Forecast Accuracy and Improvement Program

Ben Jones, Forecasting Specialist

Forecast Reference Group January 29

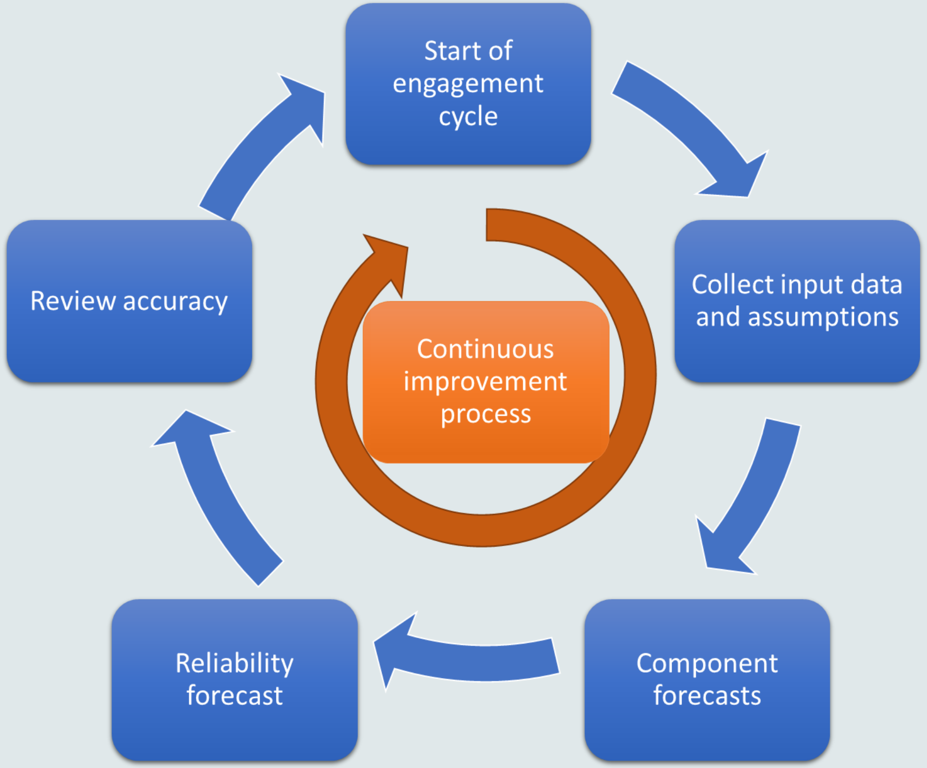
Agenda

For presentation, questions and discussion:

Forecast accuracy report

For presentation, questions and discussion to support short form written consultation:

Forecast improvement program



As per: AEMO Final Interim Reliability Forecast Guidelines. https://www.aemo.com.au/-/media/Files/Stakeholder_Consultation/Consultations/NEM-Consultations/2019/Interim-reliability-forecast-guidelines/Interim-Reliability-Forecast-Guidelines.pdf

Current & upcoming consultation

2020 input and assumptions

Stakeholder submissions due Friday 7 February 2020

https://www.aemo.com.au/Stakeholder-Consultation/Consultations/2020-Planning-and-Forecasting-Consultation-on-scenarios-inputs-and-assumptions

Email: forecasting.planning@aemo.com.au

Forecasting improvement program

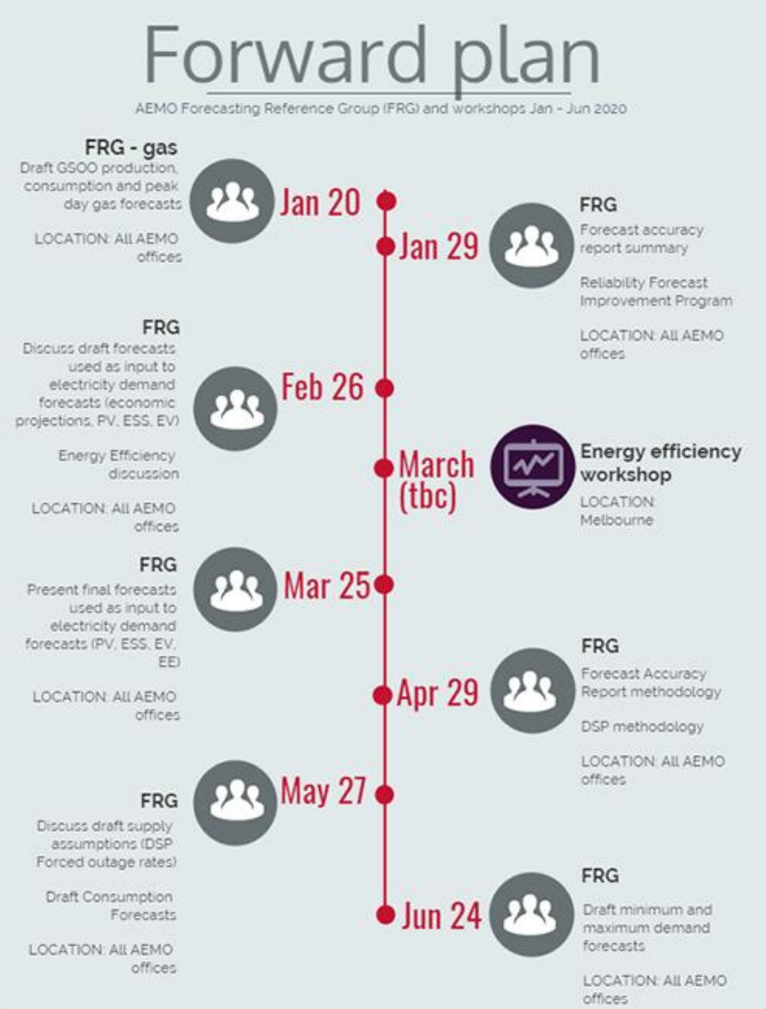
Discussion today, submissions due Friday 14 February 2020

https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/Forecasting-Accuracy-Reporting

Email: energy.forecasting@aemo.com.au

Forecast accuracy report methodology

Discussion April FRG, formal consultation throughout 2020 following AER's Forecasting Best Practice Consultation Procedures.



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Forecast Accuracy Report

Published 20 Dec 2019

https://www.aemo.com.au/-/media/Files/Electricity/NEM/Planning_and_Forecasting/Accuracy-Report/Forecast_Accuracy_Report_2019.pdf

Forecast accuracy report

- The forecast accuracy report assesses the year ahead accuracy of AEMO's 2018 ESOO for each region in the National Electricity Market (NEM). i.e. 2018-19 financial year.
- To meet RRO requirements, AEMO now assesses the accuracy of input, demand and supply forecasts; and provides information on improvements that will apply to the next ESOO.

- In 2019, AEMO commissioned the University of Adelaide to undertake a review of its forecast accuracy metrics.
  - This report suggested that "broadly, current AEMO practises are appropriate and well-supported"
  - Following FRG consultation, almost all relevant recommendations have been implemented in the report.
- Early in 2020, AEMO will commence formal consultation on the current methodology used to assess forecast accuracy.

