AEMO
AUSTRALIAN ENERGY MARKET OPERATOR

ST PASA Replacement Project

Stakeholder Workshop #4 – Uncertainty Margins, Demand Forecasting for STPASA

July 2022

We acknowledge the Traditional Owners of country throughout Australia and recognise their continuing connection to land, waters and culture.

We pay respect to their Elders past, present and emerging.

Introduction

- **Jack Fox –** Operational Forecasting lead
- **Andrew Akman –** Senior Data Scientist
- **Steve Disano –** Modelling SME

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Agenda

- Defining Uncertainty
- Uncertainty Margins
- Modelling Uncertainty Margins
- Demand Forecasting for STPASA
- Validating the system and Consultation
- Data to be published
- Project Next Steps

Uncertainty

Defining Uncertainty

- **Uncertainty**:
  - “not able to be relied upon, not known or definite, not completely confident or sure.”
  - “refers to situations involving imperfect or unknown information and is applied to predictions of future events”

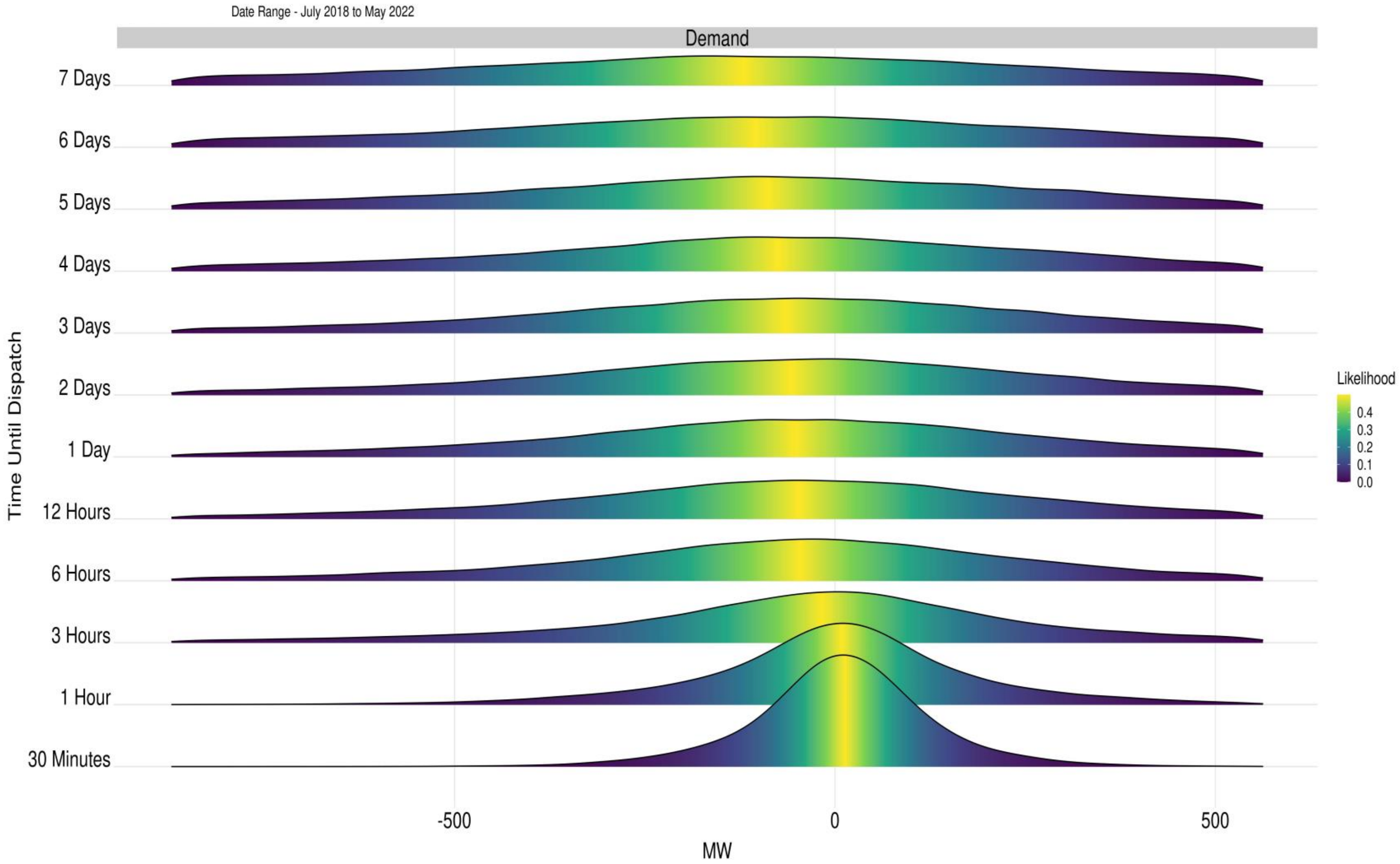
- **Metric used:**
  - ***Uncertainty*** = **Forecast** *minus* **Actual**

Uncertainty in STPASA

- The High Level Design (HLD) recognises the need to account for uncertainty in STPASA and identifies the following inputs as predominant sources of uncertainty:
  - Demand uncertainty
    - Includes the impact of behind-the-meter Distributed Energy Resources such as rooftop PV and batteries
    - Includes price-responsive demand such as demand side response and Virtual Power Plants, but excludes WDR which is separately dispatched
  - Variable Renewable Energy (VRE) Generation uncertainty
    - Semi-Scheduled wind & solar generation forecasts
    - Large Non-Scheduled wind & solar generation forecasts
  - Scheduled Generation uncertainty
    - Utilising Generator Maximum Availability (Max Avail) from bids
    - Segmented by main fuel type: (Black & Brown Coal, Natural Gas, Hydro, Grid Storage – batteries, other)

Demand uncertainty

Demand Uncertainty = Forecast Demand minus Actual Demand
NEM Total

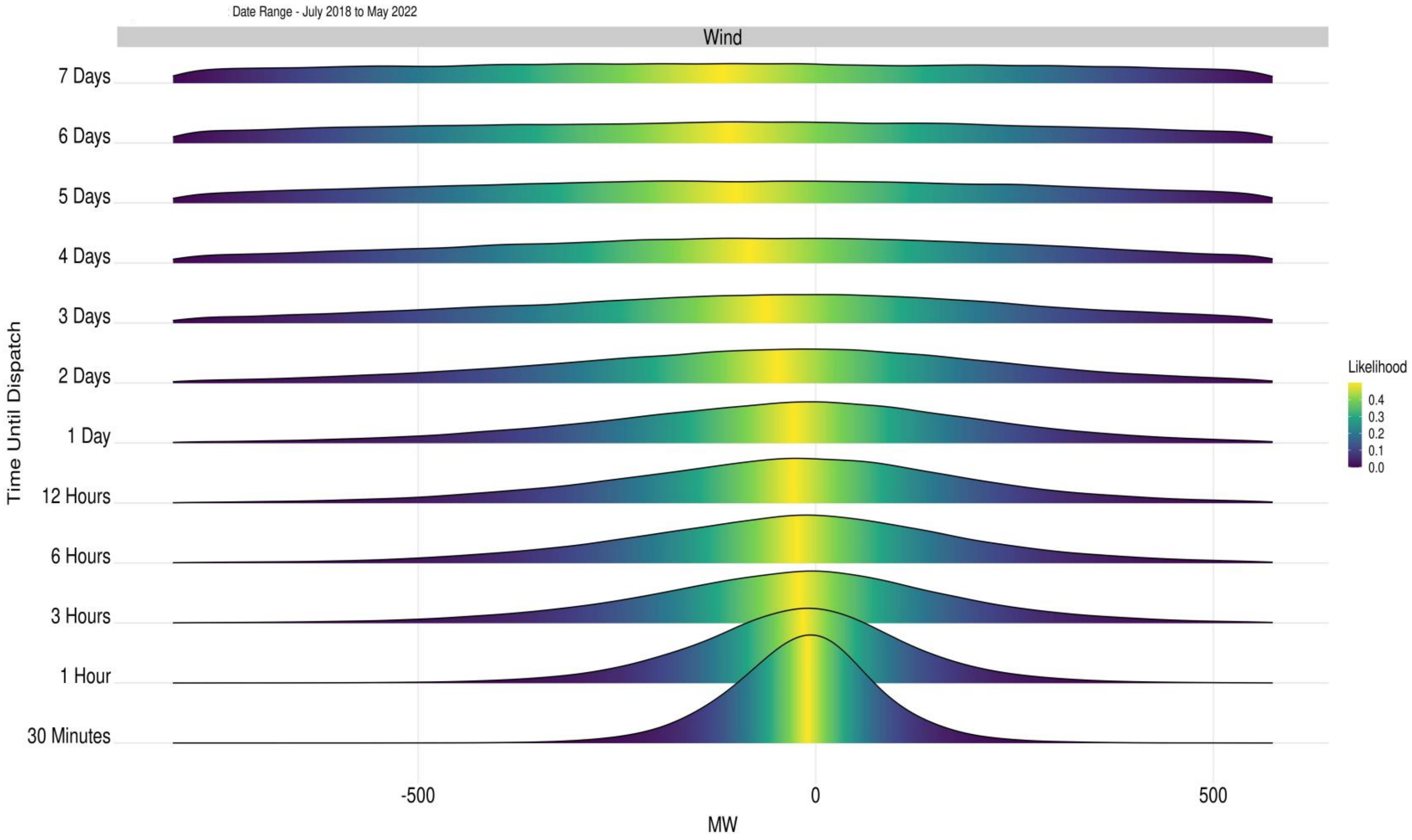


Key Takeaways

- Uncertainty reduces as the forecast horizon reduces
- At longer horizons, slight under-forecast bias. At shorter horizons this bias is not present

(VRE) Generation uncertainty Wind

Wind Uncertainty = Forecasted Generation minus Actual Generation
NEM Total



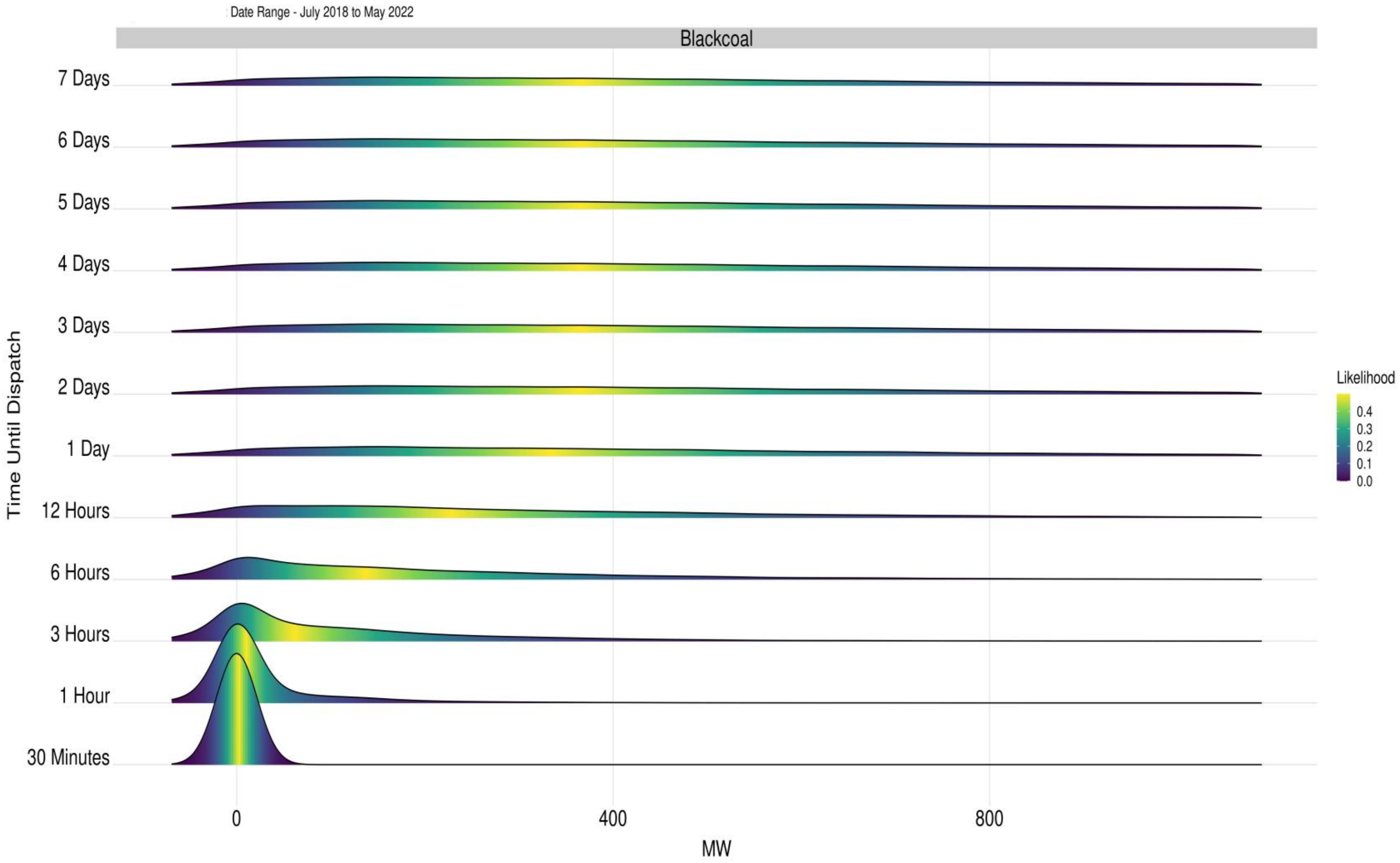
Key Takeaways

- Uncertainty reduces as the forecast horizon reduces
    - Most notably, as the forecast horizon reduces from 2 days.
- At longer horizons, slight under-forecast bias. At shorter horizons this bias reduces

Other fuel types available in appendix

Scheduled Generation uncertainty Black Coal

Black Coal Uncertainty = MaxAvail minus MaxAvail (at T-30 Minutes)
NEM Total



Other fuel types available in appendix

Key Takeaways

- Significant reduction in uncertainty as forecast horizon reduces
  - Particularly prominent when forecast horizon less than 12 Hours
- Over-forecast bias at longer horizons evidence of general reductions of MaxAvail as forecast horizon reduces. The bias is not present only at very-short horizons.

A note about confidence levels and percentiles

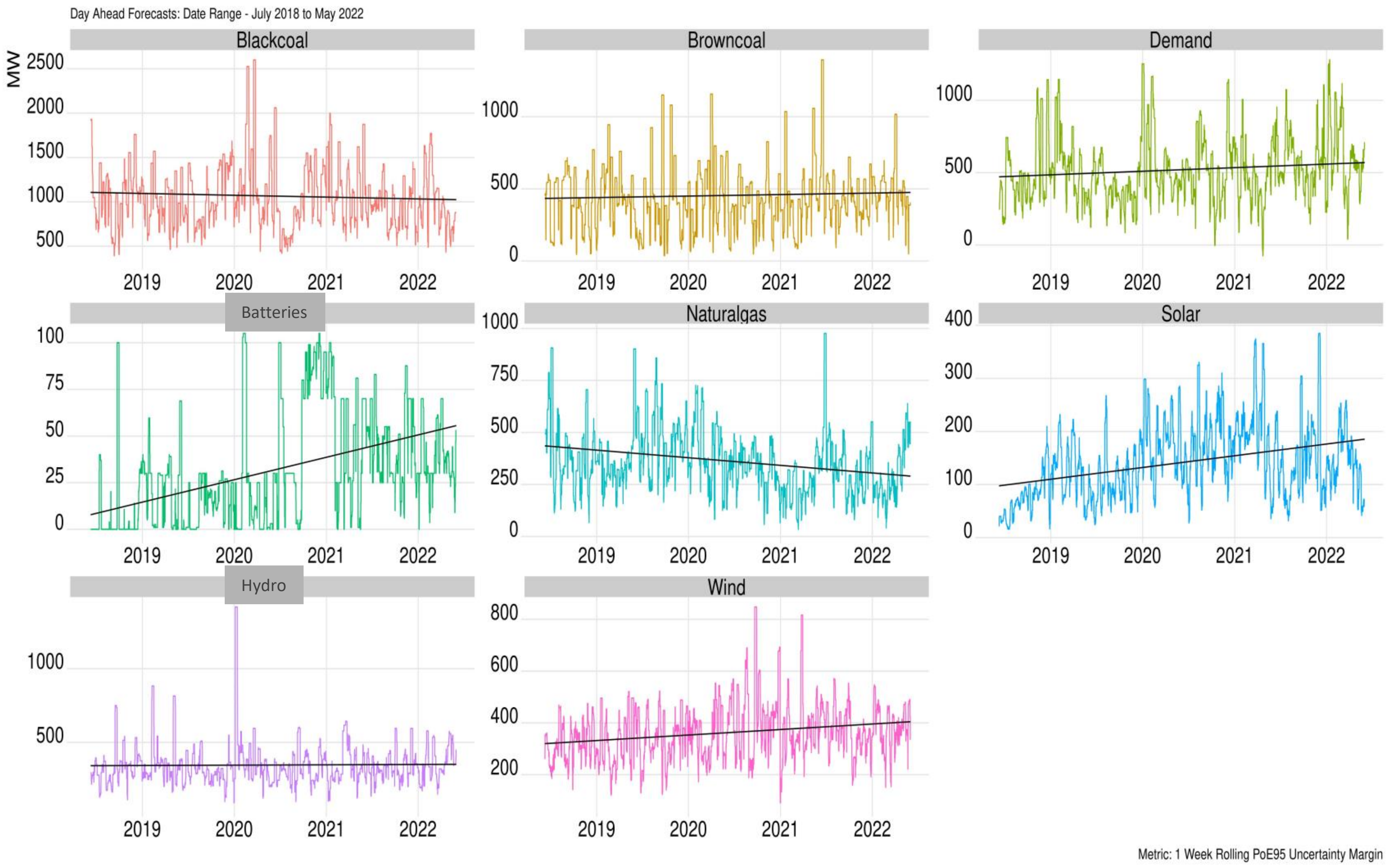
The following slides include illustrative examples which take the 95th percentile of the distribution of uncertainty, or use the 95% confidence level.

