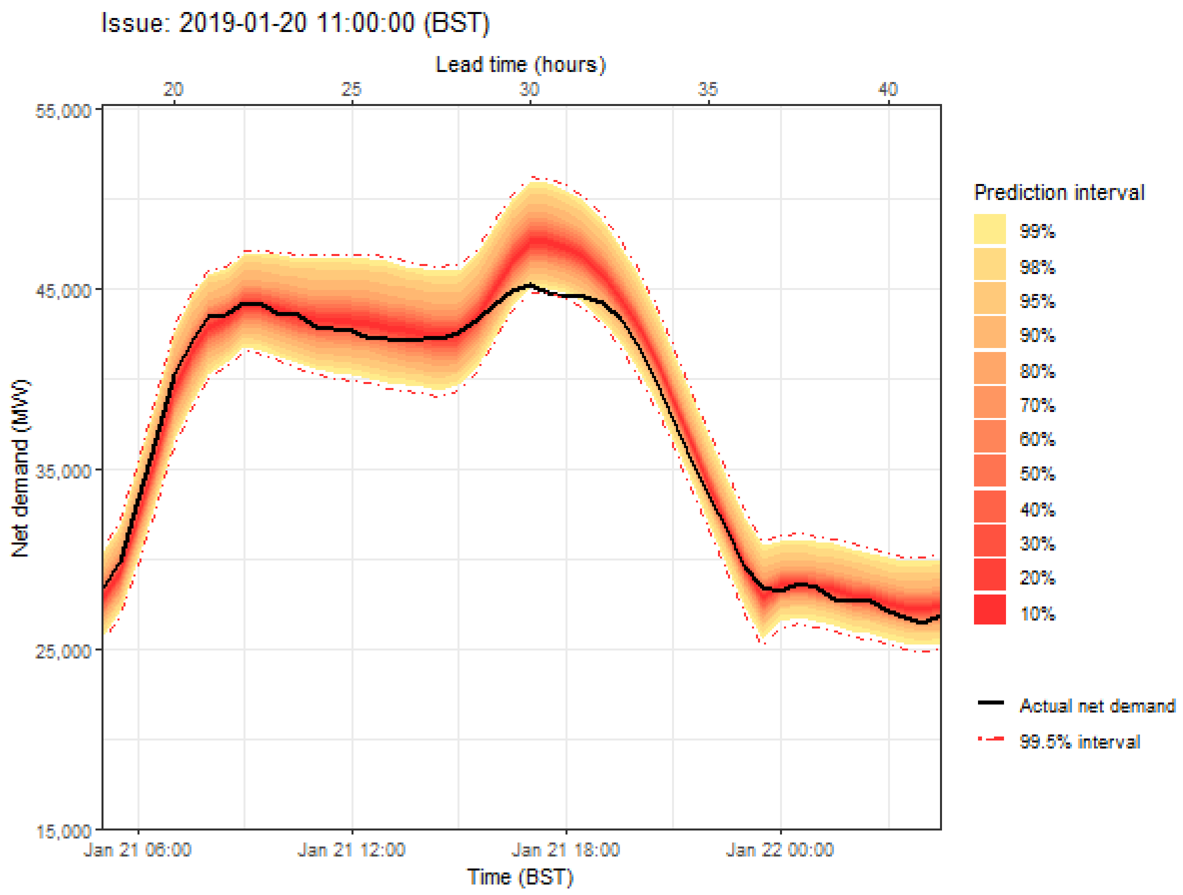
# Demand forecasts

**Forecast combinations**

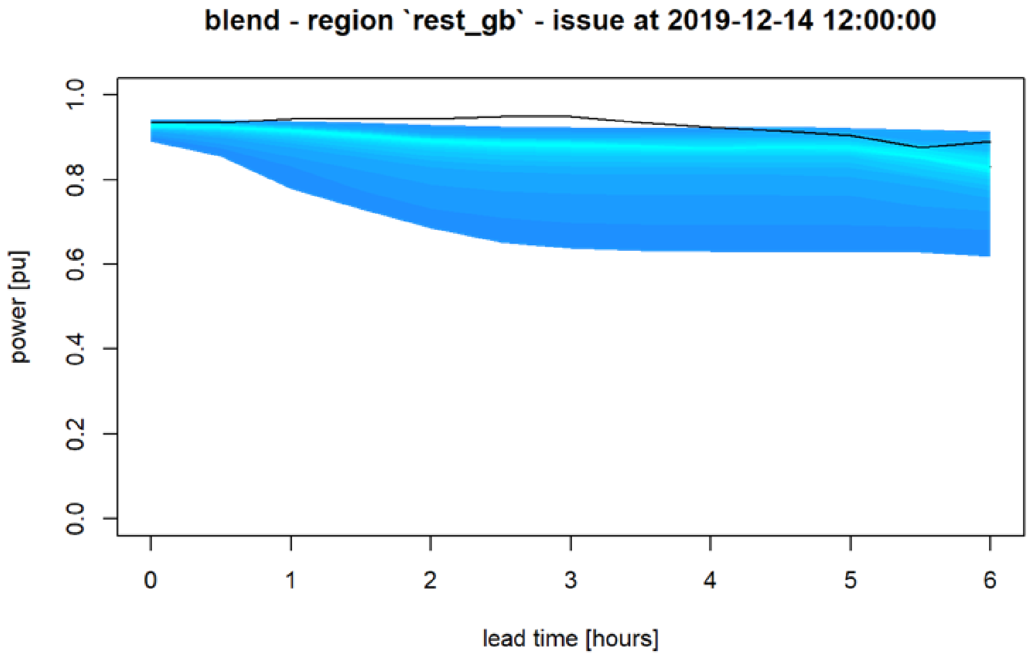
- National (net) demand, gross demand (including solar), and residual demand (excluding wind)
- National and country level