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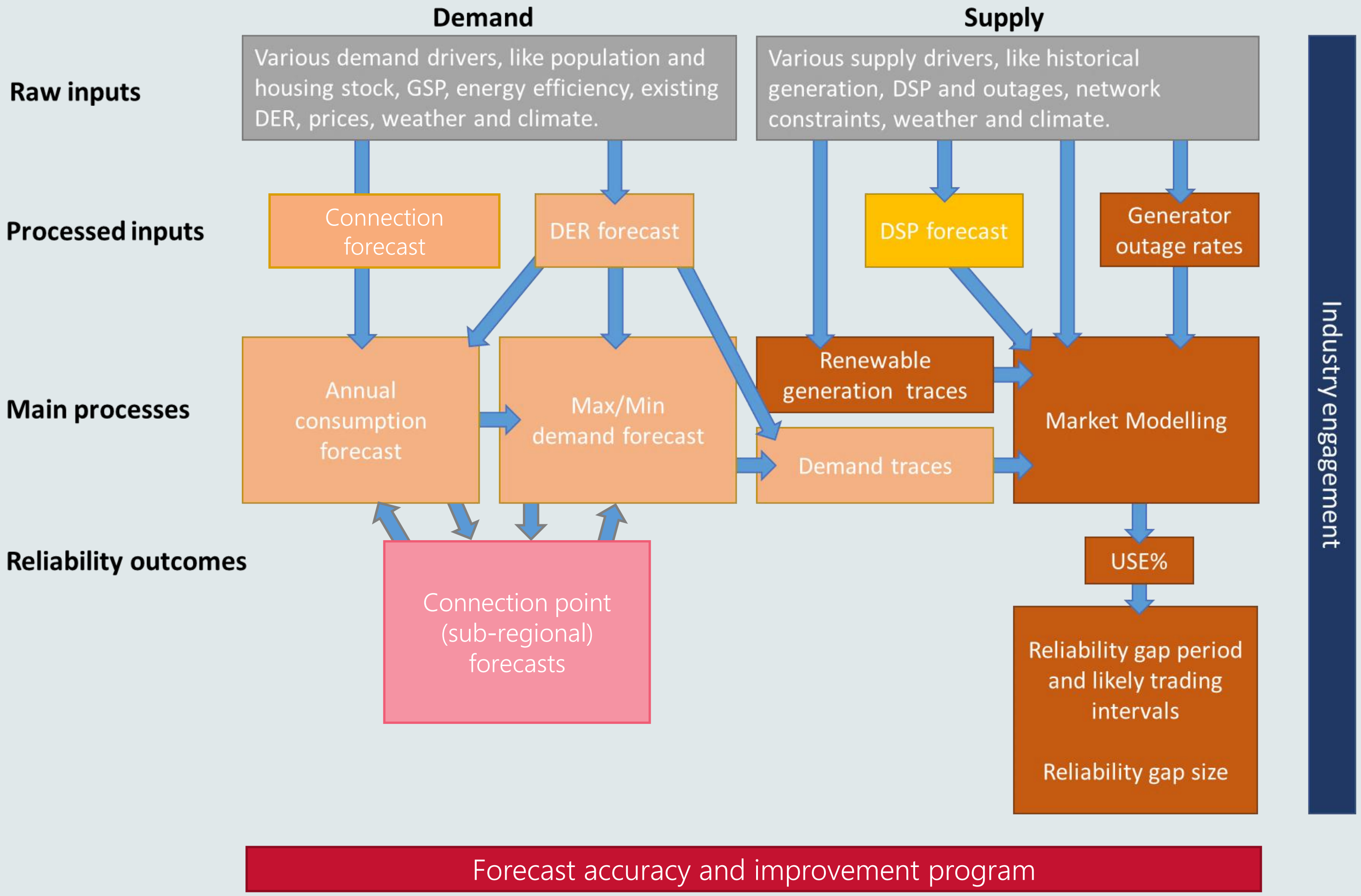
End to end high-level overview of reliability forecast process



Processes are documented in the relevant documents:

- DSP forecast and methodology paper
- Electricity demand forecasting methodology information paper
- ESOO and reliability forecast methodology document
- Interim reliability forecast guidelines
- Transmission connection point forecasting methodology report
- Forecast accuracy methodology (new in 2020)

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Accuracy summary

Forecast Component	NSW	QLD	SA	TAS	VIC	Comments
Drivers of demand						Growth in new household connections and distributed PV slower than projected in most regions.
Energy consumption						QLD above forecast due to LNG/CSG VIC below forecast due to differences not explained by variations in input assumptions
Summer maximum demand						QLD actual above forecast.
Winter maximum demand						QLD actual above forecast. VIC actual below forecast.
Annual minimum demand						Most actuals above forecast due to the overforecast of distributed PV.
Installed generation capacity						New variable renewable energy capacity installations were lower than predicted, particularly in QLD.
Summer supply availability of dominant fuel	Coal	Coal	Gas	Hydro	Coal	VIC Coal generation availability below expectation due to more forced outages than forecast.

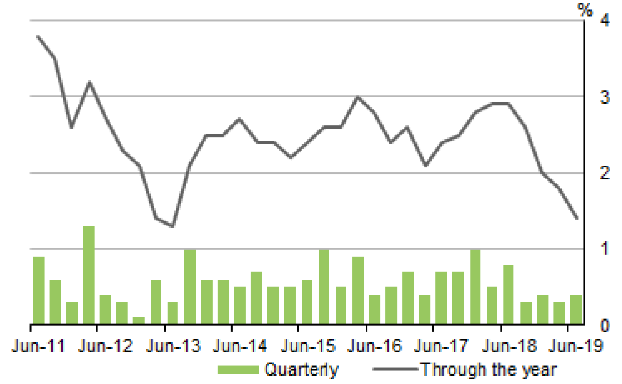
- Forecast has performed as expected
- Inaccuracy observed in forecast is explainable by inputs and assumptions. These inputs should be monitored and incrementally improved, provided the value is commensurate with cost.
- Inaccuracy observed in forecast needs attention, and should be prioritised for improvement.

Input drivers of demand

Demand models incorporate numerous forecast components, including:

- Economic growth and population.
- Rooftop photovoltaic (PV) and behind-the-meter batteries.
- Energy efficiency and appliance mix.
- Electric vehicles (EVs).
- Network losses.
- Weather variability and climate change.

Household final consumption expenditure



The observed very low growth in household final consumption expenditure was in line with the 2018 ESOO assumptions

Input variables that impact year ahead accuracy were assessed, and were not well aligned with actuals in several cases.

Some mis-alignment is expected, particularly on longer-term variables that tend to have weak relationships with year-ahead changes in demand.

Forecast and actual residential connections growth rate. 2018-19 (%)

	NSW	QLD	SA	TAS	VIC
Actual (Jun18-Jun19)	1.4%	1.4%	1.0%	1.2%	1.9%
Slow Change scenario	1.6%	1.5%	1.2%	0.7%	1.7%
Neutral scenario	1.8%	1.7%	1.3%	0.8%	1.9%
Fast Change scenario	2.0%	1.9%	1.5%	0.9%	2.1%

As the table shows, actual connections growth over 2018-19 was mostly lower than the range of scenario forecasts, except in the case of Victoria, which grew as expected and Tasmania which grew above forecast.