The selection of 95 is illustrative for the purposes of providing examples to discuss.

This selection is in no way indicative of future confidence levels as these will be determined through a consultation with stakeholders.

Changes in Uncertainty Over Time

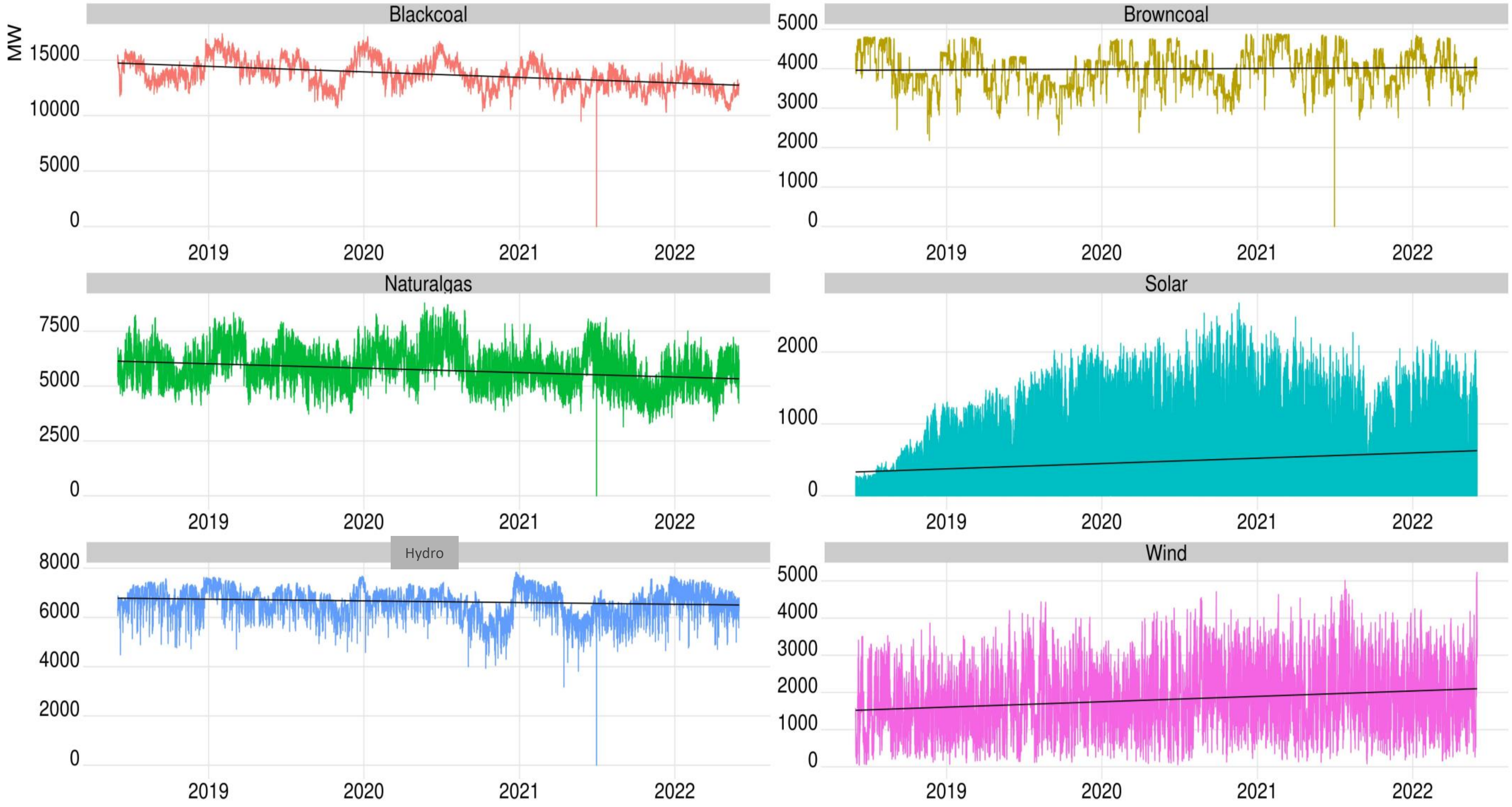
This shows the 95th percentile of the rolling 1-week uncertainty for each type and plots this over time



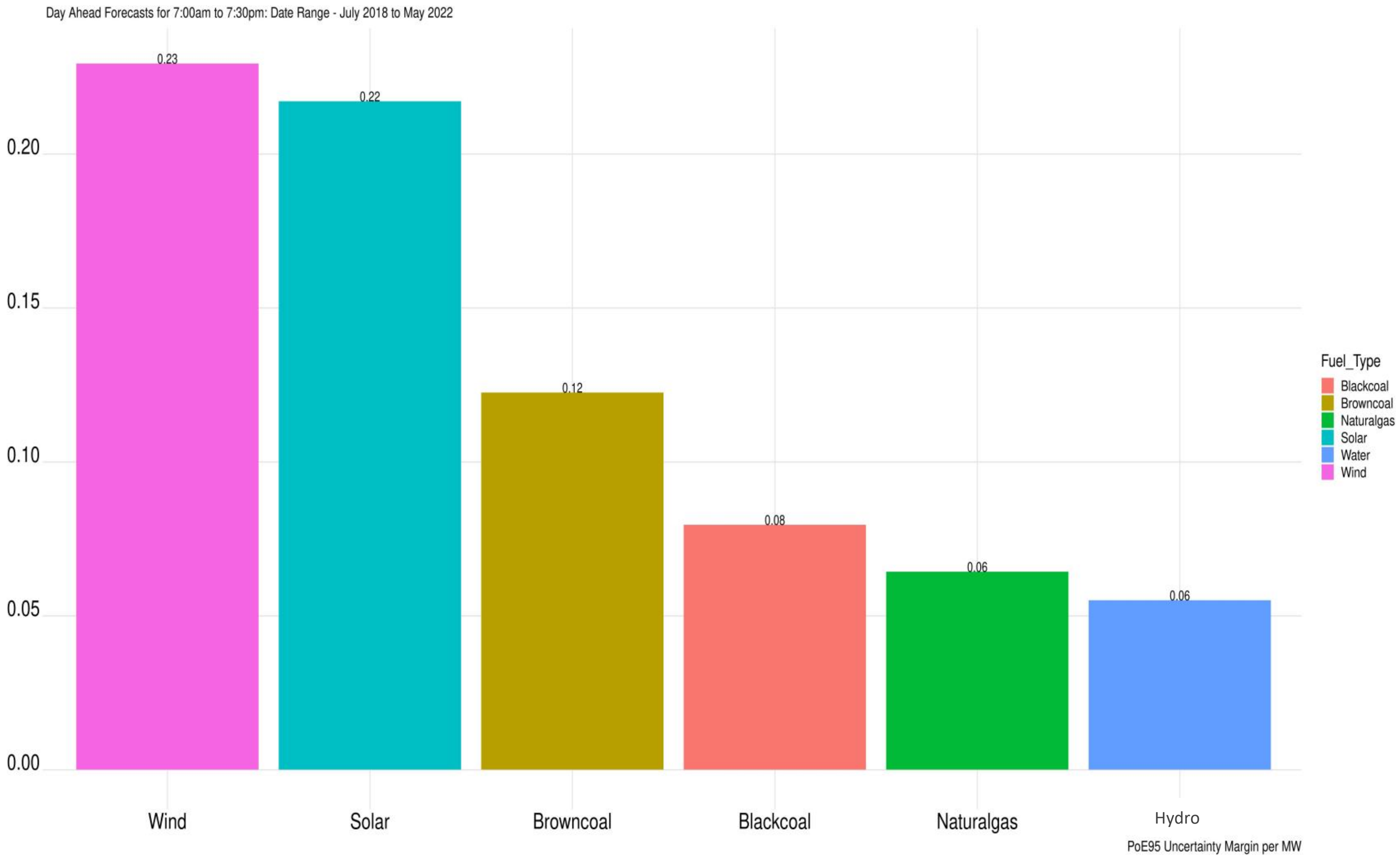
Key Takeaways

- Increasing uncertainty in VRE and batteries driven by increasing installed capacity
- Increasing uncertainty in demand driven by increasing rooftop PV, extreme weather and increasing industrial demand side response
- Declining uncertainty in Blackcoal and Gas due to declining levels of generation from these fuel types

Availability by fuel type trend over time



95th Percentile Average Uncertainty per MW of installed capacity by fuel type



Key Takeaways

- Wind and solar is 2 to 3 times less certain than other fuel types
- *Note: The results presented are a function of the market design of the NEM, and care should be taken interpreting these results if coming from another market design perspective.*

Accounting for uncertainty in STPASA

The previous slides showed uncertainty of the individual forecasting components. There is a need to combine the uncertainty to arrive at a mutually consistent total uncertainty that will affect STPASA. i.e. to allow coincident over and under forecasts to cancel each other.

Key Takeaways

- When calculating the generation by fuel type uncertainty, the total uncertainty is less than simply summing individual fuel type uncertainty, due to some over-forecasts cancelling out under-forecasts. i.e. 95th percentile of total generation uncertainty is less than sum of 95th percentile of fuel type uncertainty.

This breakdown on a regional basis is available in the appendix

Accounting for uncertainty in STPASA

- The HLD suggests two possible approaches to account for uncertainties:
  - Monte Carlo simulations with random sampling from distributions of inputs (similar to ISP modelling approach) – not feasible due to the massive number of simulations required that would be computationally impossible in an operational timeframe
  - Probabilistic approach using Uncertainty Margins, selected in a mutually consistent way that reflects expected conditions – viable option to use in an operational timeframe

Uncertainty Margins

Uncertainty Margins and Confidence Levels

- What is an Uncertainty Margin?
  - An amount of MWs that represents expected *conditional* forecast error for a specified *confidence level*
    - *Conditional* because the size of it changes depending on various factors (discussed later)
    - *Confidence level* - a 95% confidence level means 19 out of 20 times the forecast error will not exceed this value. Equivalent to “there is a 5% probability that the forecast error will exceed this value”
- How are Uncertainty Margins used?
  - Demand forecast is adjusted by adding the demand Uncertainty Margin
  - VRE forecast is adjusted by subtracting the VRE Uncertainty Margin
  - Scheduled generation MaxAvail is adjusted by subtracting the MaxAvail Uncertainty Margin

A note about signs and Confidence Levels

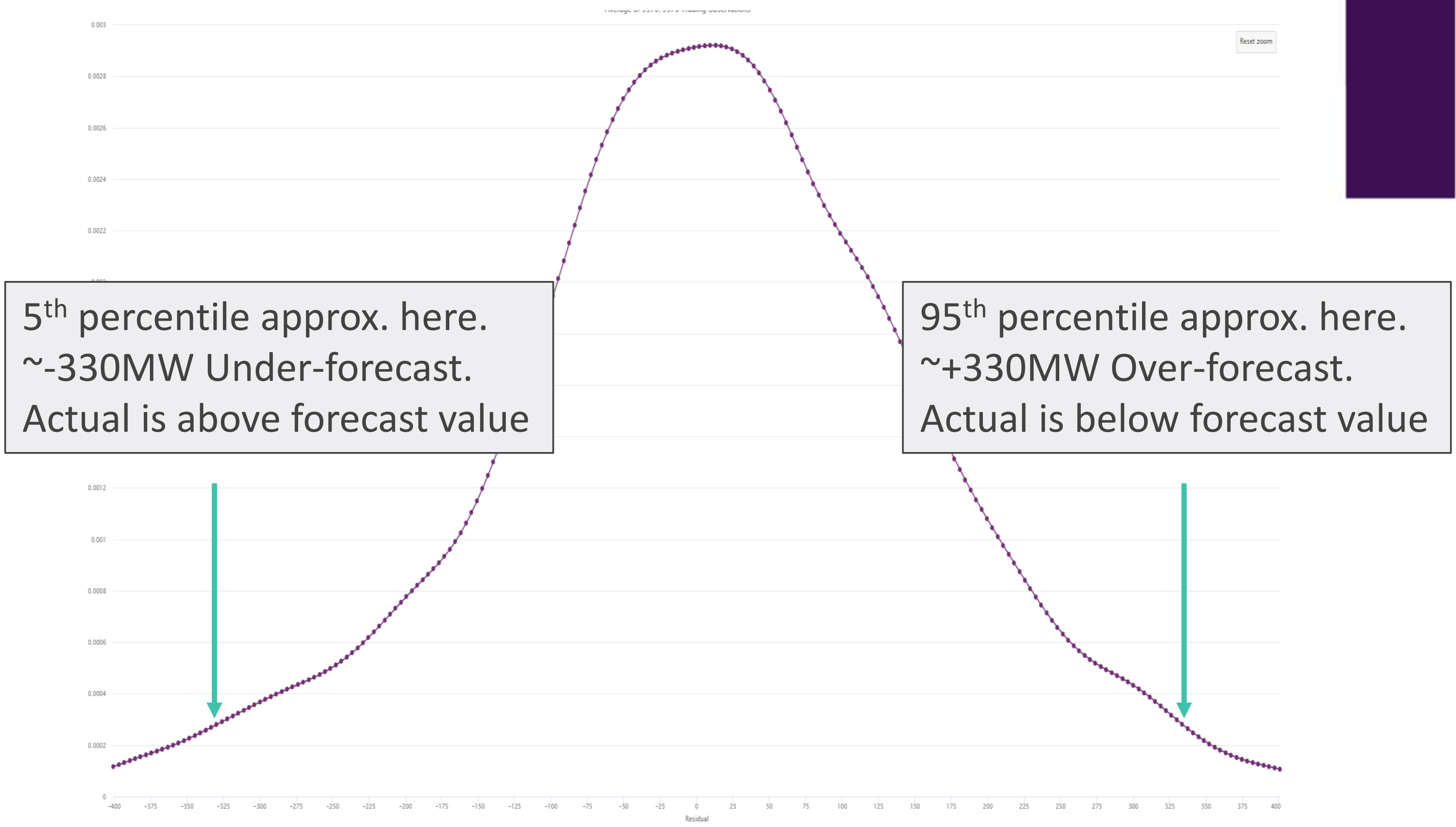
The convention used to define uncertainty (forecast error) is *Forecast minus Actual*

This convention means that the 95th percentile of uncertainty is an Over-forecast, i.e. the actual is below the forecast value.