- Three days-ahead, day-ahead, and very short-term (30 minutes to 12-hours)

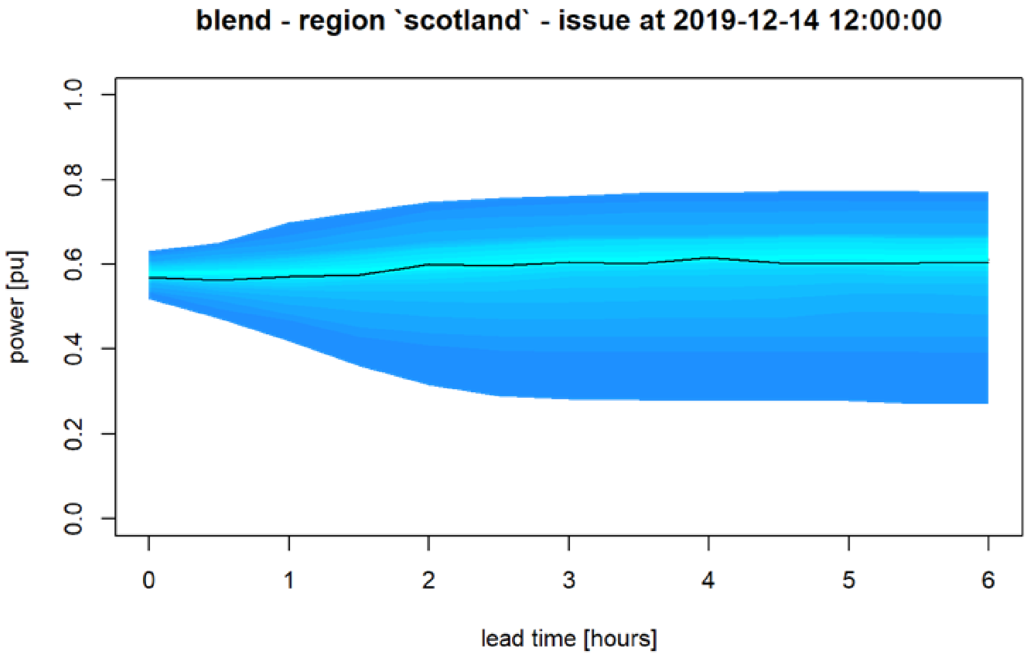
**Forecast method**

Multiple quantile regression via Generalised Additive Models (GBMs) using `R` and `ProbCast`, with some bespoke functionality.
Trained and evaluated using k-fold cross-validation.