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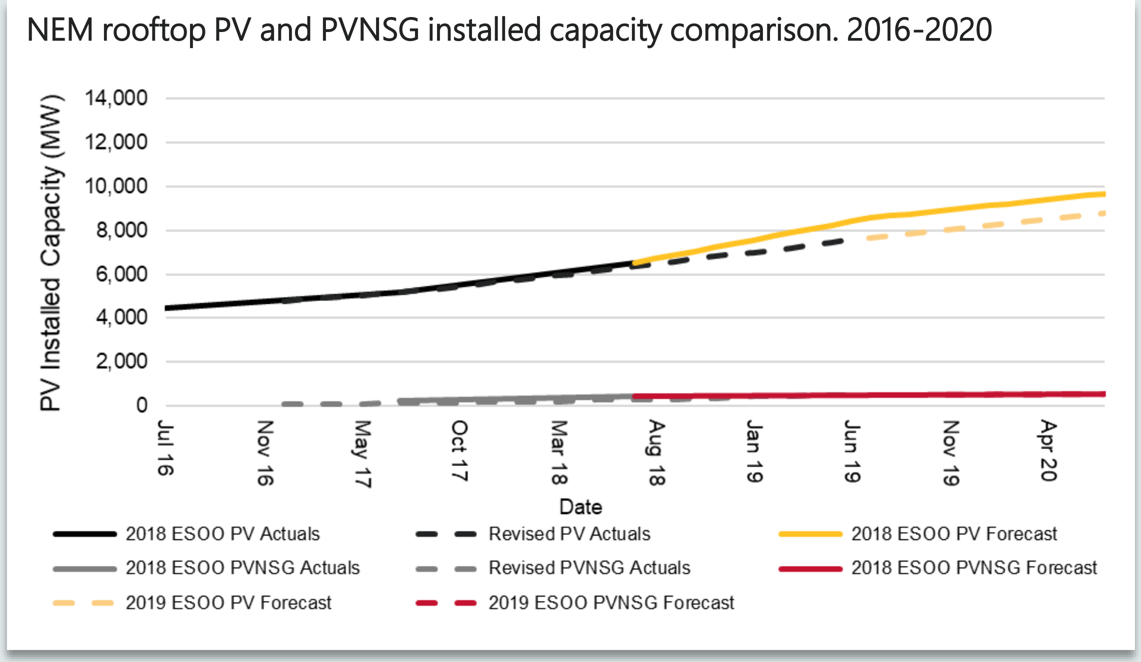
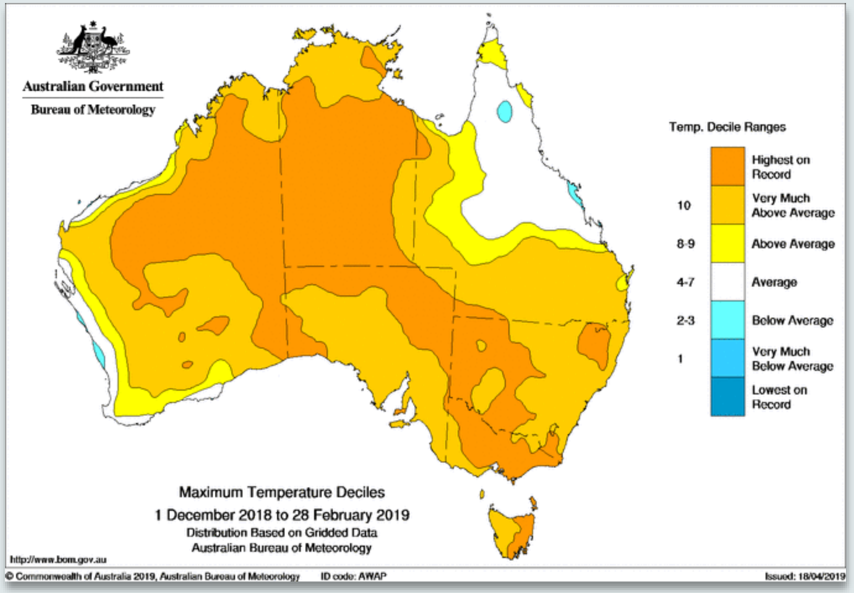
Input drivers of demand

- In aggregate, PV installations were over-forecast with variation between regions.
- The lower number of PV systems installed compared to forecast resulted in an under forecast of grid supplied consumption and an over estimate of the rate of decline in minimum demand in the 2018 ESOO.
- Early signs indicate that the 2019 ESOO PV forecast is now under-forecasting capacity.

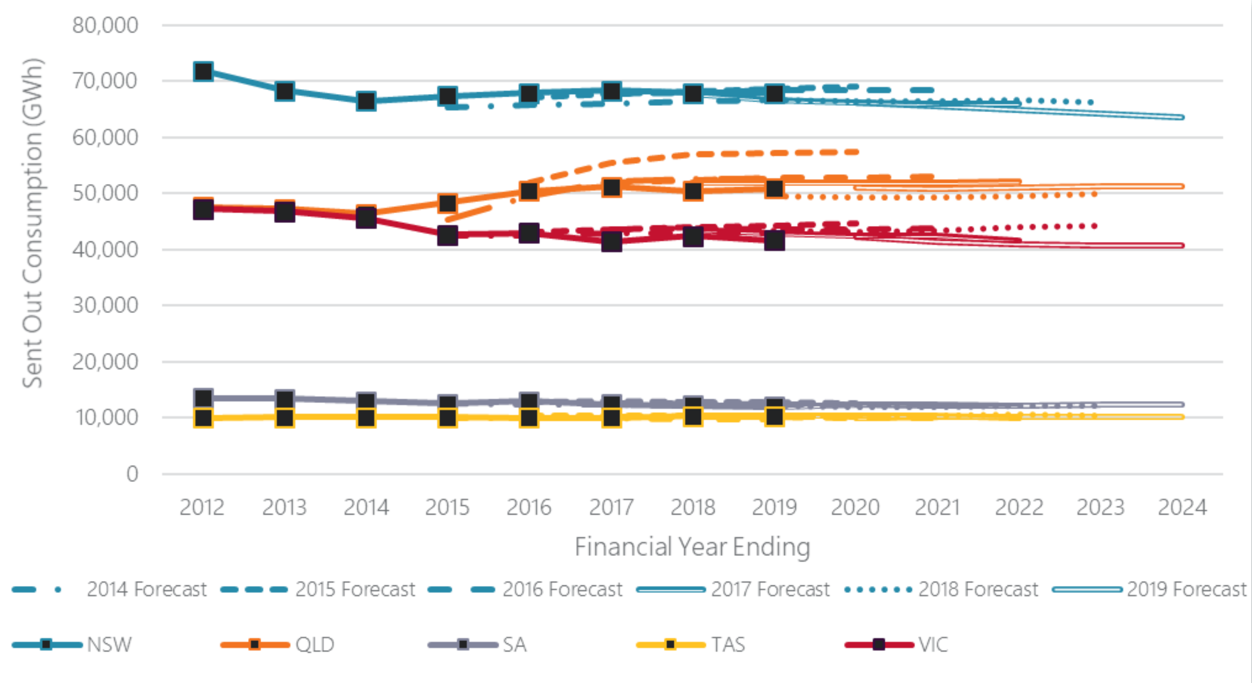




- Demand forecasting processes are not fitted to a specific weather prediction, or seasonal outlook.
- Instead they consider short, medium and long term weather and climate trends through numerous simulations.
- Weather observed was within the range of conditions simulated including the above average temperatures in 2018-19 summer.

Operational energy consumption

- Energy consumption is forecast as a 'point forecast', a single value per scenario, per year. This allows accuracy to be presented using a simple percentage error metric.
- In the last four years, all regions have a percentage error less than 5%. For some regions, the one year ahead forecasting performance has improved over time, while in others the error has increased.
- The annual operational consumption (sent out) actuals for 2019 were within 3% of forecast for South Australia, Tasmania, and New South Wales, while Queensland and Victoria were not.



One-year ahead annual operational consumption accuracy (%)	2014 NEFR forecast in 2014-15	2015 NEFR forecast in 2015-16	2016 NEFR forecast in 2016-17	2017 ESOO forecast in 2017-18	2018 ESOO forecast in 2018-19
New South Wales	3.2%	1.2%	0.8%	0.1%	1.8%
South Australia	-0.2%	1.6%	-1.6%	0.8%	0.8%
Tasmania	2.3%	-3.5%	-2.4%	0.1%	-1.3%
Queensland	6.7%	-2.6%	-1.6%	-2.8%	3.1%
Victoria	0.3%	-0.5%	-5.0%	-2.5%	-3.7%