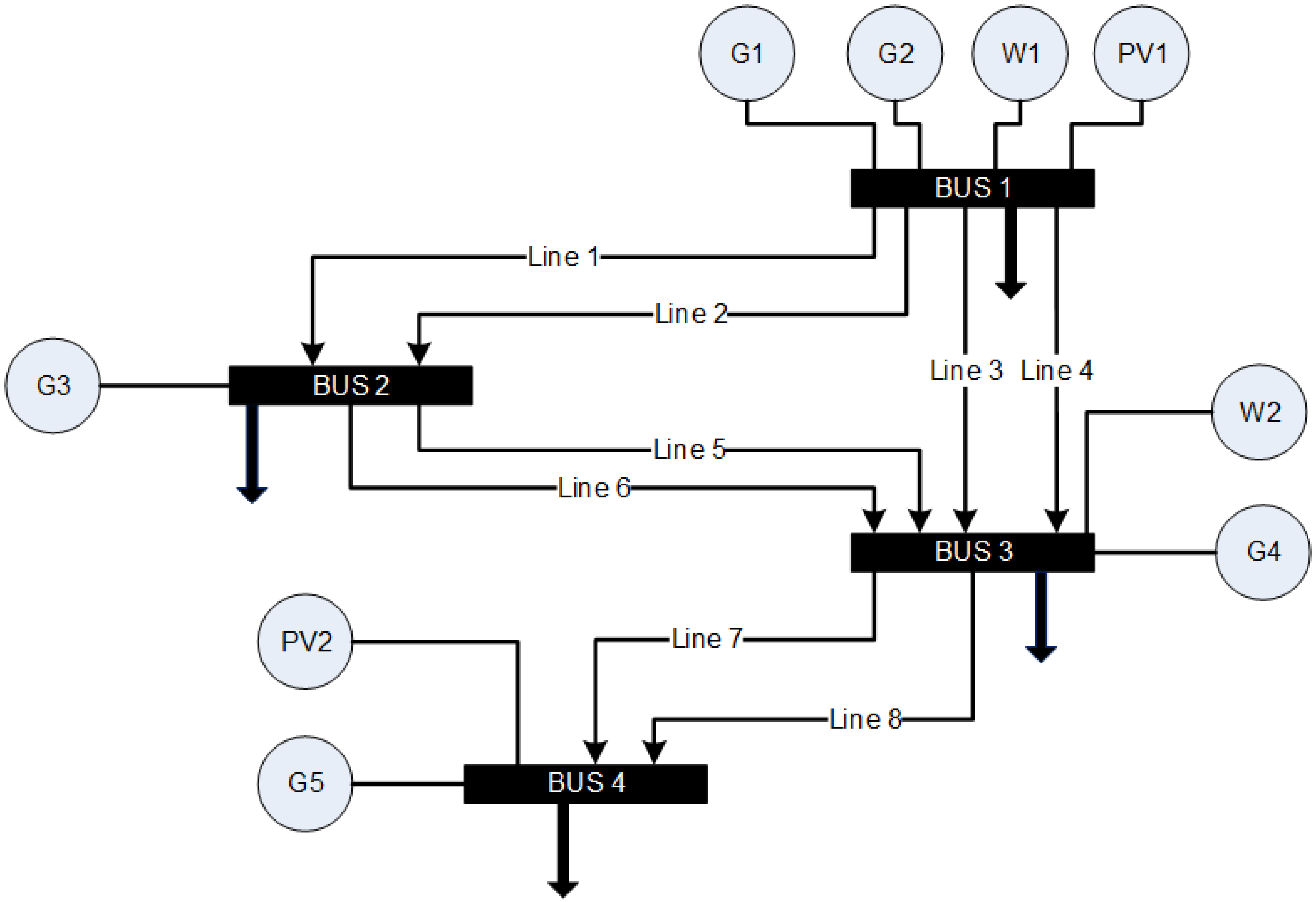
This is appropriate for Supply because we are interested in cases Supply does not meet the expected level.

However, this is not appropriate for Demand because we are interested in cases where Demand exceeds the expected level.

To correct this, while ensuring consistency when referring to Confidence Levels for Demand we actually take the “1 minus Confidence Level” percentile in order to convert to the Under-forecast uncertainty. E.g. if we are taking the 95th percentile Confidence Level, we actually take the 95th percentile of Supply uncertainty but take the 5th percentile of Demand uncertainty.