# Renewable generation forecasts



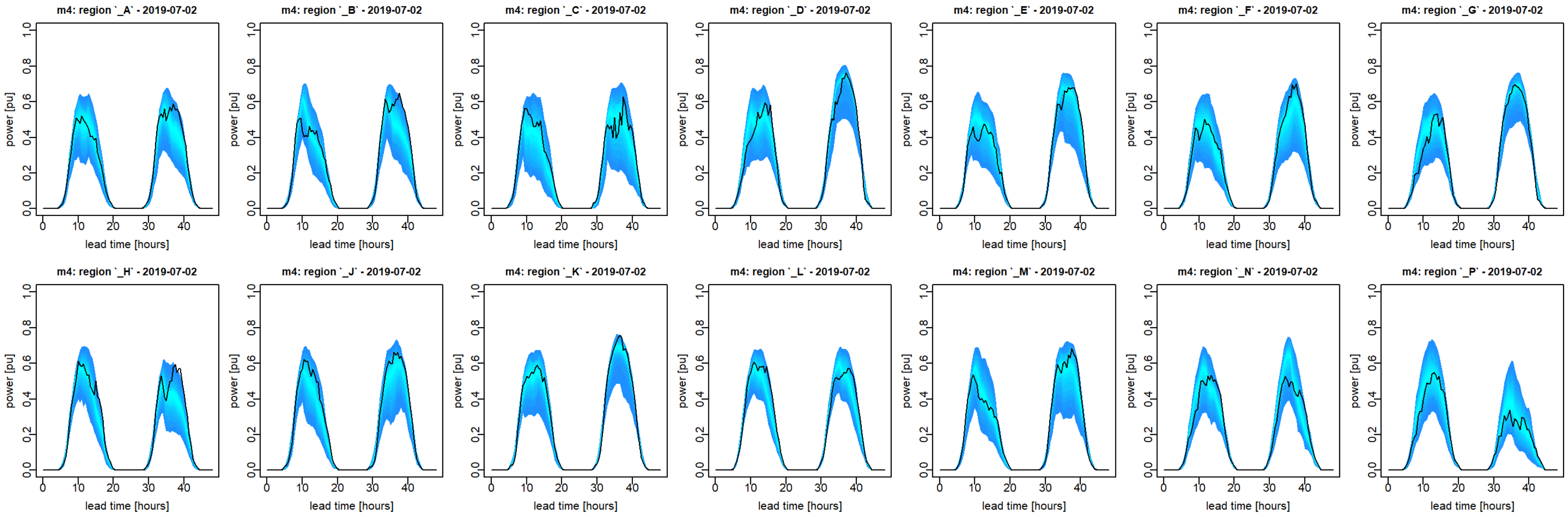

**Forecast combinations**

- Transmission wind, and embedded solar
- National, country level, and GSP group
- Short term (0 – 5 days), and very-short term (up to 6 hours)

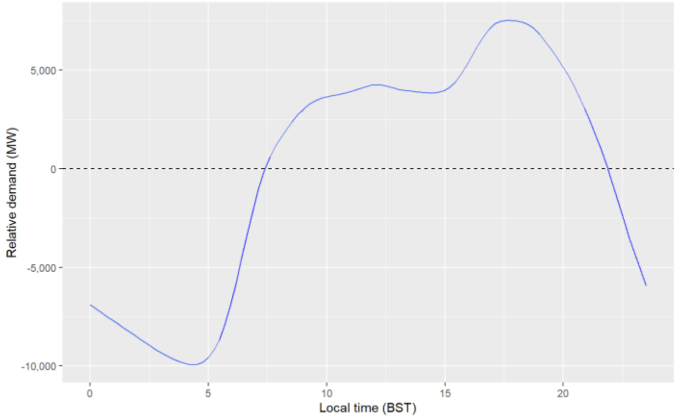
**Forecast method**

Multiple quantile regression via Gradient Boosting Machines (GBMs) using `R` and `ProbCast`.