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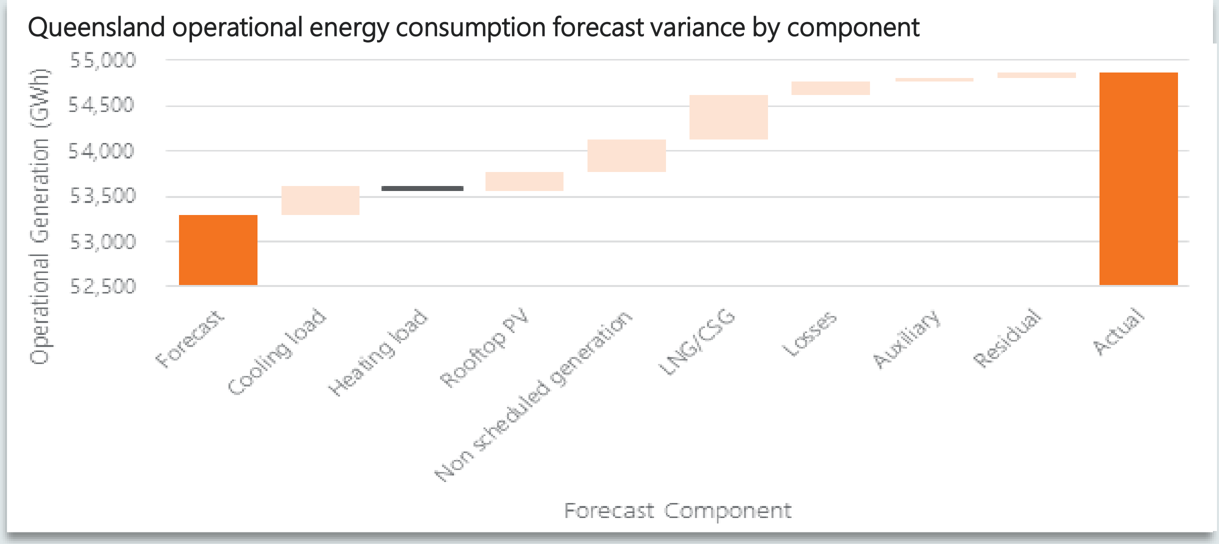
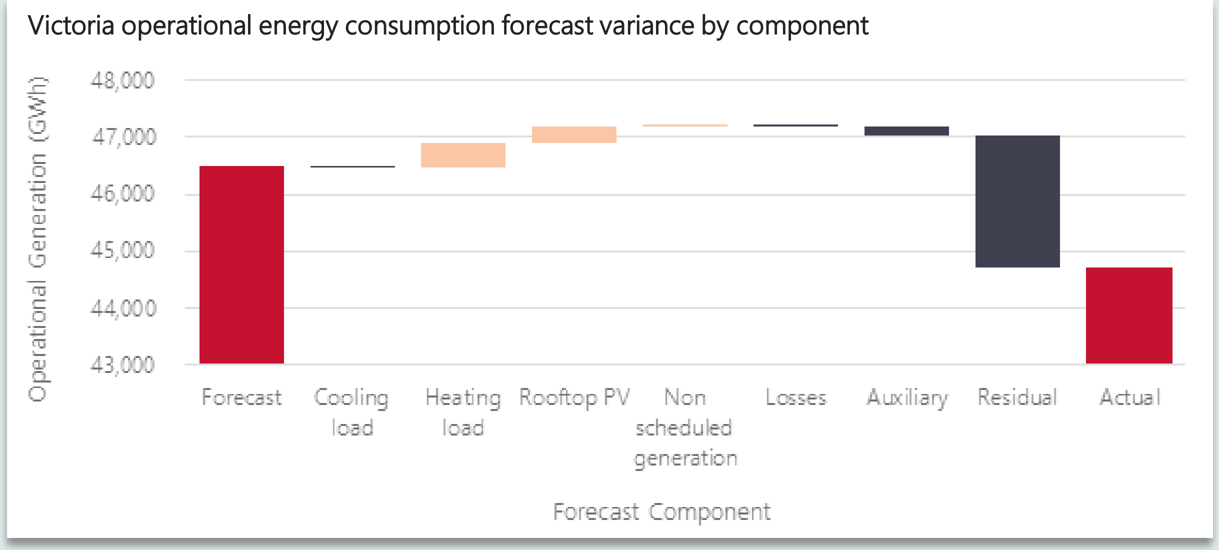
Operational energy consumption

- The +3.1% error for Queensland is mostly explained by higher than forecast demand from the CSG/LNG sector and lower than forecast uptake of PV capacity.
  - Improvements should therefore focus on improving model inputs
- The -3.7% error for Victoria cannot be explained by model inputs, and appears to be impacted by poor alignment between energy consumption history and forecast component based trends.
  - Improvements should therefore focus on improving the model itself.
- Once variations in model inputs were considered for other regions, energy consumption models performed well, although there is some evidence of minor misalignment.





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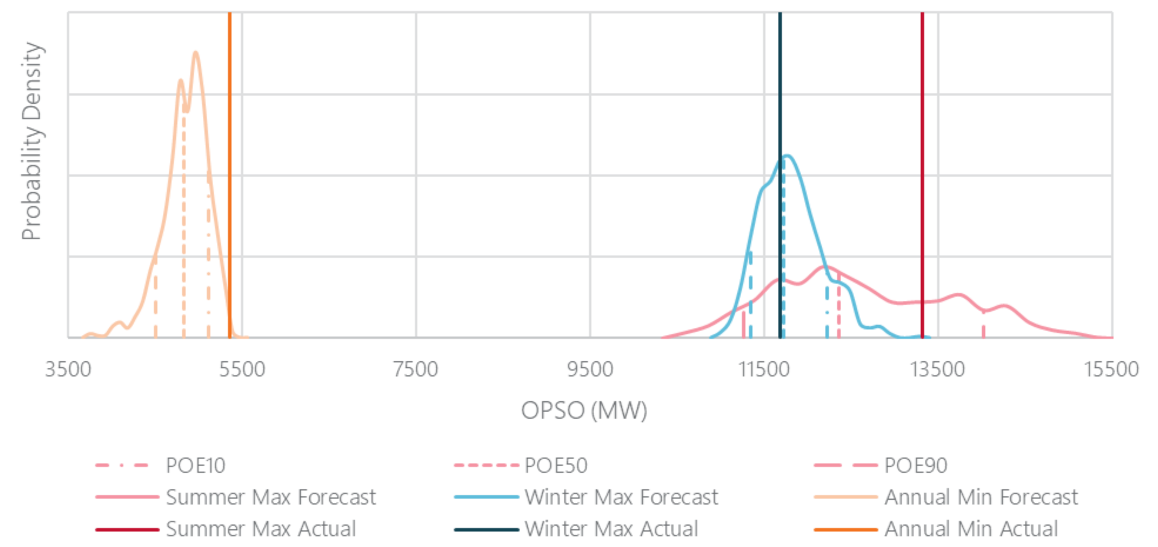
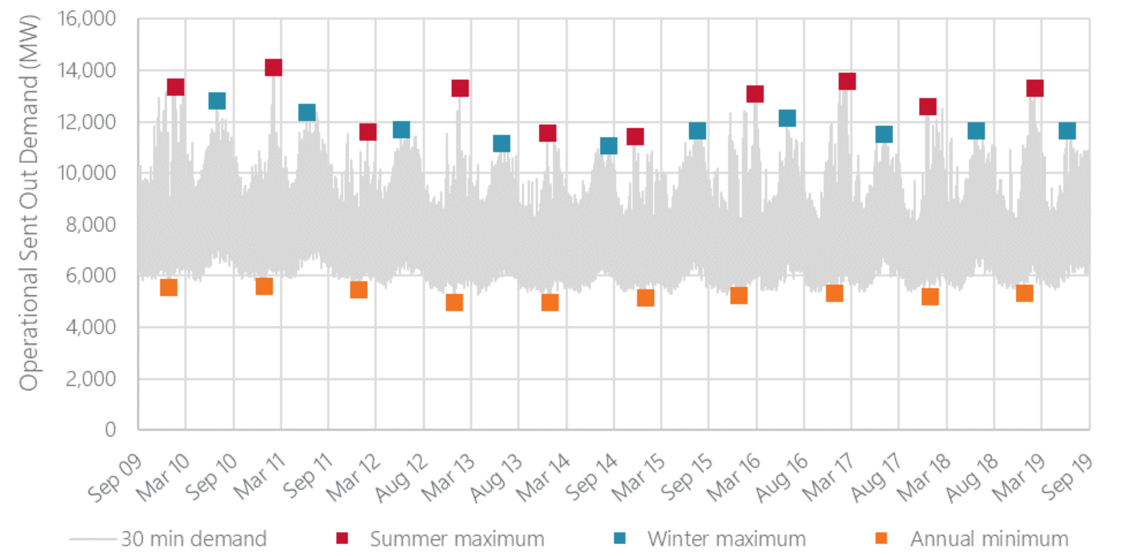
Maximum and minimum demand

Demand extremes (summer maximum, winter maximum, annual minimum) are forecast as a probability distribution. This complicates the assessment of accuracy.