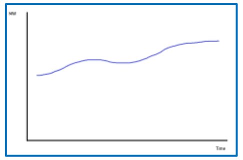


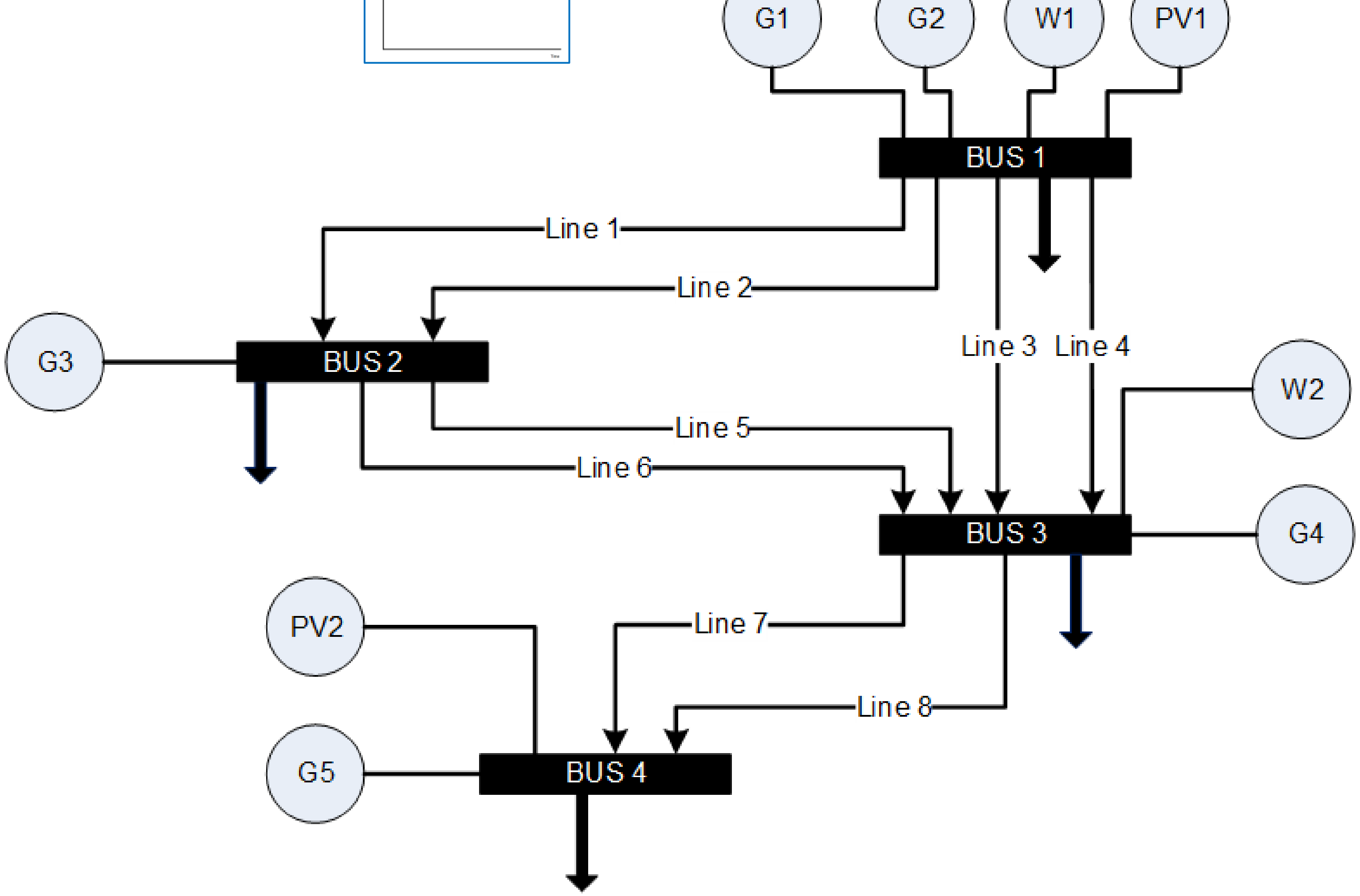
Uncertainty Margin example



Uncertainty Margin example

Step 1: determine total (regional) Uncertainty Margin

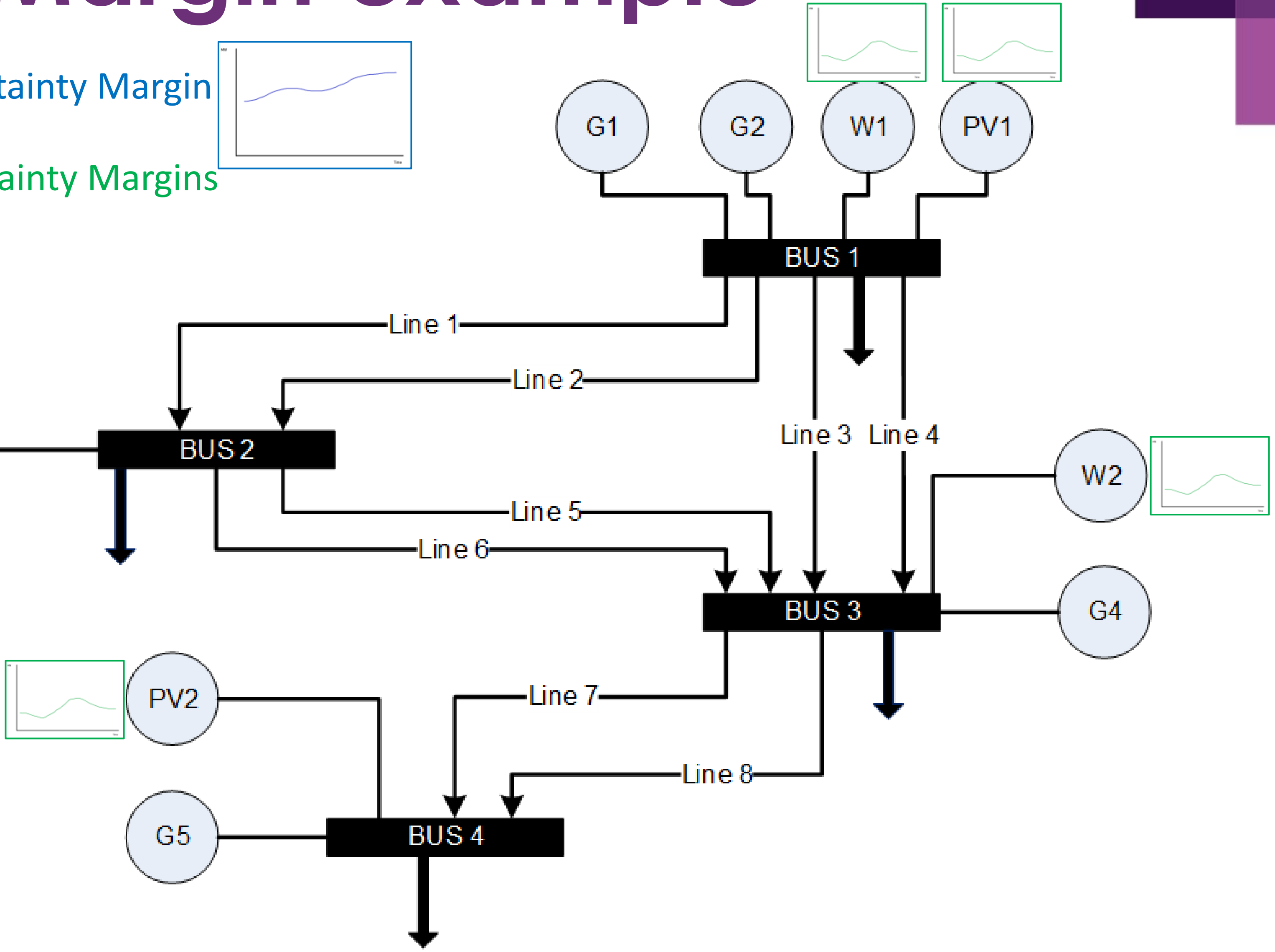




Uncertainty Margin example

Step 1: determine total (regional) Uncertainty Margin

Step 2: determine individual VRE Uncertainty Margins

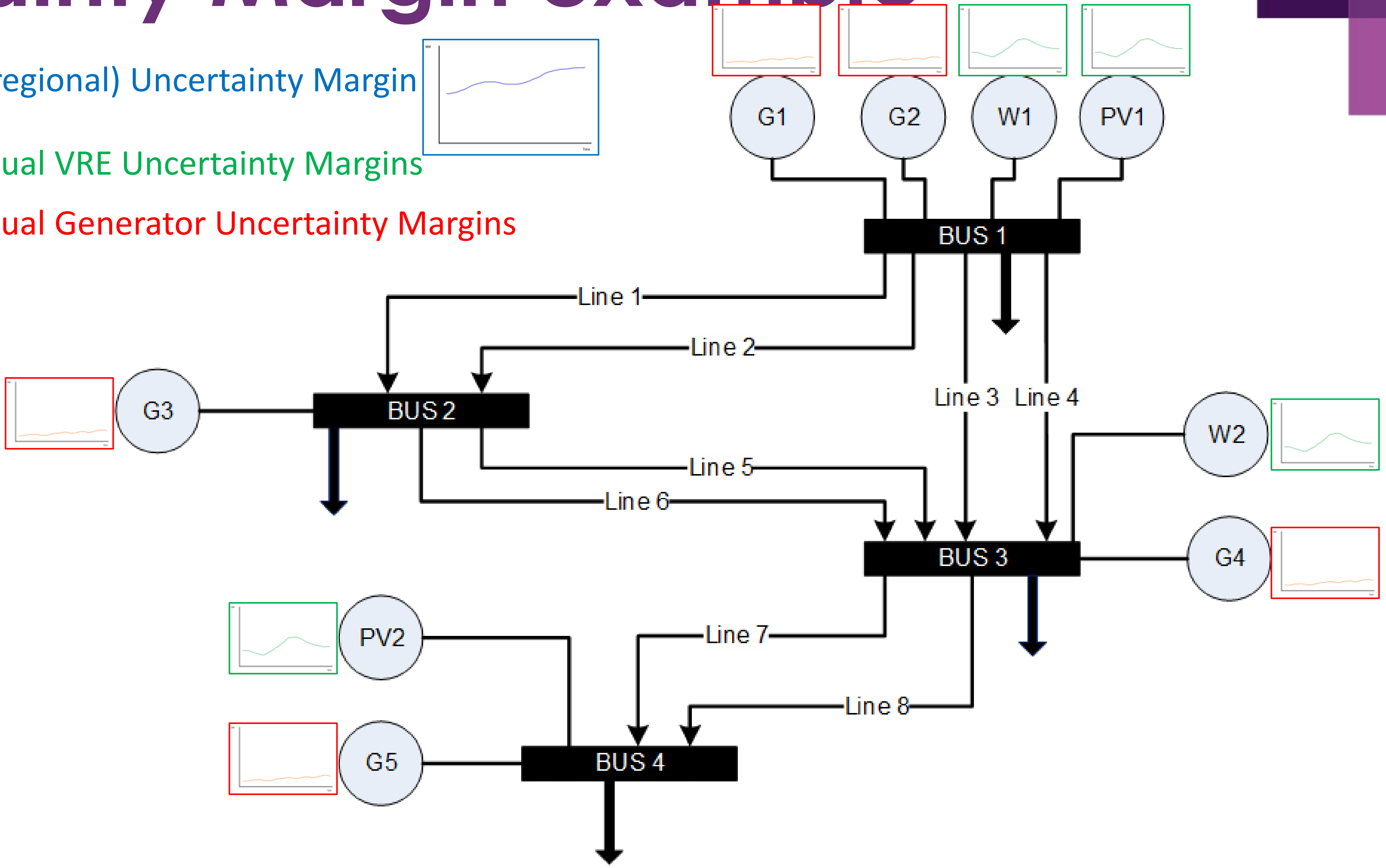


Uncertainty Margin example

Step 1: determine total (regional) Uncertainty Margin

Step 2: determine individual VRE Uncertainty Margins

Step 3: determine individual Generator Uncertainty Margins



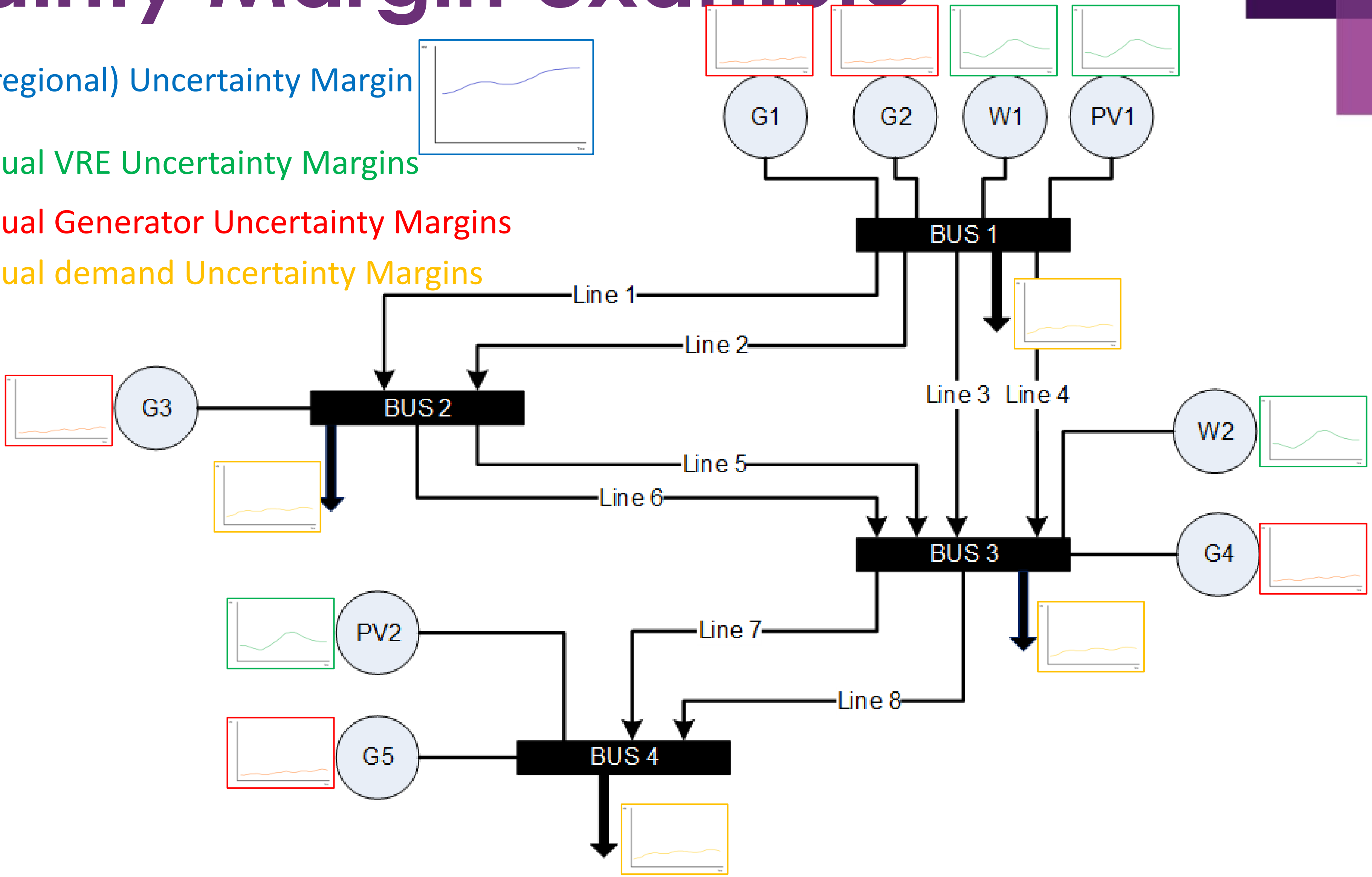
Uncertainty Margin example

Step 1: determine total (regional) Uncertainty Margin

Step 2: determine individual VRE Uncertainty Margins

Step 3: determine individual Generator Uncertainty Margins

Step 4: determine individual demand Uncertainty Margins



Uncertainty Margin example

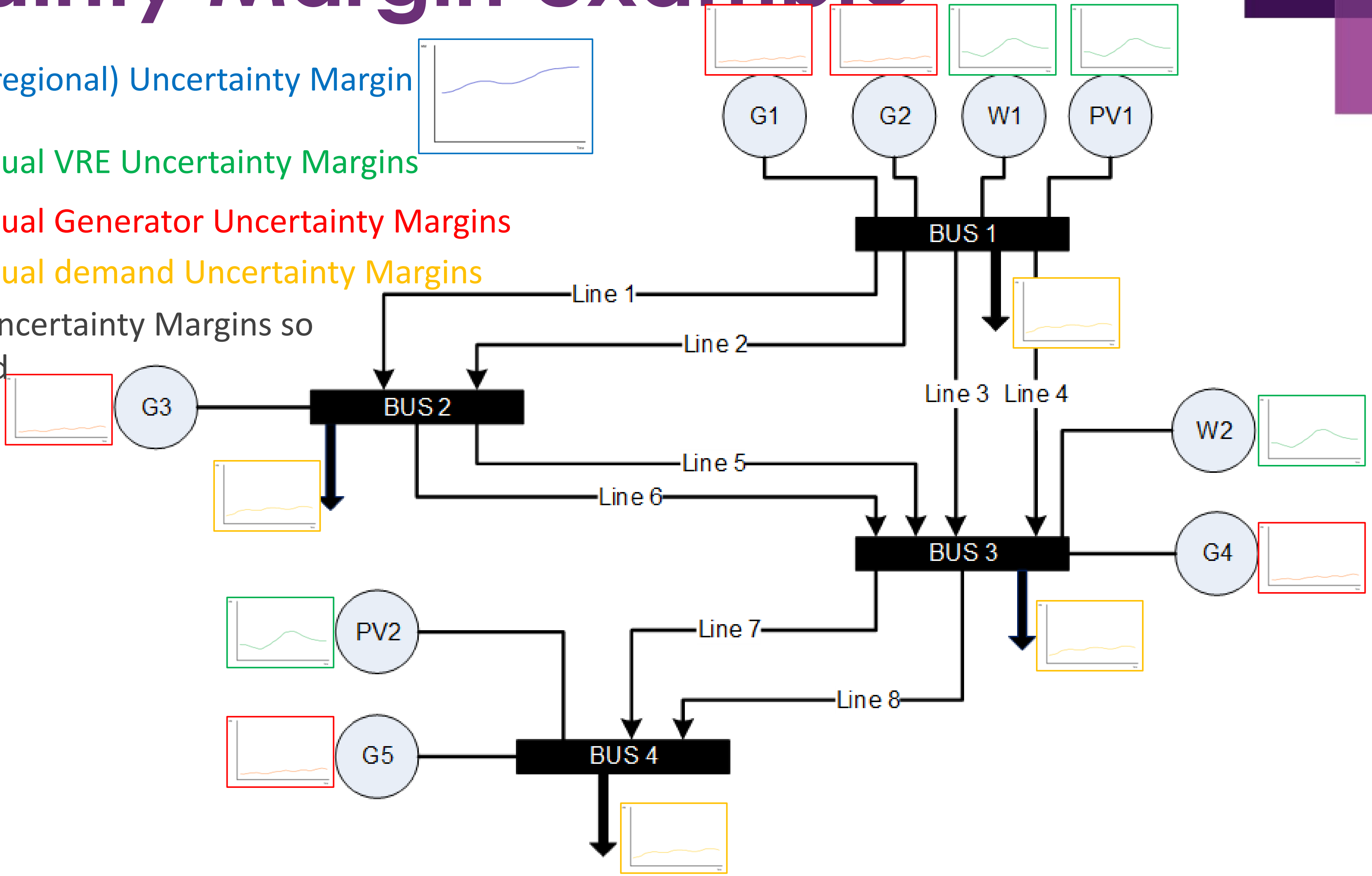
Step 1: determine total (regional) Uncertainty Margin

Step 2: determine individual VRE Uncertainty Margins

Step 3: determine individual Generator Uncertainty Margins

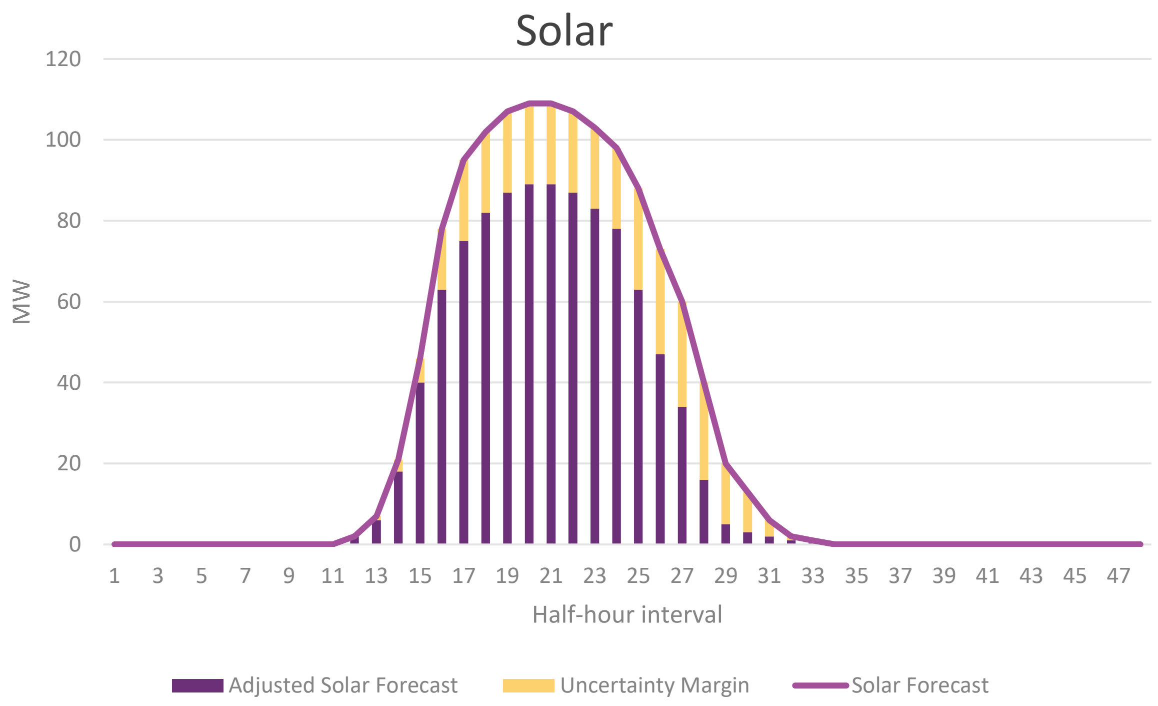
Step 4: determine individual demand Uncertainty Margins

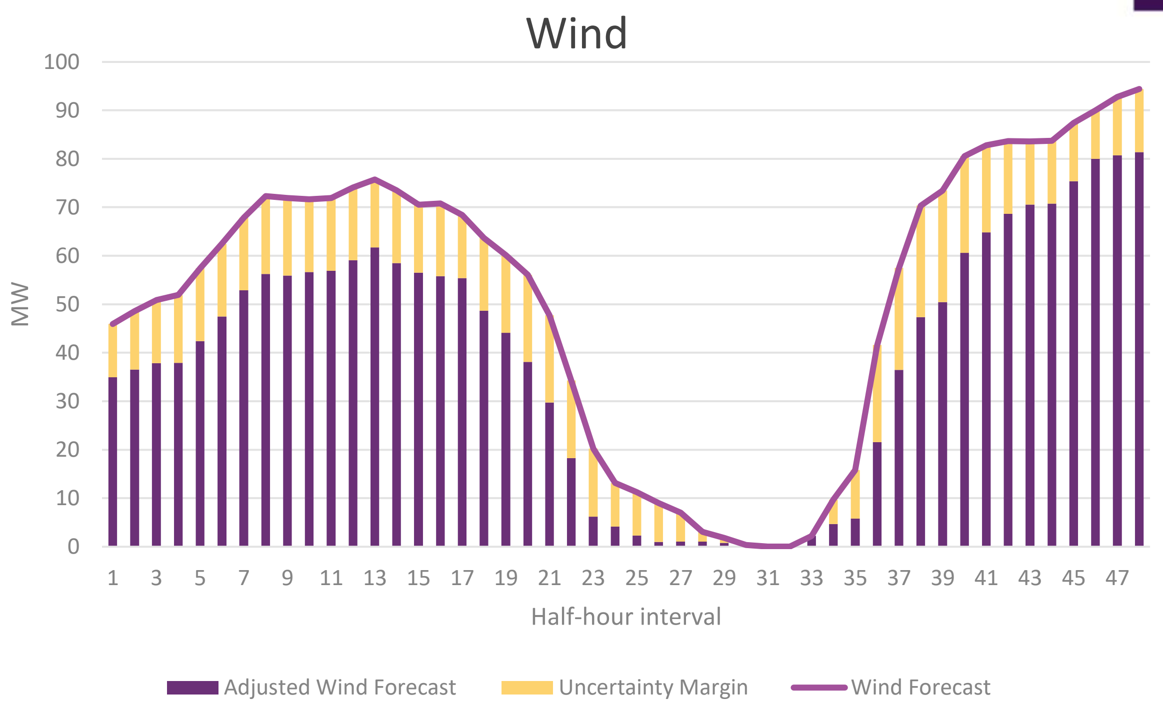
Step 5: scale individual Uncertainty Margins so that sum does not exceed total (regional) Uncertainty Margin



Uncertainty Margin example

- Step 6: adjust unit VRE forecast by **subtracting** corresponding Uncertainty Margin. Repeat for each VRE unit.

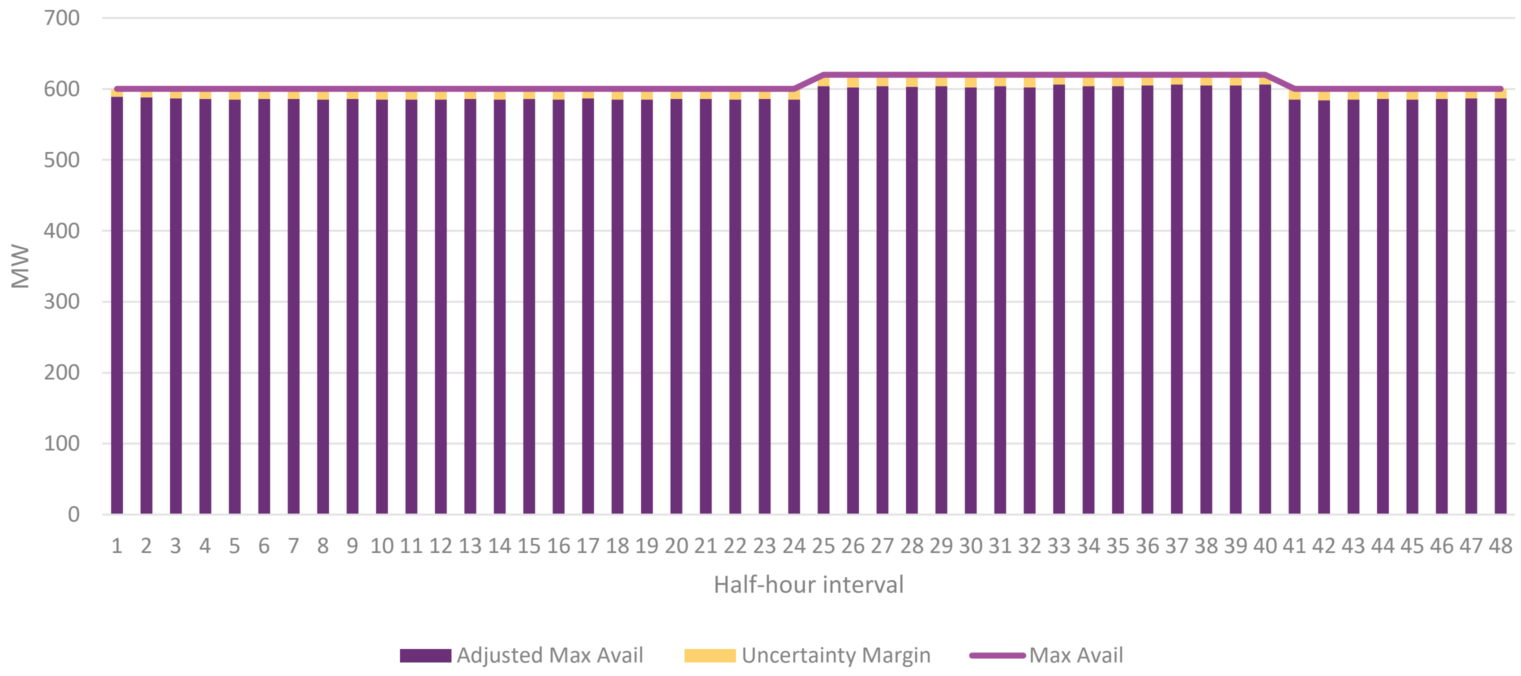




The Uncertainty Margins in this example are indicative only and do not reflect the size of expected Uncertainty Margins

Uncertainty Margin example

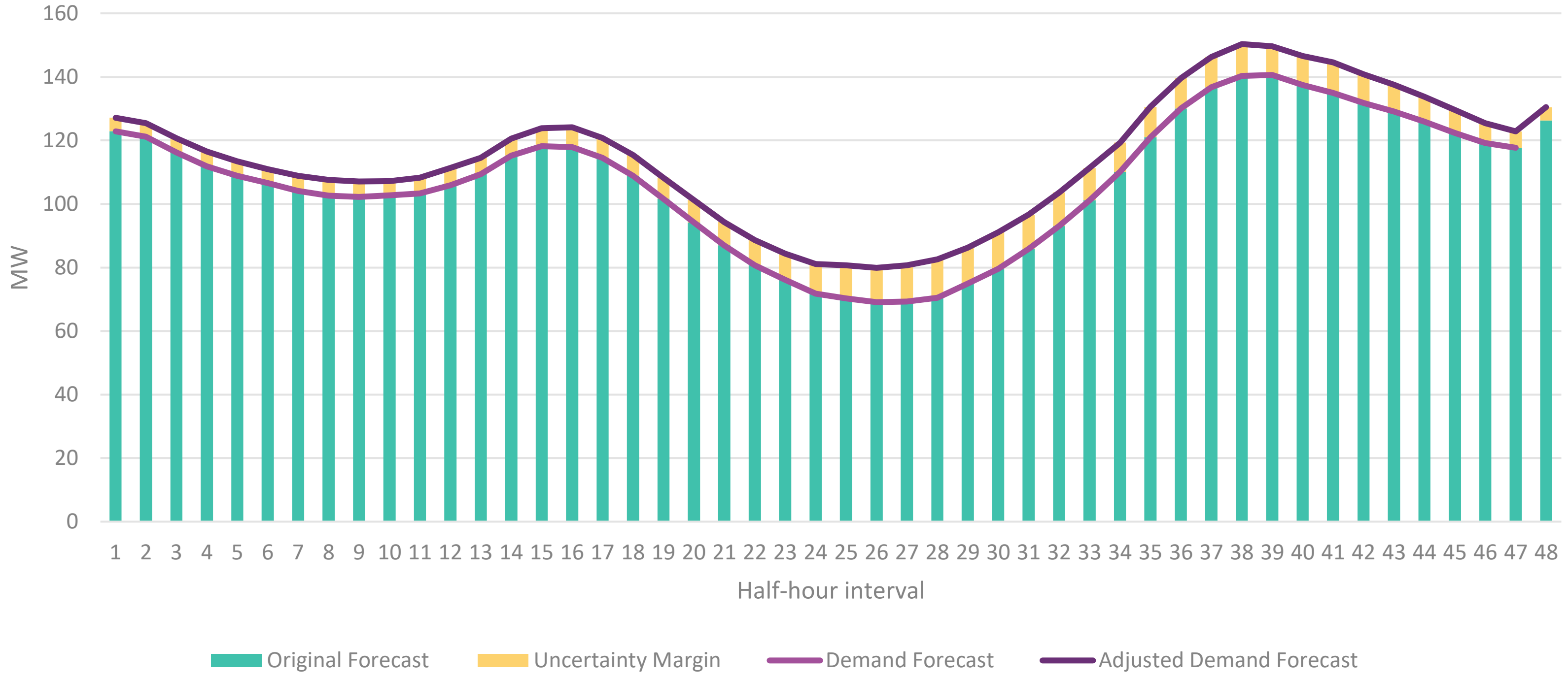
- Step 7: adjust scheduled generator MaxAvail by **subtracting** corresponding Uncertainty Margin. Repeat for each scheduled generator.