# Generation forecasts



# Generalised additive models

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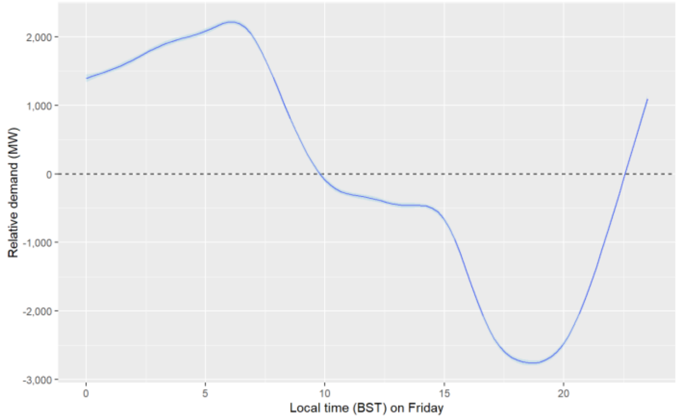


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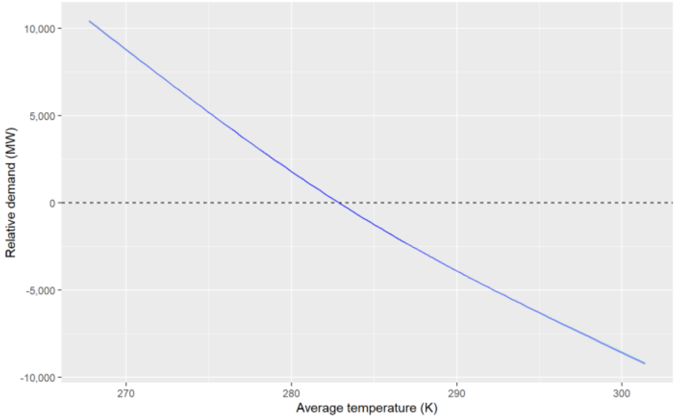


This class of model adds together lots of non-linear functions to explain electricity demand

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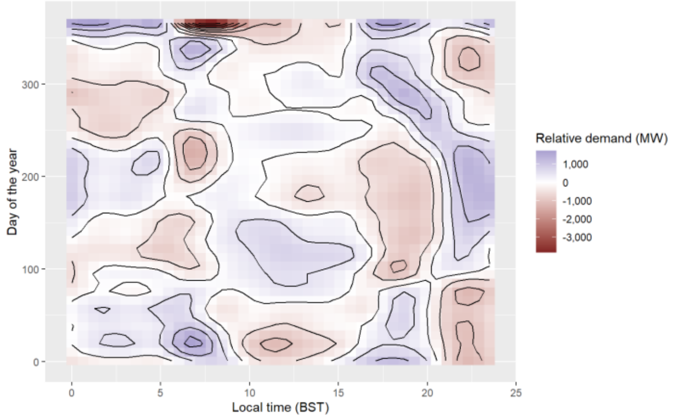


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# Out of sample cross-validation