New South Wales simulated extreme event probability distributions with actuals



New South Wales demand with extreme events identified



Following guidance from the University of Adelaide 'Review of Forecast Accuracy Metrics' report, AEMO has discontinued the use of 'backcasting' in favour of visualisations. The distributions allow comparison of simulated versus actual outcomes for model inputs and outputs.

https://www.aemo.com.au/-/media/Files/Electricity/NEM/Planning_and_Forecasting/Accuracy-Report/ForecastMetricsAssessment_UoA-AEMO.pdf

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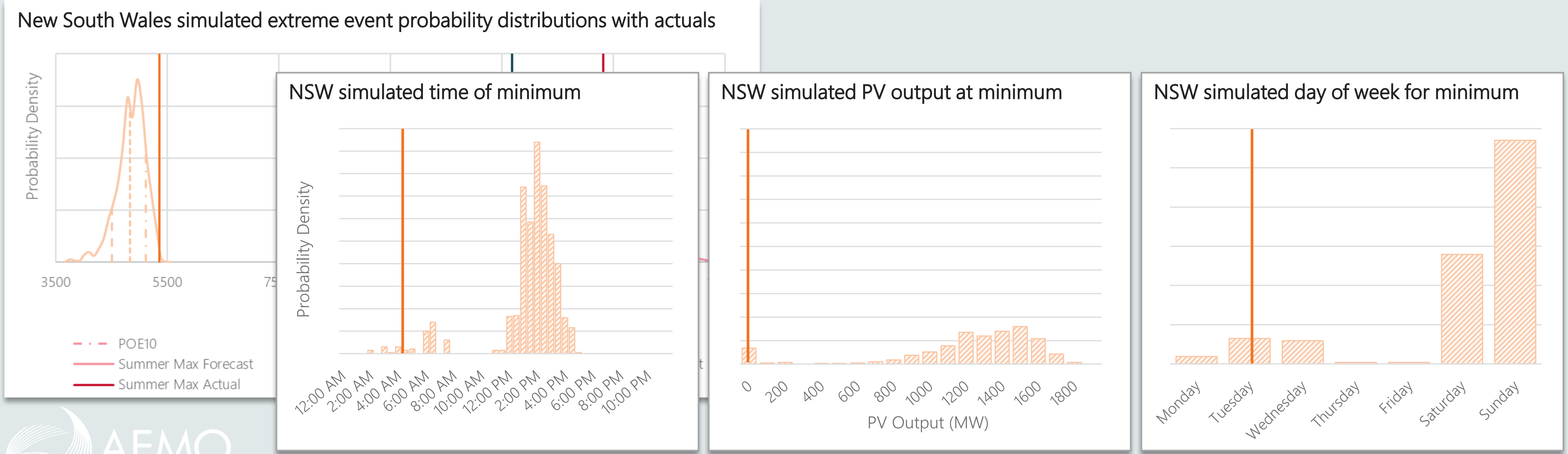
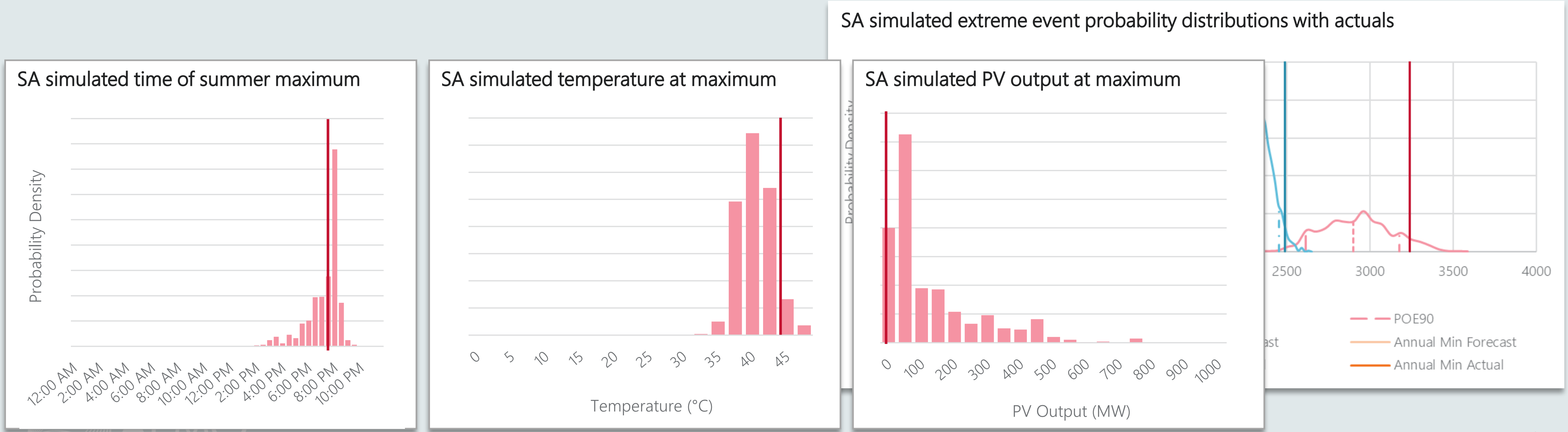
Maximum and minimum demand

- In this example, the actual minimum demand for New South Wales was 230MW above the 10% POE at the top of the forecast distribution.
- The minimum was expected to occur on a weekend afternoon, with a large contribution from PV. Instead, the minimum occurred early on a weekday morning before sunrise.
- The variation in model inputs draws us to conclude that the under-forecast of minimum demand was caused by the over-forecast of PV capacity.
  - Improvements should therefore focus on improving model inputs



Maximum and minimum demand

- In this example, the actual summer maximum demand for South Australia was above the 10% POE forecast.
- South Australia experienced a hot period in late January, with an annual maximum temperature recorded earlier in the day of 46.6°C. The day also saw the hottest minimum daily temperature of 30.7°C.
- The maximum was expected to occur late in the day, when PV output was low or zero. Actual maximum demand occurred late in the day, with zero PV output, at a temperature towards the upper end of the expected temperature distribution.
- The observed heatwave and observed variation in model inputs draws us to conclude that the 2019 maximum demand event exceeded a 1-in-10 year probability and that the forecast is fit for purpose.