The Uncertainty Margins in this example are indicative only and do not reflect the size of expected Uncertainty Margins

Uncertainty Margin example

- Step 8: adjust demand forecast by **adding** corresponding Uncertainty Margin. Repeat for each load on each bus.



- Step 9: supply the adjusted values as inputs to the SCED. Repeat this for every timestep in the STPASA forecast horizon.

The Uncertainty Margins in this example are indicative only and do not reflect the size of expected Uncertainty Margins

Uncertainty Margin modelling

Uncertainty Margin Modelling Overview

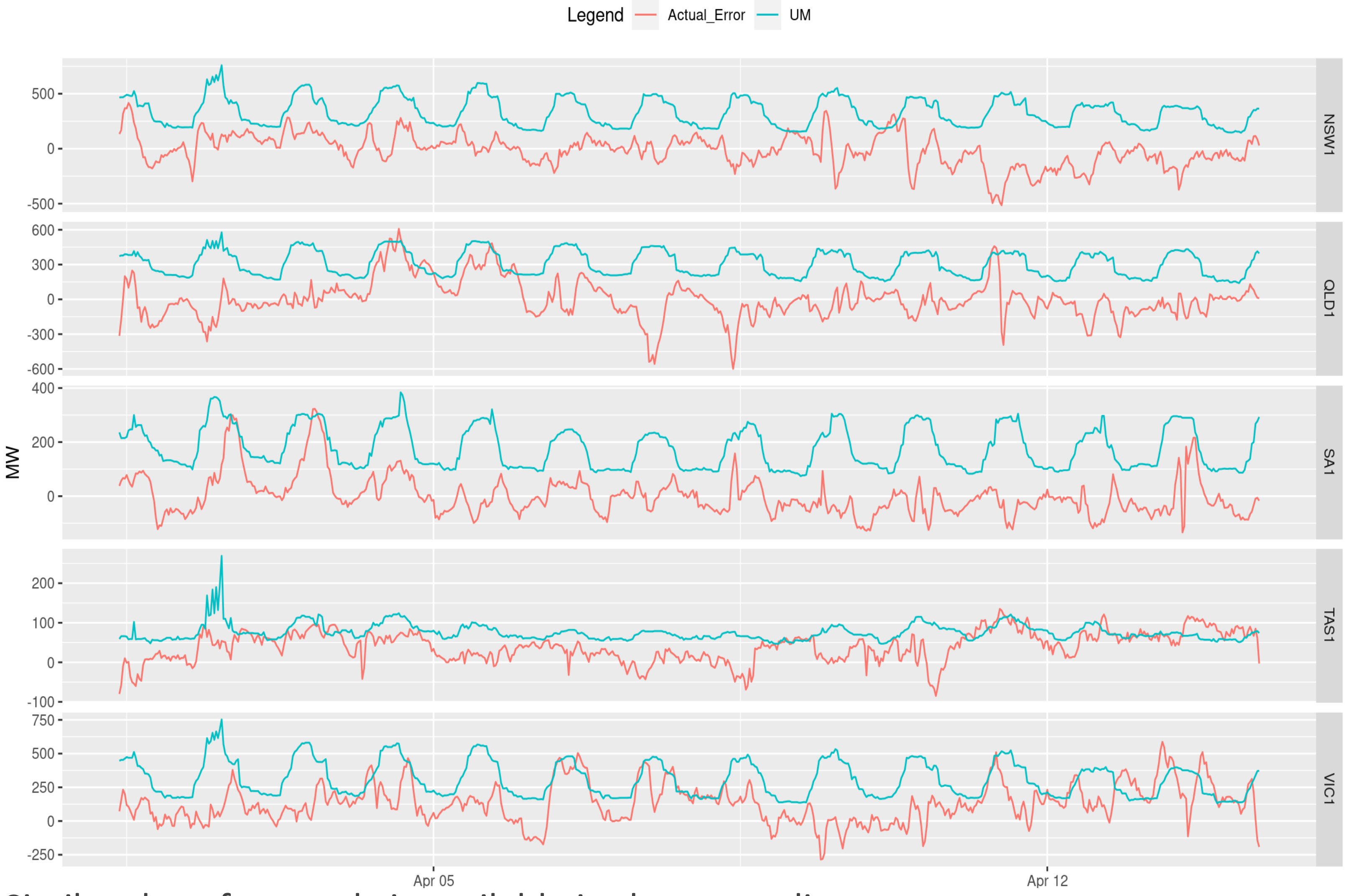
1. Developed an end-to-end Uncertainty Margin (UM) model training and validation pipeline:
   i. UM for wind and solar generators based on AWEFS & ASEFS forecasts
   ii. UM for scheduled generators based on Max Avail from bids
   iii. UM for demand based on AEMO load forecasts
   iv. UM at the Regional Level calculated from regional generation and demand uncertainty (used to scale individual UMs so that sum does not exceed regional UM for mutual consistency)
2. Validation of UMs
   1. Breaches match expected breach rate given confidence level
   2. Reasonability of UMs
      1. By time-of-day
      2. By forecast horizon

UM Model Framework

- H20 machine learning models to predict UM
- Standardised set of inputs used as explanatory variables/features:
  - Temporal features and cyclical features e.g. time trend, time of day, time of year etc
  - Weather forecast features e.g. temperature forecast, humidity forecast, wind speed forecast etc
  - Fuel type availability features based on Max Avail from bids and AWEFS/ASEFS forecasts
  - Selected based on feature importance, principal component and correlation analysis, and considering feature forecast accuracy
- Probability of Exceedance (PoE) of 95% has been the initial model development threshold (subject to change)
- Models predict UM for every 30 minute interval for STPASA horizon

Region Level Uncertainty Margin - Demand

Day ahead predicted demand Uncertainty Margin (95% confidence level) vs Actual Error by Region



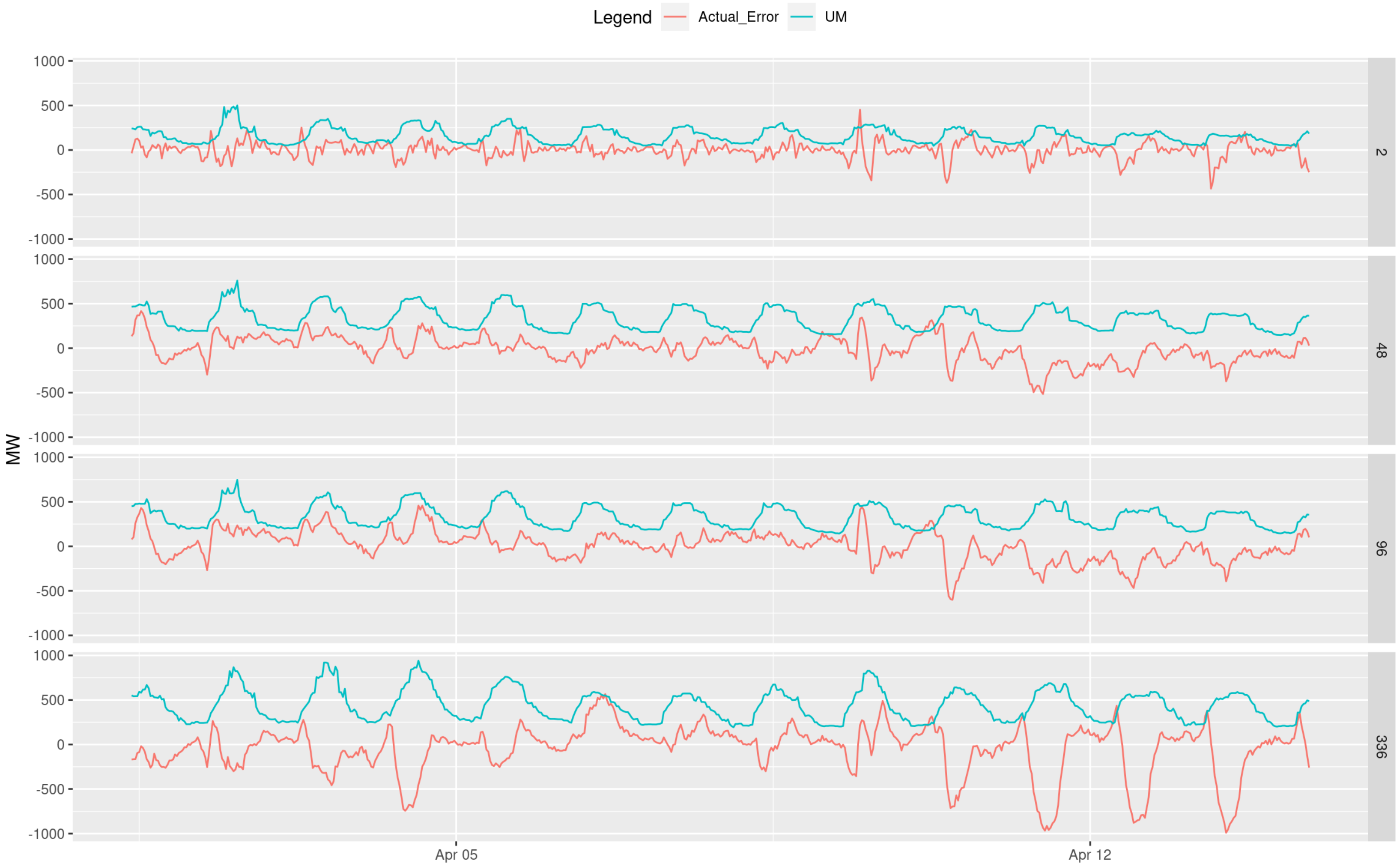
Similar chart for supply is available in the appendix

Key Takeaways

- These show the predicted demand Uncertainty Margin vs the actual error day ahead. Given a confidence level of 95% we would expect over a large enough sample that 5% of the intervals have an actual error above the predicted UM.
- UM has a reasonable daily profile which increases during the day and decreases at night.
- The magnitude of the UM across the states also appears reasonable.

Region Level Uncertainty Margin - Demand

Predicted demand Uncertainty Margin (95% confidence level) for NSW vs Actual Error by forecast horizon



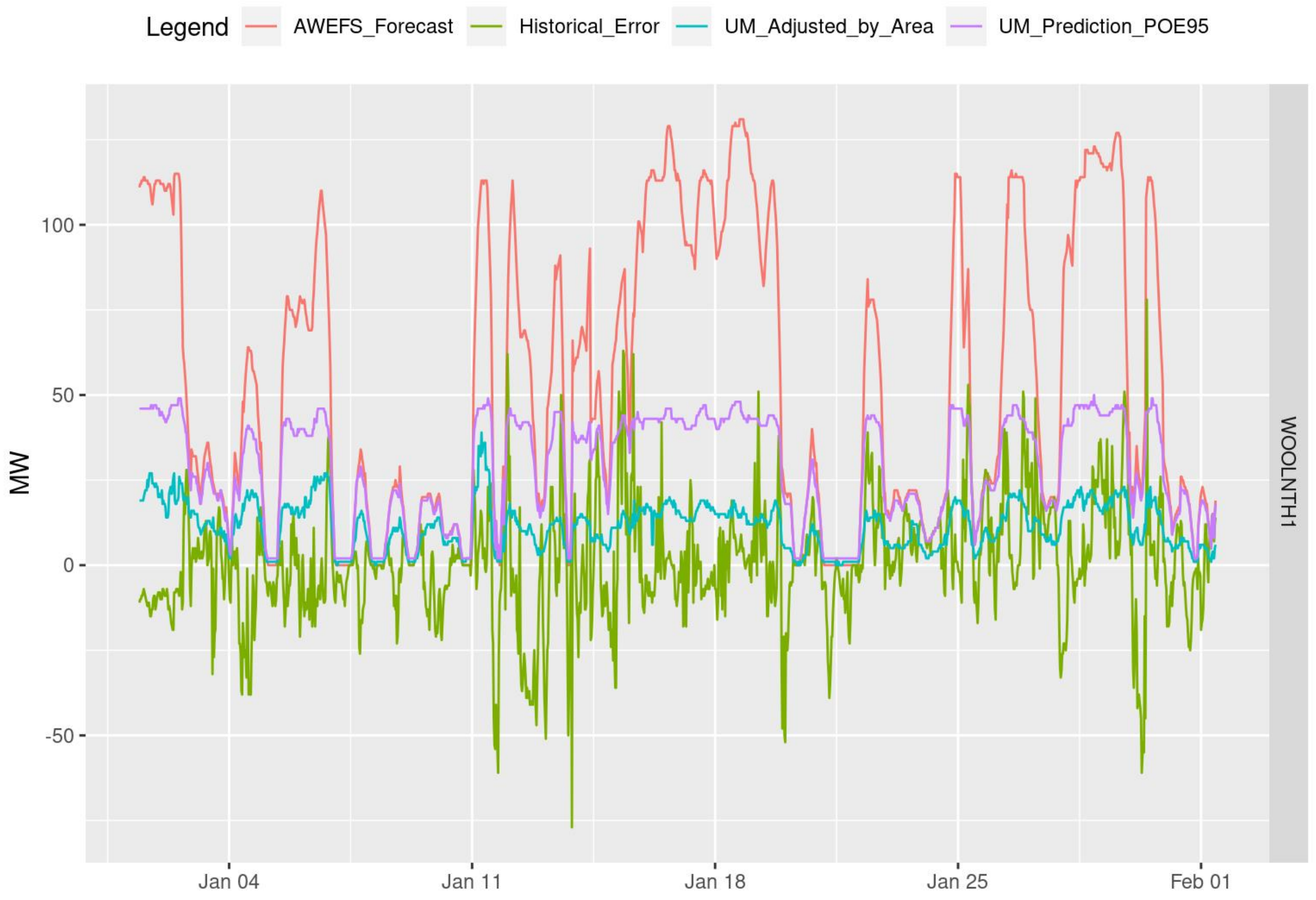
Key Takeaways

- The magnitude of the UM across Forecast Horizons appears reasonable as it increases the further ahead in time we are forecasting.

Similar chart for supply is available in the appendix

Example of Regional scaling of Uncertainty Margin – Wind forecast

Day ahead wind forecast and predicted Uncertainty Margin vs Actual Error



Key Takeaways

- Proportion of adjustment to UM (i.e. regional scaling) is dynamic and dependent on fuel mix

Uncertainty Margin comparison

- The Forecast Uncertainty Measure (FUM) is how forecast uncertainty is accounted for in the current STPASA.

	Uncertainty Margin (future)	Forecast Uncertainty Measure (current)
What uncertainty factors are accounted for?	• Demand forecast uncertainty • Individual VRE forecast uncertainty • Individual scheduled generator MaxAvail uncertainty	• Demand forecast uncertainty • Regional VRE forecast uncertainty • Regional scheduled generator MaxAvail uncertainty split into Energy Limited and non-Energy Limited components • Regional interconnector support uncertainty
Inputs to the model	• Temporal features • Weather forecast features • Fuel type availability features	• Temperature forecasts • Solar irradiance forecasts • Regional VRE forecasts • Current demand forecast error • Current regional fuel supply mix
How it is used?	Used to adjust demand/supply inputs into the SCED	Used as a post-process after the solver to set the reserve requirement level

Refer to the Reserve Level Declaration Guidelines for more information.