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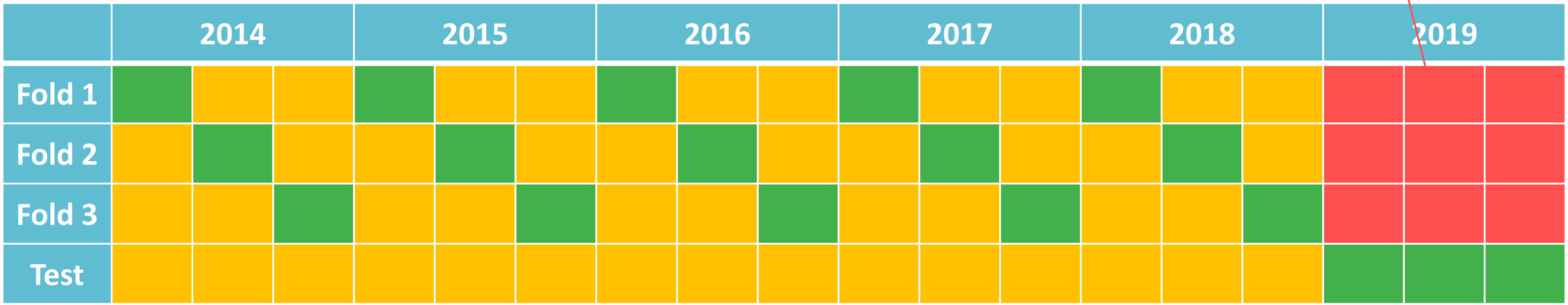
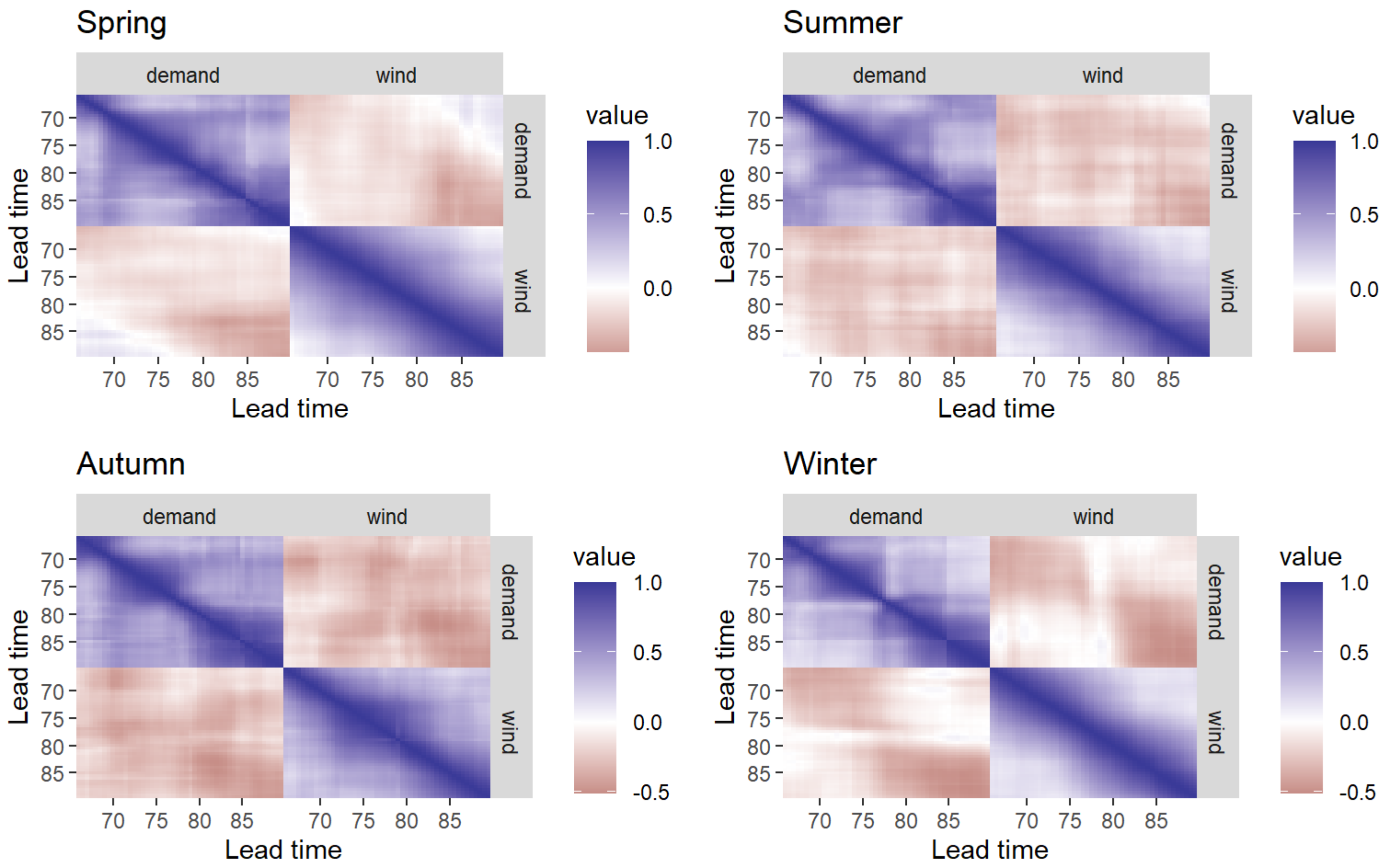
- We evaluate the forecasts on *out of sample* data
- This is to protect against *overfitting*
- So we actually have *four* different models – one for each ***cross-fold***
- *Example: we train using the data in **yellow***
  *and evaluate predictions on the data in **green***