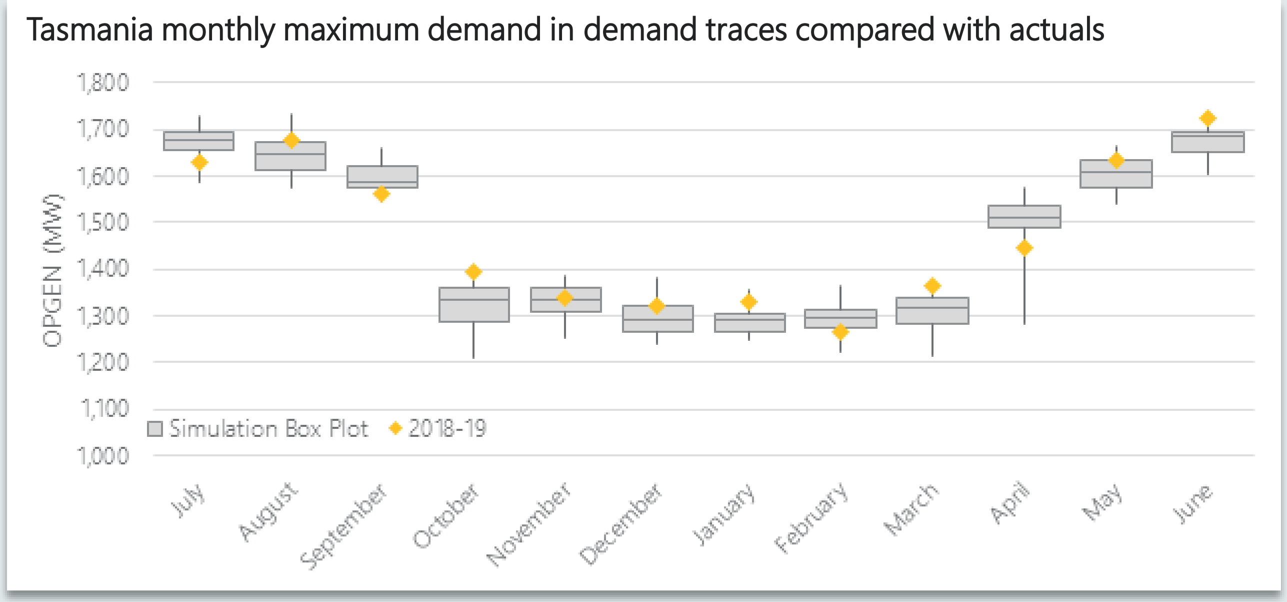
Maximum and minimum demand

- The summer maximum demand actuals occurred within forecast expectation given observed weather for all regions, except Queensland, for which the actual exceeded forecast expectation.
- The winter maximum demand actuals occurred within forecast expectation for all regions, except Queensland and South Australia, which exceeded expectation, and Victoria, which was below expectation.
- The annual minimum demand forecasts did not perform particularly well; actuals were above forecast in New South Wales, South Australia, and Victoria, while actuals were below forecast in Tasmania.
- In most cases, the discrepancy can be explained by model inputs. For example:
  - PV is a significant driver of daytime minimums. The overforecast of PV therefore had a material impact on minimum forecasts across most regions.
  - Energy consumption forecasts are used within demand models to shape trends. The underforecast of LNG/CSG in Queensland resulted in an underforecast of all Queensland maximums and minimums.

Forecast Component	NSW	QLD	SA	TAS	VIC	Comments
Summer maximum demand	🟢	🟡	🟢	🟢	🟢	QLD actual above forecast.
Winter maximum demand	🟢	🟡	🟢	🟢	🟡	QLD actual above forecast. VIC actual below forecast.
Annual minimum demand	🟡	🟢	🟡	🟡	🟡	Most actuals above forecast due to the overforecast of distributed PV.

Demand traces

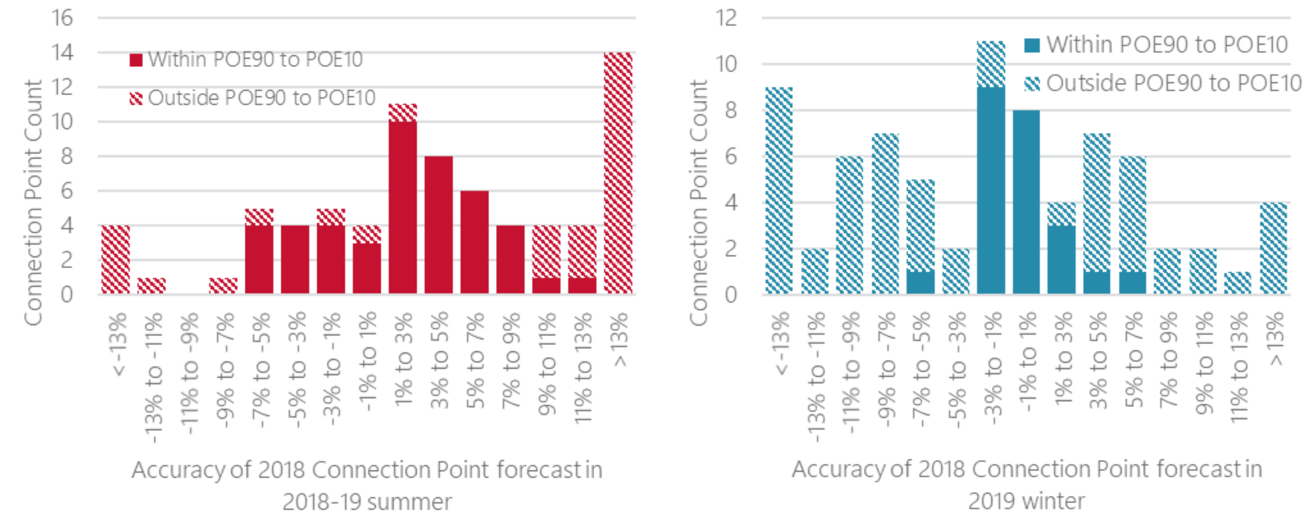
- Half hourly demand traces are developed using historical demand years, adapted to meet the operational energy consumption and extreme demand forecasts.
- These demand traces are used in ESOO and MTPASA market modelling alongside supply and transmission traces for reliability assessments
- To evaluate their impact on monthly reliability, the actual monthly maximum was compared to the range of monthly maximums taken from the reference years
- The box plot contains both POE50 and POE10 traces
- In all cases, the accuracy observed in the demand traces is consistent with the accuracy observed in the energy consumption and extreme demand forecasts.



Connection point forecasts

- Connection point forecasts are developed for Network Service Providers as part of AEMOs broader national transmission planner role.
- Actual connection point maximum demands that are more than 13% inaccurate are likely affected by load switching and network reconfiguration,
- Once removed, accuracy was broadly normally distributed with minor differences (in this case: -1.3% lower in winter, and 2.4% higher in summer), consistent with the regional forecast.
- In all regions, observed minor variations aligned with variation observed in regional demand extremes.

Victoria connection point accuracy, summer and winter maximums



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Generator new entrant and capacity information

- AEMO collects generation information reported from generation industry participants.
- There were a number of new projects in Queensland that were expected to be operational but were not operating at all during the key summer months.
- Fewer delays in operational commencement were experienced in other regions however all regions other than Tasmania had less capacity than forecast.

Forecast and actual generation count and capacity, February 2019

	Facilities forecast to operate		Facilities actually operating[A]		Difference in Capacity (forecast – actual)	
	Count	MW	Count	MW	MW	%
New South Wales VRE	19	1,870	20	1,767	103	-5.5%
New South Wales all generation	70	16,134	72	16,065	69	-0.4%
Queensland VRE	24	1,860	15	958	902	-48.5%
Queensland all generation	78	13,547	69	12,645	902	-6.7%
South Australia VRE	23	2,012	23	1,856	156	-7.8%
South Australia all generation	69	4,770	69	4,614	156	-3.3%
Tasmanian VRE	2	308	2	308	0	0.0%
Tasmania all generation	49	2,601	50	2,809	-208	8.0%
Victoria VRE	19	1,977	19	1,900	77	-3.9%
Victoria all generation	81	10,879	81	10,802	77	-0.7%