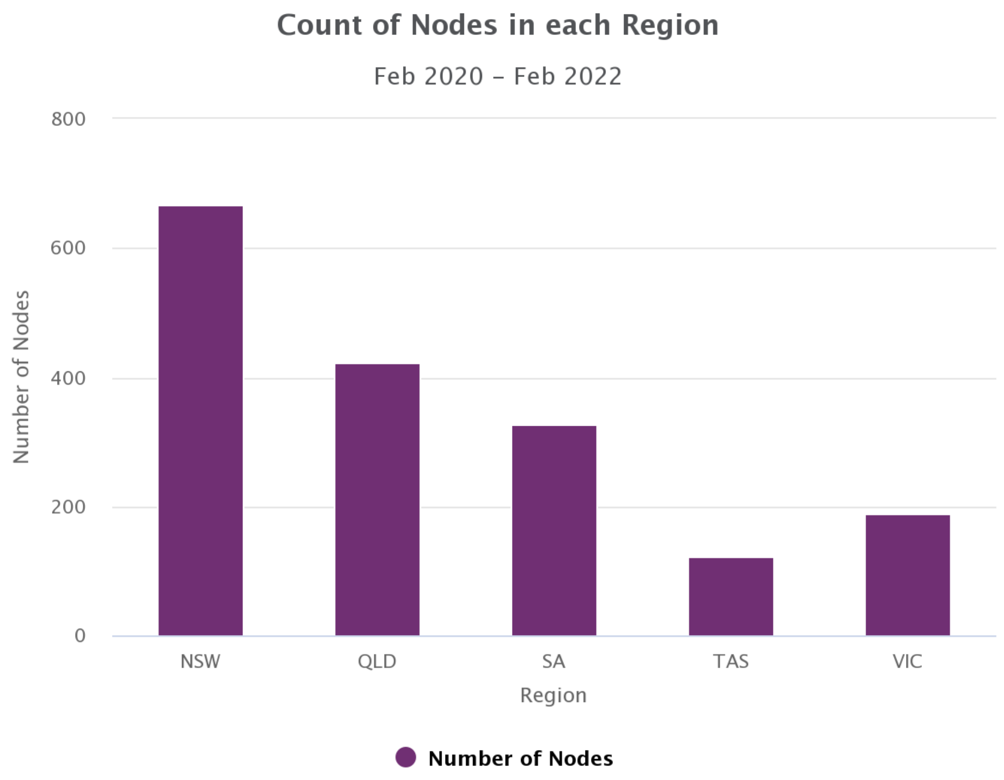
Load forecasting for STPASA

Nodal Loads across the NEM

In the context of the full network model, a nodal load represents a load on a bus bar and is equivalent to a grid exit point where load is withdrawn from AEMOs operational zone.

As the SCED is solving for a full network model, a requirement is to produce a nodal load forecast.

There are over 1,700 nodal points across the NEM – more than half of these in NSW & QLD



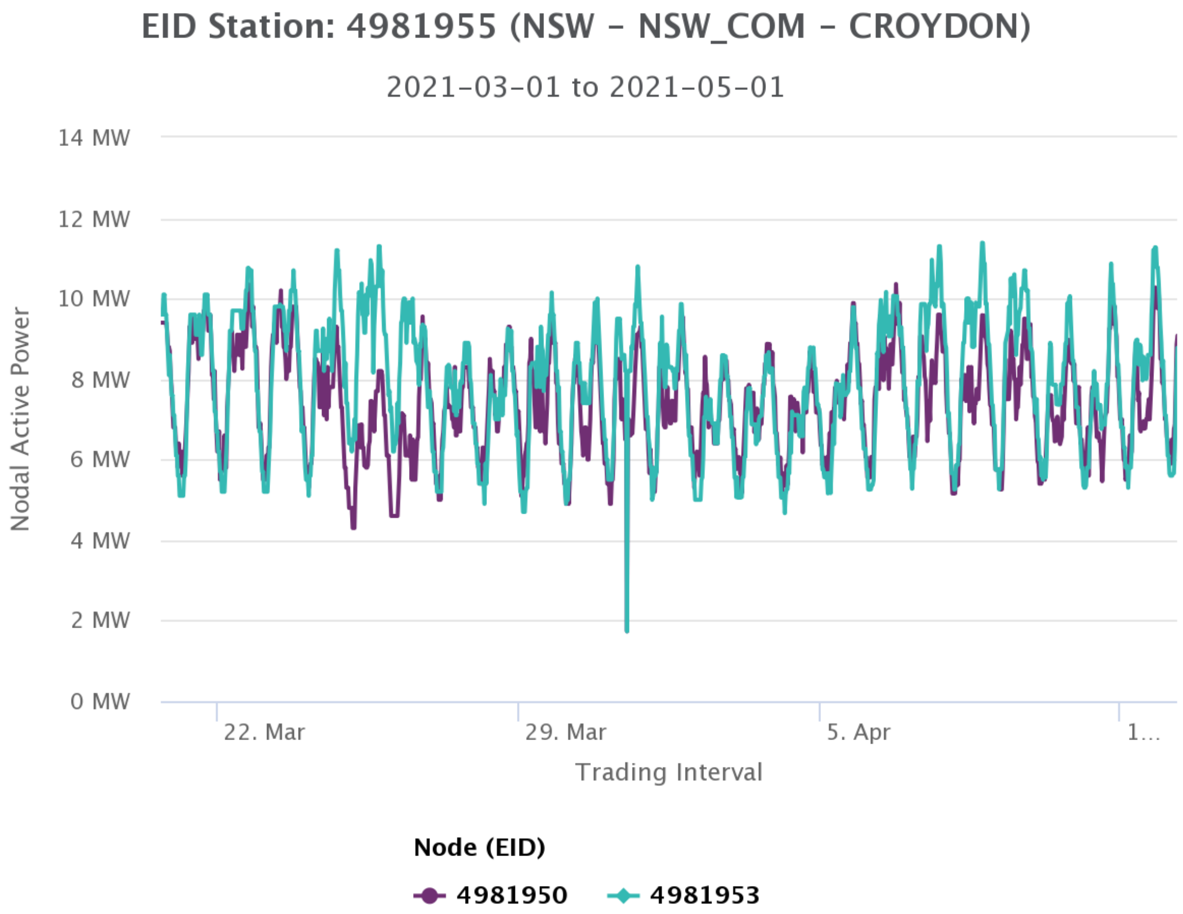
Challenges & Characteristics of Nodal Data

When modelling nodal points across the entire NEM, we must strive to find a balance between a ‘one size fits all’ method with more bespoke approaches.

Each node can have it’s own characteristics and behaviour, making it difficult to find the right data and relevant underlying drivers to model with.

Fortunately, we have identified many common challenges and characteristics shared across these nodes

> *<u>Challenge & Characteristic #1</u>*
> *Two nodes at the same substation can be highly correlated, but understanding why & when deviations in Active Power occurs can be time-consuming and costly if we were to model each single node individually*



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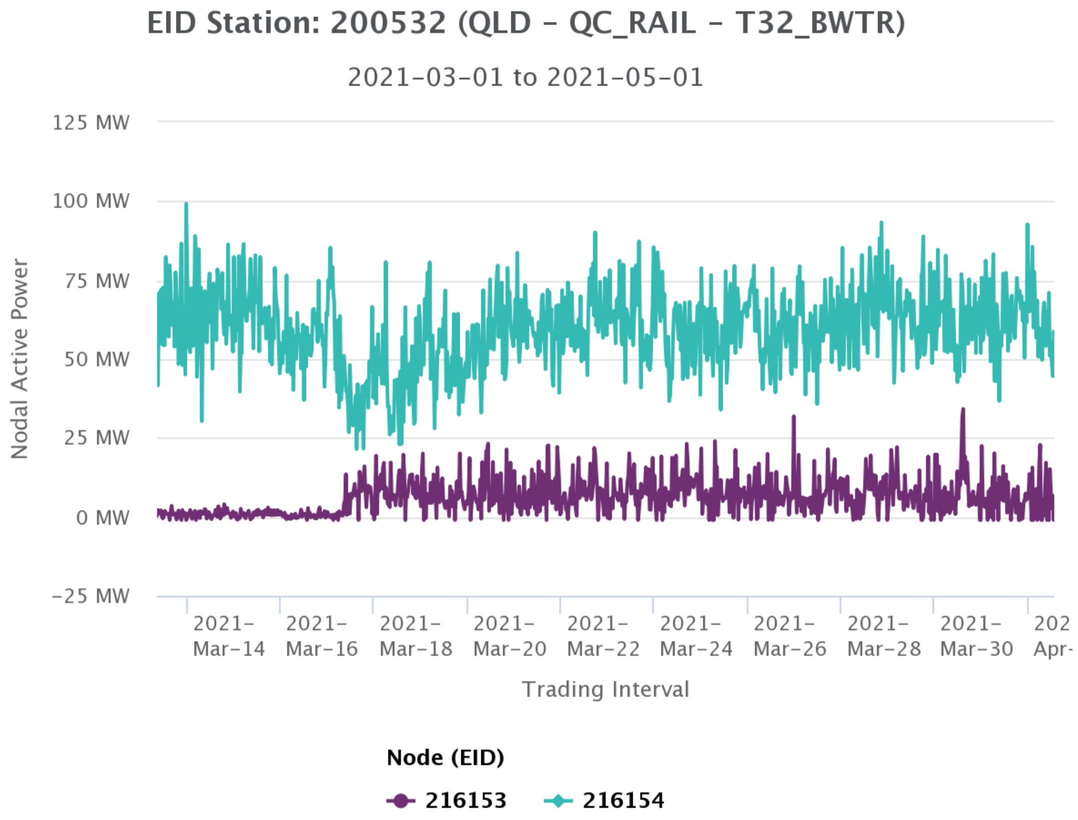
<u>Challenge & Characteristic #2</u>
Some nodes are so highly variable that many appear as random noise. A forecast model would simply be limited in its ability



Challenges & Characteristics of Nodal Data

When modelling nodal points across the entire NEM, we must strive to find a balance between a 'one size fits all' method with more bespoke approaches.

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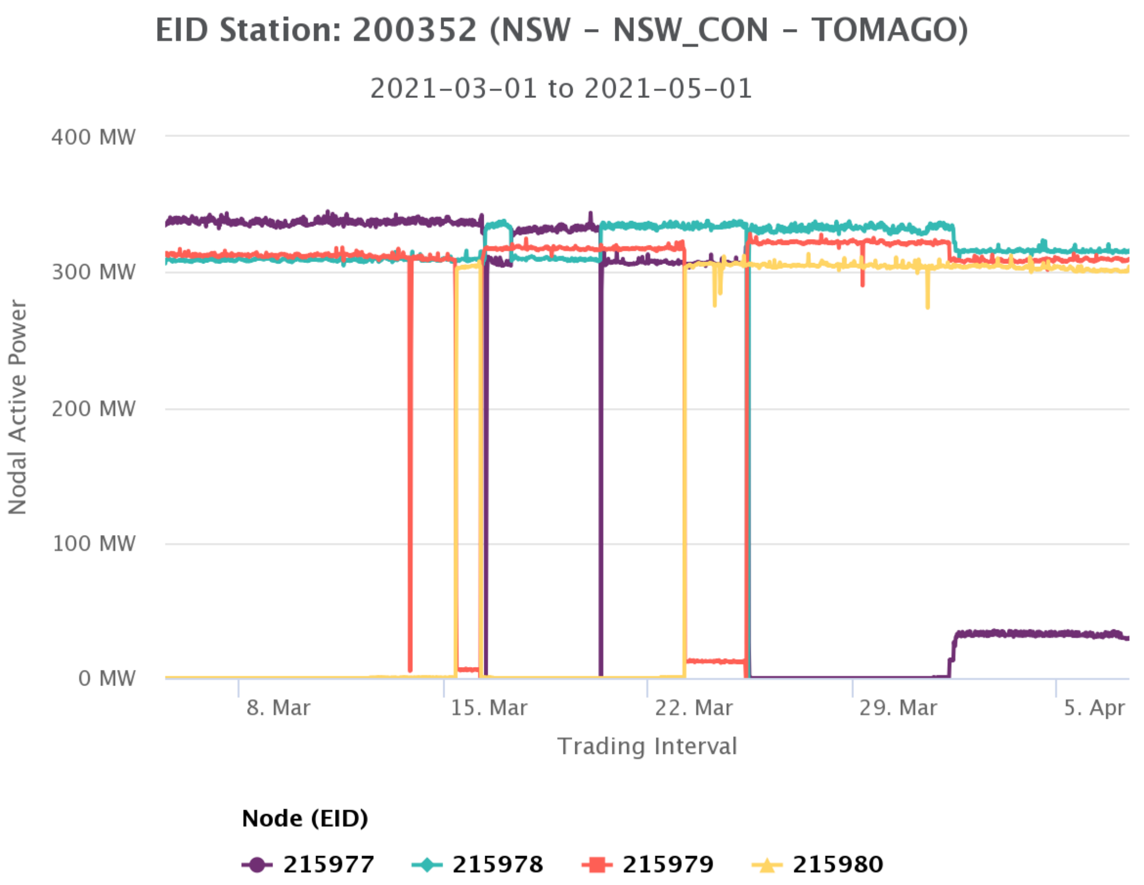
Fortunately, we have identified many common challenges and characteristics shared across these nodes

<u>Challenge & Characteristic #3</u>
Some stations experience such high ramps and rapid switching that a forecast model would not be able to anticipate this behaviour without additional information from TNSPs or participants



Nodal Modelling

Rather than predict the Power Demand at each node, we could instead target the ***Regional Nodal Rate***.

This is the nodes proportion of the total Regional Power Demand.

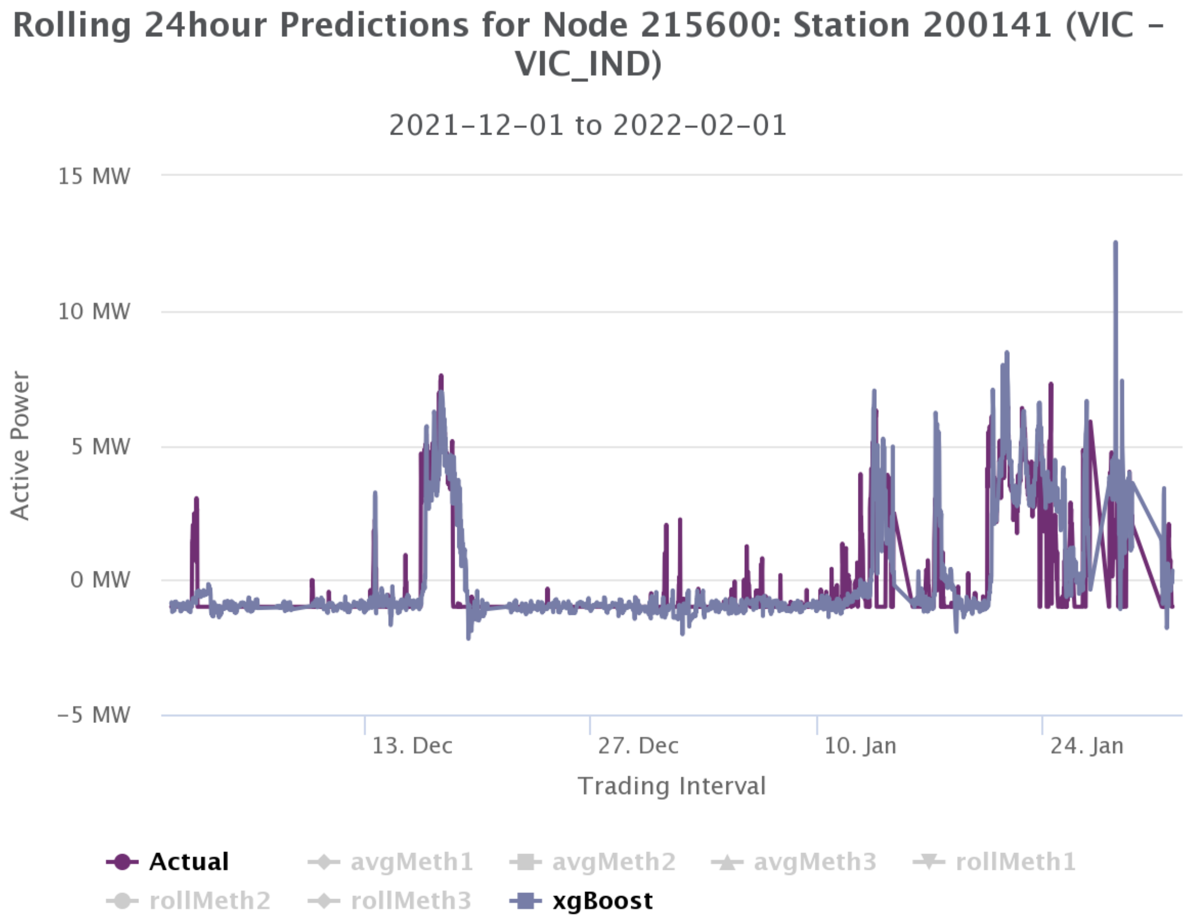
Regional Nodal Rate

$$= Node_{PowerDemand} / Region_{PowerDemand}$$

This presents a more stable and consistent target and enables us to model Nodes concurrently as all nodes are now standardised between 0 & 1.