We don't use the test data in any of the model training



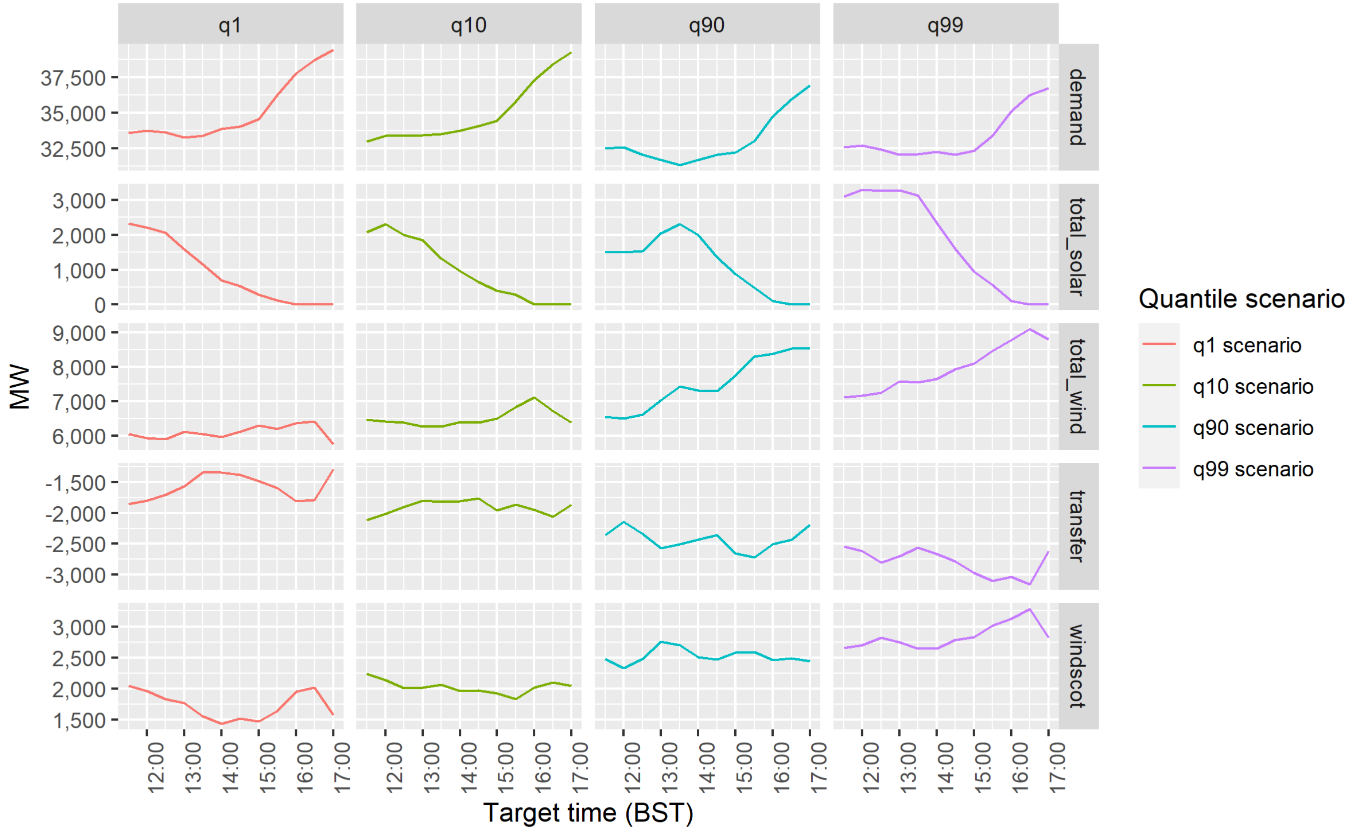
# Dynamic dependencies

- Some approximate treatment of dynamic changes in dependency – e.g. different seasonal covariance matrices.
- But these are not modelled – they are just empirical estimates.



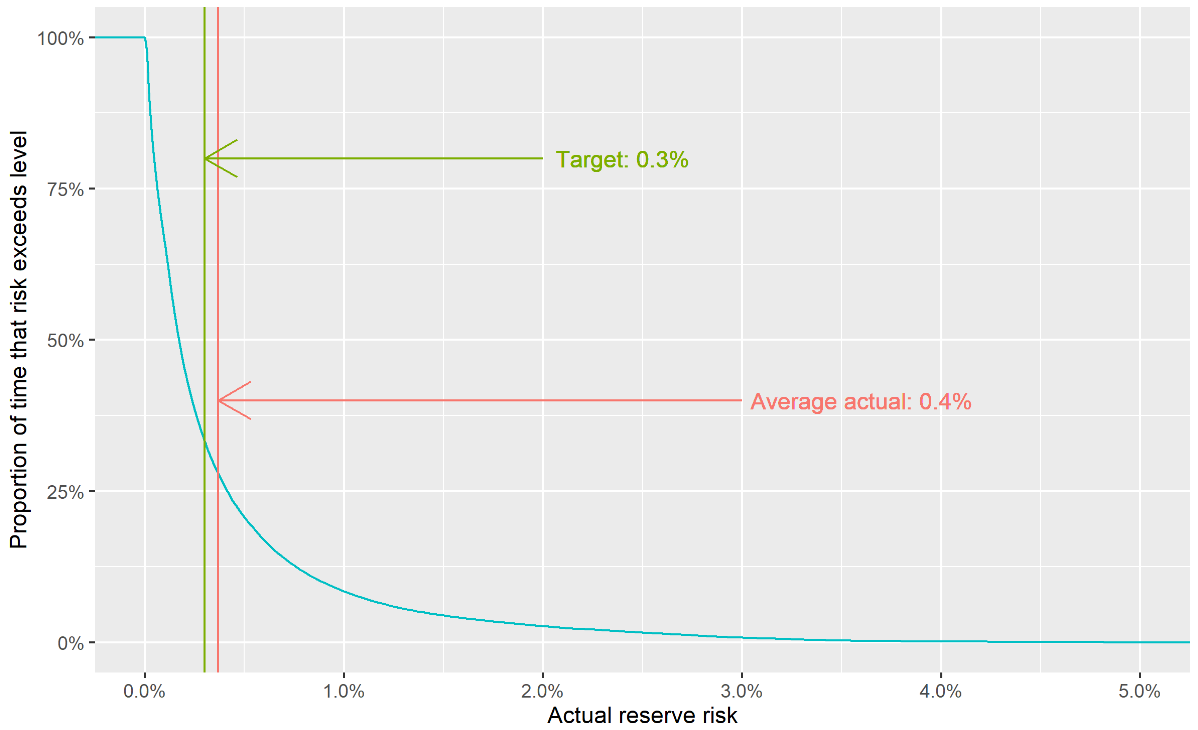
# Scenarios and visualisation

- Some early exploration of visualising scenarios generated from the probabilistic forecasts.



# System risk exposure

- Using the counterfactual reserve approach, the amount of risk on the system varies quite significantly, from effectively 0% risk at time, to >1% at other times.



# Volumes of corrective actions

- Calculate the expected value of demand that is unserved by the calculated level of reserve, using functions within ProbCast.