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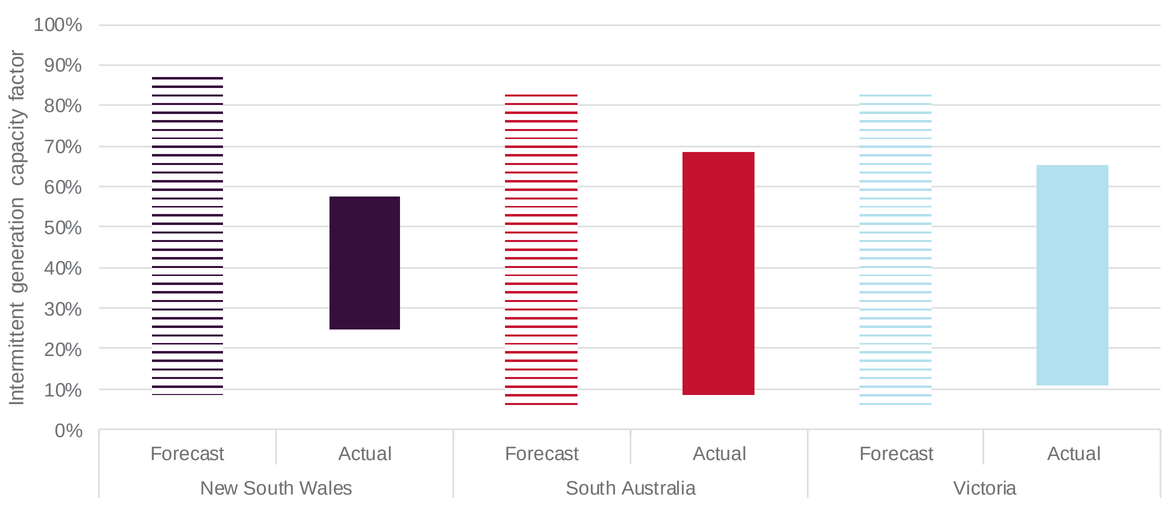
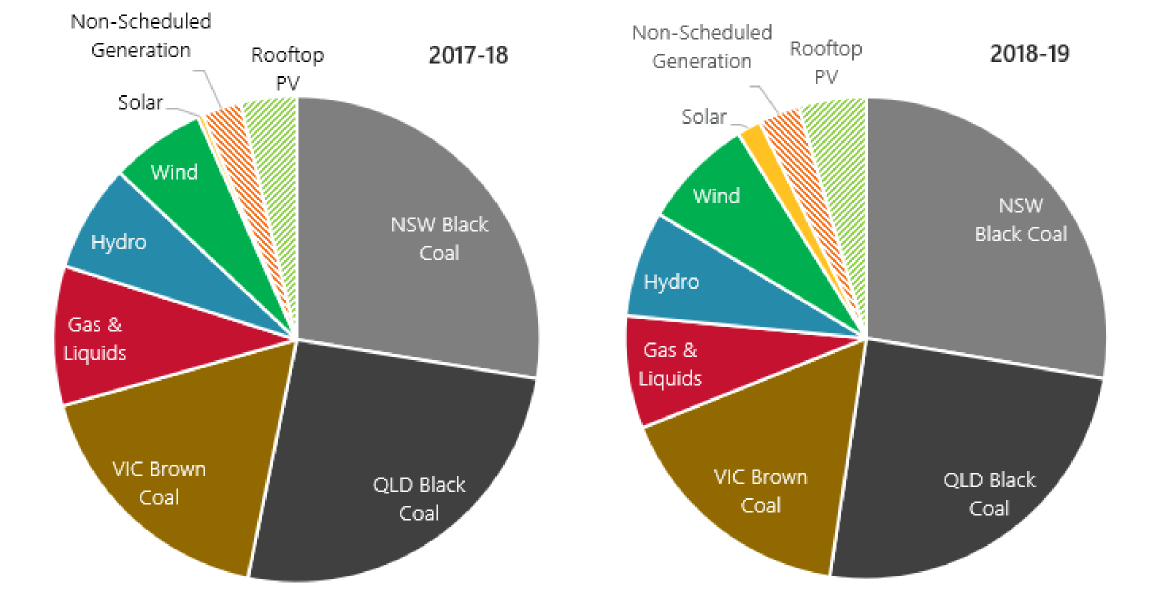
Supply availability

- Solar, wind and rooftop PV have shown the largest increase in supply proportions between 2017-18 and 2018-19.
- Despite the growth in variable renewable energy (VRE) supply proportions, availability of coal generation is currently a larger contributor to the risk of unserved energy

VRE capacity factor range during identified hot temperature days



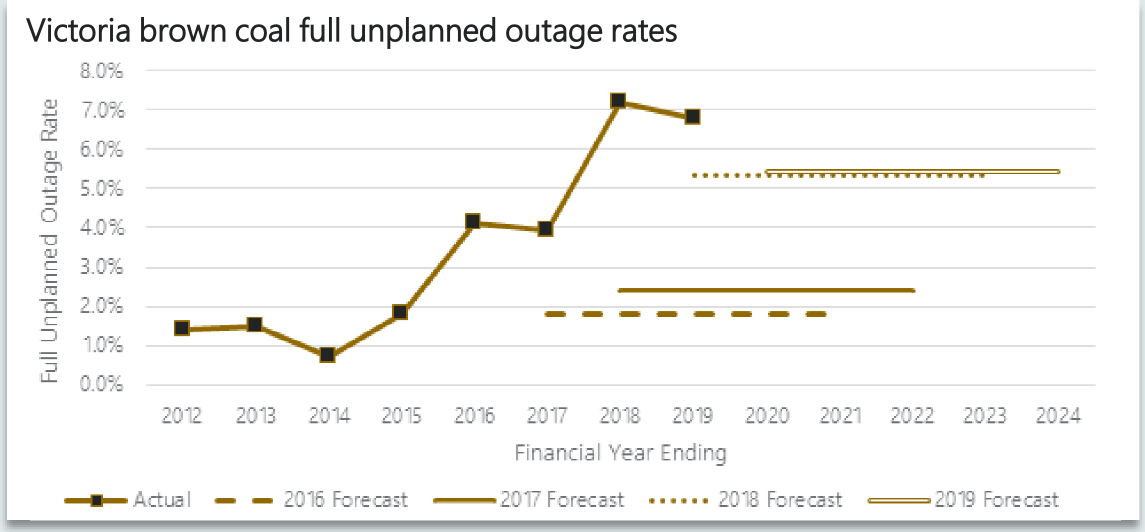
NEM generation mix by energy, including demand side components

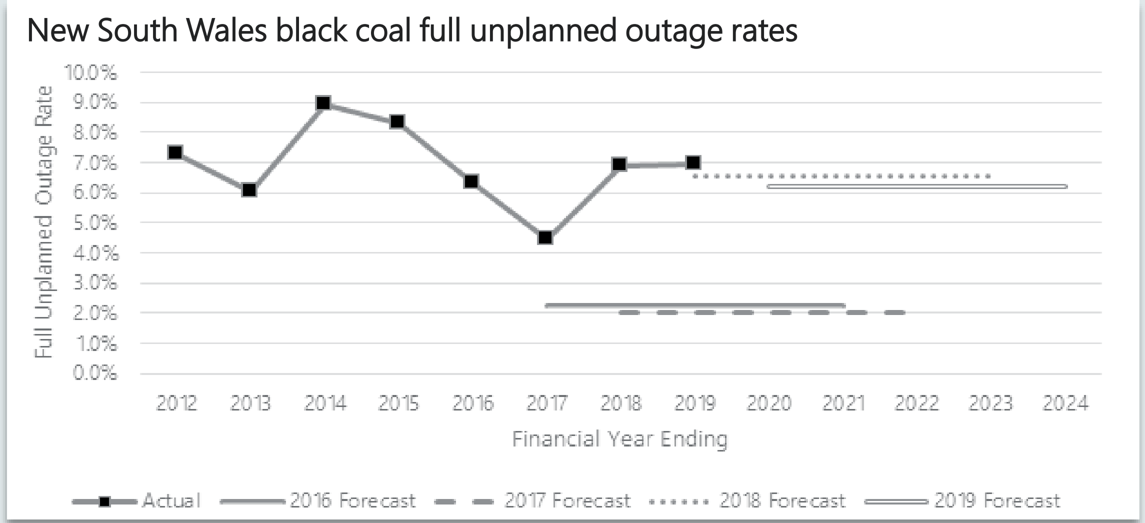


- All VRE sources operated within forecast range during identified hot temperature days.

Supply availability

- Actual supply availability was well aligned with forecast for New South Wales and Queensland coal generators.
- The 2018 ESOO over-forecast the reliability of brown coal in Victoria and CCGTs in the NEM.
  - Observed brown coal aggregated forced outage rates were over five times the rate observed between 2011-12 and 2014-15.
  - The impact of the higher than expected brown coal-fired generation forced outage rates produced a material impact on supply availability, contributing to observed supply scarcity, particularly in Victoria.
- The actual supply availability for Hydro, OCGTs, and VRE was well aligned with forecast.
- In some periods throughout summer with moderate temperatures, supply availability was above forecast
  - This is due to the use of summer generator capacities regardless of temperature, and the preparations undertaken by generator participants for summer readiness.