A Proof of Concept was trialled with Machine Learning models & other conventional techniques to assess how well the Regional Nodal Rate could be forecasted under different circumstances

Machine Learning Proof of Concept



Machine Learning takeaways:

- Nodes with high variation and random-like behaviour will be challenging to predict with any forecasting method.
- By grouping nodes together in the same training pool, ML models are able to learn what drives variation across different nodes with shared variables (such as temperature, regional demand, and time of day).
- Can be **proactive** in predicting changing behaviour under the right conditions (rather than *reactive* to recently observed movements like ramps).
- Large Ramps & Nodes switching at the station will always be difficult to predict without additional information to inform this behaviour.
- Post-processing rules (such as flooring & capping of forecasts) will need to be considered so large errors can be limited

Validating the system

Validating the system

Ongoing validation will occur from now through to 2024.

- The results of validation will be shared with stakeholders during future industry workshops in 2023-24.

1. Model validation
   - To ensure Uncertainty Margin models are fit for purpose
   - To ensure Nodal Load Forecasting models are fit for purpose
2. System testing and backcast
   - To integrate forecasting components with the SCED
   - To determine performance over extended historic periods to confirm operational readiness
   - To consult with stakeholders on appropriate Confidence Levels

Model validation

- Uncertainty Margin models
  - For all Confidence Levels and forecast horizons: breach rate matches expected
    - By time of day, season, forecast horizon, weather conditions etc
  - Reasonability check against current reserve requirements (LCR/LCR2/FUM)
    - To give an indication of confidence levels
  - Analysis of distribution of Uncertainty Margins for given confidence levels
    - Does the distribution match the distribution of observed uncertainty at that confidence level
  - Time series analysis
    - To confirm Uncertainty Margins for a fixed interval from successive runs are stable and suitable for operational decision making

- Nodal Load Forecasting models
  - Accuracy assessment of nodal load forecasts

System testing and backcast

- A backcast is the process of running the system end-to-end over an extended historic period using all inputs as they would have been at each runtime in history.
  - It is a way to understand what results the system would have produced had it been running at that time in the past.

- High-level backcast methodology
  1. Create base case with Uncertainty Margins of 0MW – fix any issues and compare load deficits to existing system. This will potentially identify issues caused by the nodal load forecasting model.
  2. Repeat with different confidence level Uncertainty Margins
  3. Analyse results to determine if UMs or nodal load forecasts are causing any erroneous load deficits → may indicate need for post-processing prior to input into SCED
  4. Analyse suitability of results for operational decision making, for example, are results repeatable and stable from run-to-run
  5. Consult with stakeholders on appropriate Confidence Levels in recognition of Reliability Standard annual Unserved Energy metric

Confidence levels and uncertainty

- The Confidence Levels used are critical:
  - Determine size of Uncertainty Margins
  - Impact how often forecast/actual reserve conditions are declared
  - Ultimately influence AEMO intervention (e.g. RERT or directions)
- The Reliability Standard defines the annual unserved energy
  - However there is no theoretical framework for how to turn an annual unserved energy metric into an operational probabilistic uncertainty margin

Confidence levels and uncertainty

- Appropriate confidence levels can be determined empirically
  - AEMO intends to use the backcast results to empirically calculate Confidence Levels that would approximate annual unserved energy requirements of the Reliability Standard
- There are challenges with empirical analysis such as:
  - Ensuring backcast period is sufficiently long and represents all expected future conditions
  - Cases of intervention in the past may have prevented the forecast event from occurring i.e. self destroying prophecy
- AEMO anticipates that the Confidence Level will not necessarily be the same for every interval of the STPASA forecast horizon

Consultation

- AEMO is committed to a formal rules consultation with stakeholders to determine the methodology to develop Confidence Levels used in STPASA
  - This will be part of the formal rules consultation process to commence late 2022 / early 2023
  - This will include updating the Reserve Level Declaration Guidelines (RLDG) to include the methodology with provision for the confidence level values to be separately published (not in the RLDG)

Consultation

- AEMO will then run another round of consultations to determine the confidence levels to be used to determine the reserve conditions in STPASA
  - This consultation will occur in 2024-25, prior to go-live of the new STPASA
  - During the consultation, AEMO will present detailed results from the backcast showing which Confidence Levels would have achieved the Reliability Standard unserved energy metrics over the historic period of the backcast and will seek feedback from stakeholders
  - This will not be part of a formal rules consultation process
- AEMO is keen to hear thoughts from stakeholders on this approach to consultation

Data to be published

Data to be published

- After every scheduled run of STPASA, AEMO intends to publish the following Uncertainty Margin and Load Forecasting data from the STPASA run:
  - Region level Uncertainty Margins
  - Uncertainty Margins for each entity (load on bus, generator) before and after regional scaling
  - Load forecasts for each load on bus
  - Next-day public: Actuals for each load on bus
- Anything else stakeholders would like?

Project Next Steps

Workshop timetable

Workshop	Topic	Proposed Date
1	Generator Recall Process – current and future	Thursday 7 April 2022
2	Overview of the new process	Thursday 19 May 2022
4	Demand Forecast, Uncertainty Margin and Confidence Levels	Thursday 21 July 2022
3	**Rescheduled** PASA Run types	Thursday 4 August 2022
5	Information to be made publicly available	Thursday 11 August 2022

Feedback and questions

Frequently asked questions

Why Max Avail? Why not PASA Avail?

- We analysed PASA Avail and Max Avail and found PASA Avail did not reflect reductions in availability and was thus not suitable for modelling

What is the impact of demand side response (or Demand Side Participation (DSP)) on the UM?

- If the demand side response is regular and predictable, then it has no impact on the UM and the behaviour is trained into the load forecast models. For example, Energy Queensland ripple control (Tariff 31 and 33) of air conditioners and hot water load
- If the demand side response is un-forecastable (or a change in behaviour for regular demand side response), then this would affect the UM. Instances of industrial demand side response are increasing – where identifiable industrial demand side response has occurred these instances will be corrected in the UM training data. Instances of residential/commercial demand side response are rare and small in magnitude and AEMO considers these to have minimal impact on the UM at present.
- AEMO considers that as VPPs continue to grow in size, their behaviour may materially impact the UM. AEMO is intending to use the mechanisms proposed in the Scheduled Lite project to provide visibility of this behaviour and where identifiable to correct instances in the UM training data.
- AEMO will further investigate cases of demand side response as part of the backcast and provide further information to stakeholders on how the system will behave

Frequently asked questions

When it is a hot day with a forecast afternoon cool change, the timing of the change can be critical to reserve outcomes on that day. How will the system behave under these conditions?

- This is a challenging scenario where the forecasts are highly dependent on the accuracy of the weather forecast. In general the load forecast will reflect the best estimate of the load reduction due to the arrival of the cool change. The UM will likely similarly reflect the highly uncertain nature of this scenario.
- AEMO will further investigate these types of scenarios as part of the backcast and provide further information to stakeholders on how the system will behave

How will opportunistic outages (maintenance outage taken due to expected period of low prices) versus forced outages be handled in UMs? How do economic commitment/decommitment decisions affect the UM?

- Correlation analysis of which factors are correlated with MaxAvail changes indicates pre-dispatch prices are not significantly correlated with MaxAvail changes. This implies that it is not necessary to include price as an input to Uncertainty Margins; it would be better to focus on stronger drivers with more significant correlations (such as Temperature and Wind) that are not self-referential. The UM models currently do not distinguish between opportunistic vs forced outages, or economic commitment/decommitment decisions.
- AEMO is investigating if filtering of UM MaxAvail training data using simple heuristics is necessary, and will provide further information to stakeholders in a future workshop.

Frequently asked questions

Is uncertainty due to Generator Forced outages overly conservative due to UMs and n-1 contingencies in certain runtypes of the SCED?

- AEMO is committed to selecting Confidence Levels (and UMs) that achieve the reliability standard via empirical backcasting and consultation.
- The n-1 contingency runs solve for the loss of a generator and all the other generators that are used to make up for that loss are limited to their Max Avail reduced by their UM.
- AEMO will present more information on runtypes in the next workshop

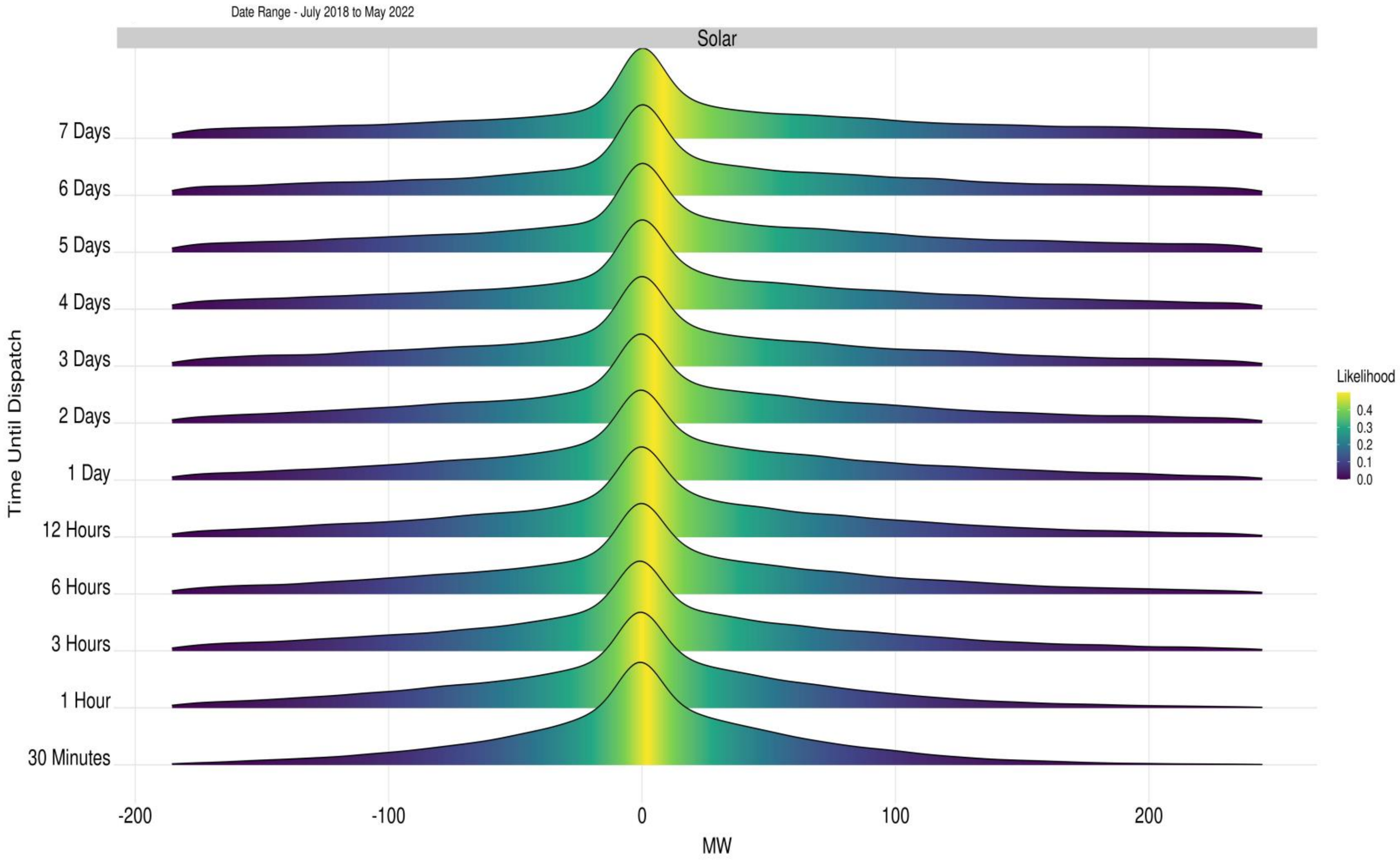
Glossary

Term	Definition
BDU	Bi-directional unit
FUM	Forecast Uncertainty Measure
LCR	Largest Credible Risk
LOR	Lack of reserve
MRC	Maximum Responsive Component
NMI	National Metering Identifier
NOS	Network Outage Scheduler
NSP	Network Service Provider
PASA	Projected assessment of system adequacy
PD	Pre-dispatch time frame
POE	Probability of exceedance. A 50% PoE load forecast is one which will be exceeded 50% of the time
SCED	Security Constrained Economic Dispatch optimiser
ST	Short term time frame
UM	Uncertainty Margin
WDR	Wholesale Demand Response

Additional slides

(VRE) Generation uncertainty Solar

Solar Uncertainty = Forecast Generation minus Actual Generation
NEM Total (day time only)

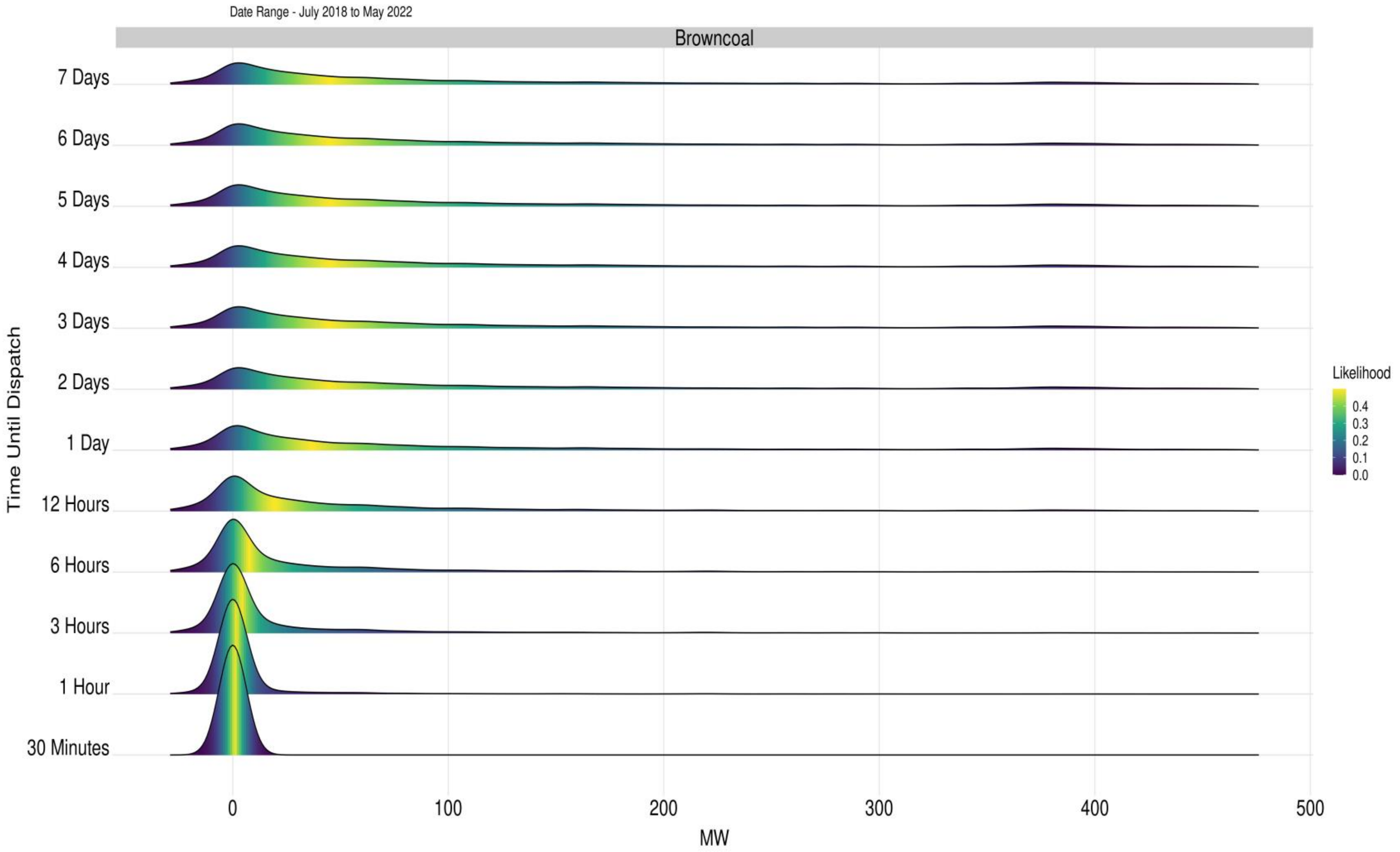


Key Takeaways

- Uncertainty reduces as the forecast horizon reduces but it is not as significant a reduction as others

Scheduled Generation uncertainty Brown Coal

Brown Coal Uncertainty = MaxAvail minus MaxAvail (T-30 Minutes)
NEM Total

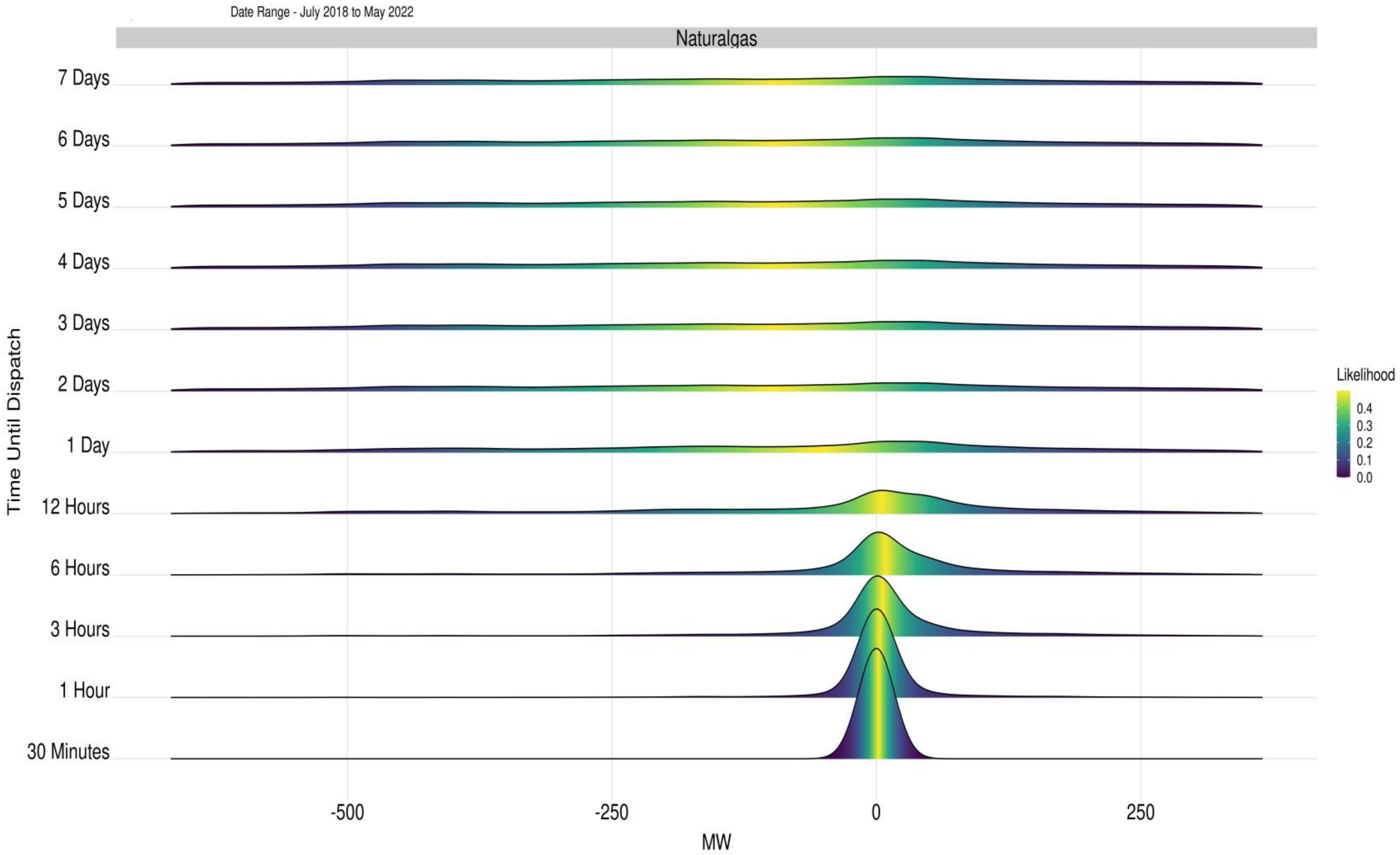


Key Takeaways

- Reduction in uncertainty as forecast horizon reduces
- Over-forecast bias at longer horizons evidence of general reductions of MaxAvail as forecast horizon reduces. At shorter horizons there is no bias.

Scheduled Generation uncertainty Natural Gas

Natural Gas Uncertainty = MaxAvail minus MaxAvail (T-30 Minutes)
NEM Total

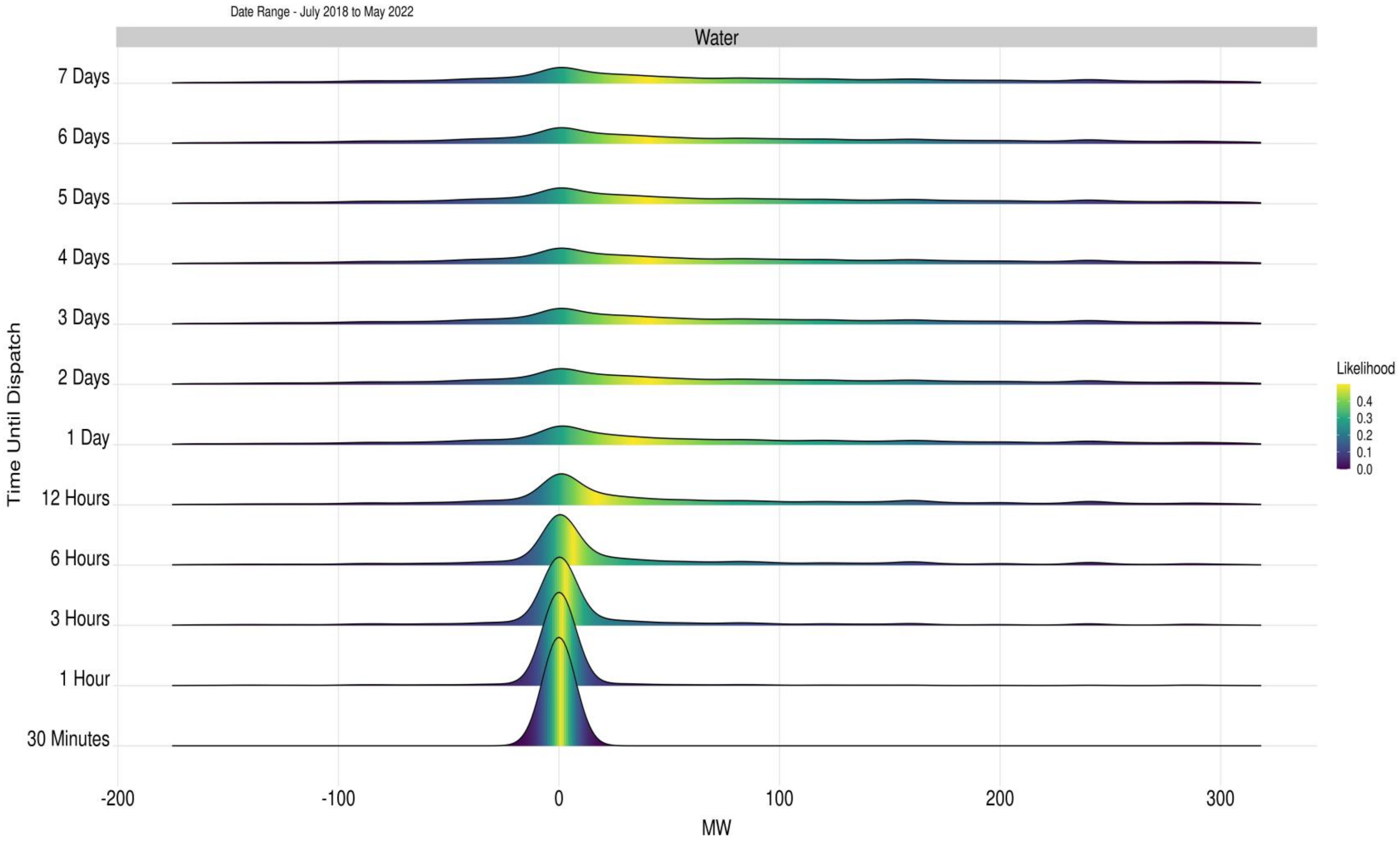


Key Takeaways

- Most significant reduction in uncertainty occurs less than 12 Hours ahead, as intra-day commitment decisions are finalised
- MaxAvail increases as forecast horizon reduces
  - Perhaps due to commitment decisions based on market or portfolio conditions

Scheduled Generation uncertainty Hydro

Hydro Uncertainty = MaxAvail minus MaxAvail (T-30 Minutes)
NEM Total

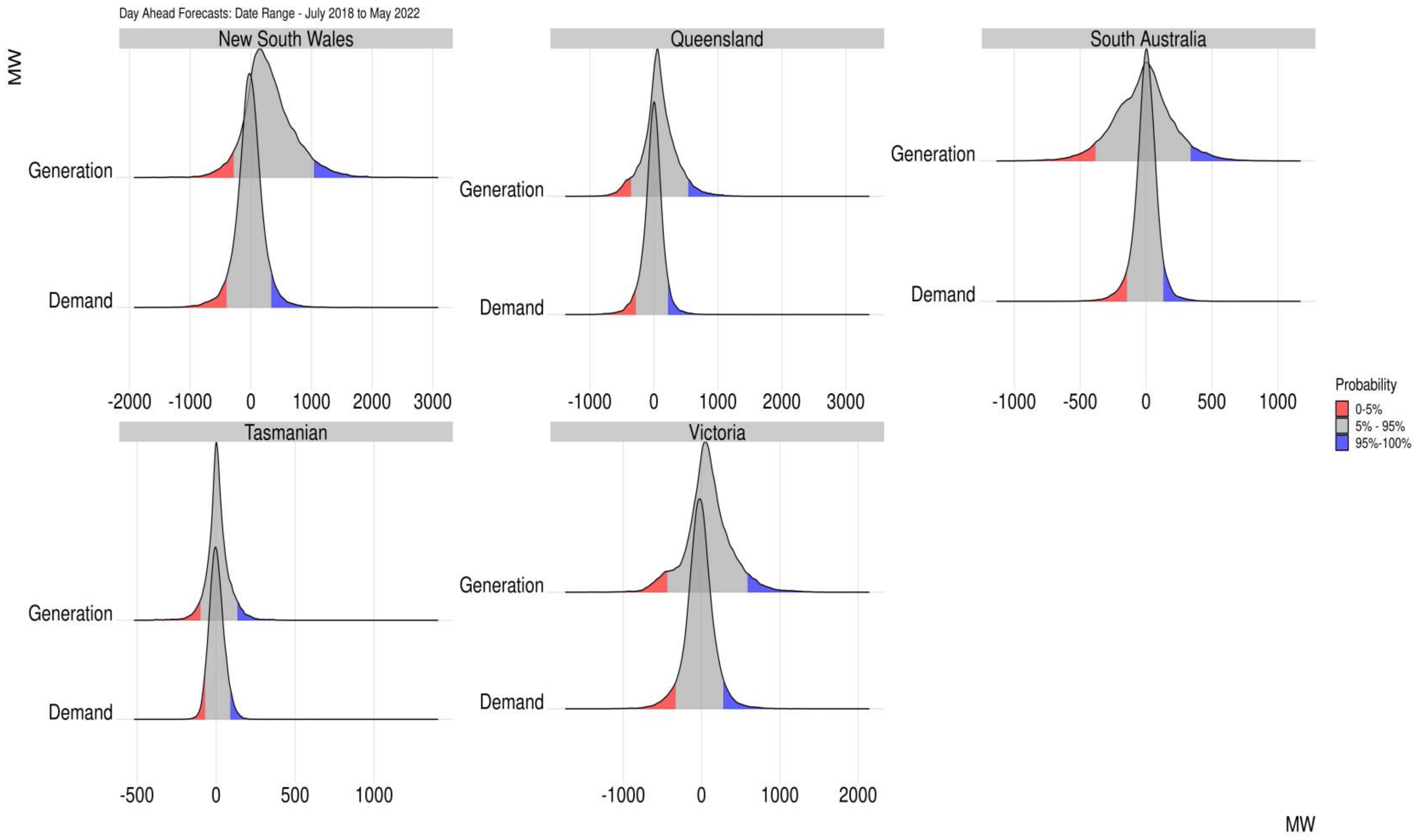


Key Takeaways

- Most significant reduction in uncertainty occurs less than 12 Hours ahead, as intra-day commitment decisions are finalised
- There is no bias at shorter horizons.

Accounting for uncertainty in STPASA

These visualisations drill down into the NEM total Generation and Demand Uncertainty from the previous slide, on a region basis.

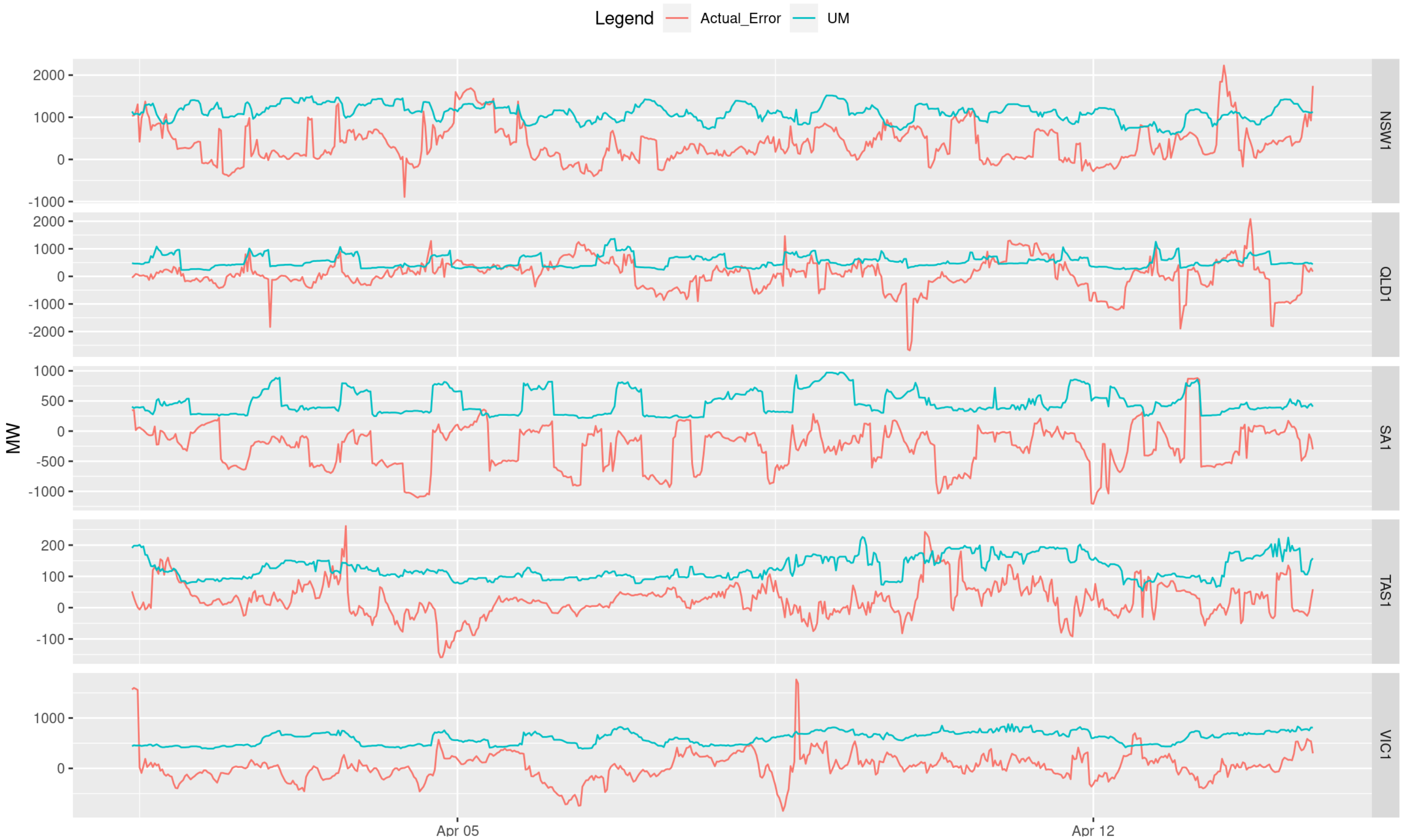


Key Takeaways

- The distribution of regional uncertainty is large and must be accounted for.

Region Level Uncertainty Margin - Generation

Day ahead predicted generation Uncertainty Margin (95% confidence level) vs Actual Error by Region



Key Takeaways

- These show the predicted generation Uncertainty Margin vs the actual error day ahead. Given a confidence level of 95% we would expect over a large enough sample that 5% of the intervals have an actual error above the predicted UM.
- UM has a daily profile which is dependent on the type of generation mix in each state.
- The magnitude of the UM across the states also appears reasonable.

Region Level Uncertainty Margin - Generation

Predicted generation Uncertainty Margin (95% confidence level) for NSW vs Actual Error by forecast horizon

Key Takeaways

- The magnitude of the UM across Forecast Horizons appears reasonable as it increases the further ahead in time we are forecasting.

Correlation plots showing Forecasts changes to various factors