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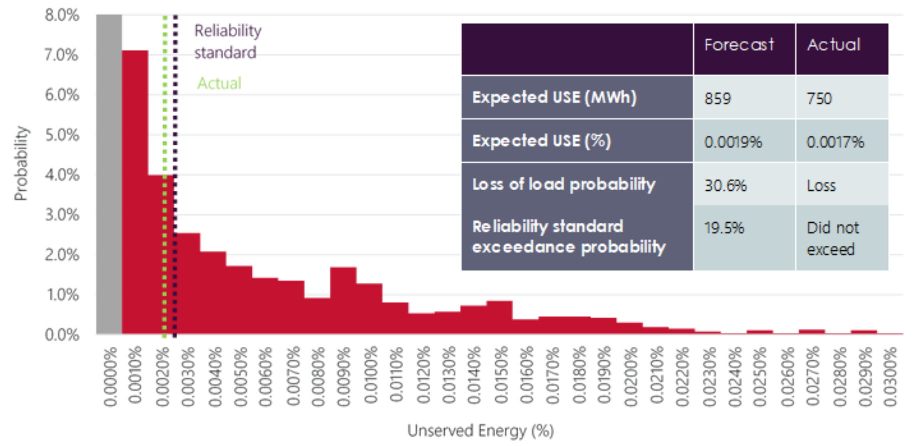
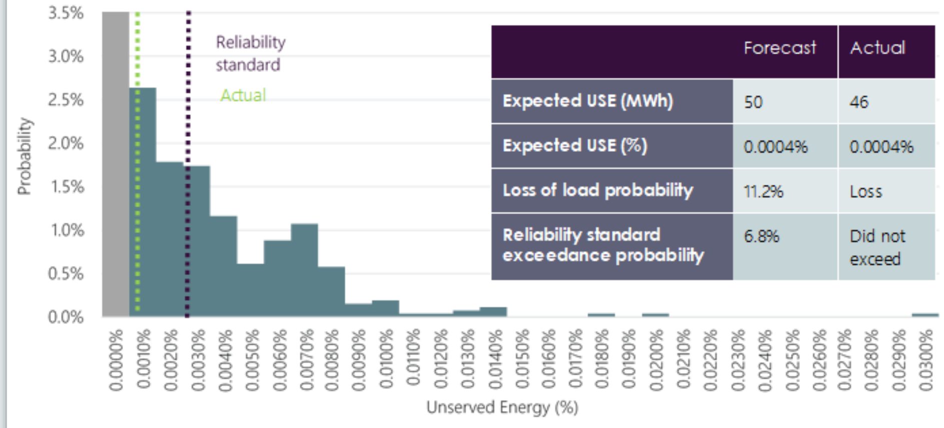
Reliability

- South Australia and Victoria experienced supply shortfalls driven by high demand and coincident generator outages. These incidents were within the wide range of reliability outcomes forecast possible.
- Despite higher than forecast demand in Queensland and lower than forecast newly installed VRE capacity, there was sufficient supply capacity avoided loss of supply in this region.
- All demand was met in Tasmania and New South Wales; in both cases, demand and supply availability were within forecast expectation.

Victoria forecast USE distribution for 2018-19 summer



South Australia forecast USE distribution for 2018-19 summer



Forecast Improvement Program

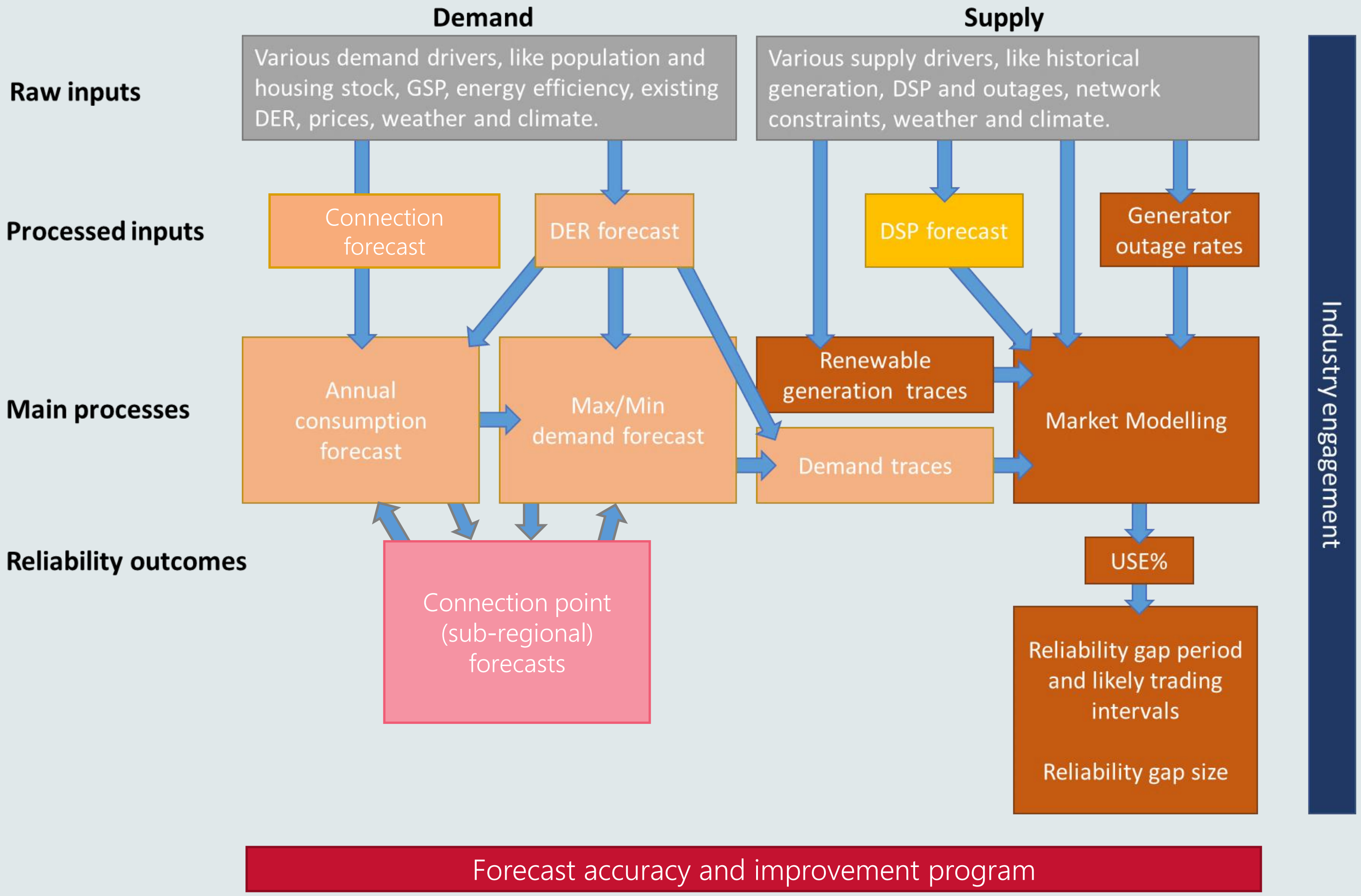
Forecast improvement program

Improvement priority	Count
Improvements already implemented	5
Highest priority improvements	2
Lower priority improvements	5
Investigations	5
Connection point improvements	3

Highest priority improvements address material drivers of inaccuracy as identified in the Forecast Accuracy Report. Lower priority improvements will all be implemented, but were not material drivers of inaccuracy as identified in the same report.

As implemented, improvements will be documented in the relevant documents:

- DSP forecast and methodology paper
- Electricity demand forecasting methodology information paper
- ESOO and reliability forecast methodology document
- Interim reliability forecast guidelines
- Transmission connection point forecasting methodology report
- Forecast accuracy methodology (new in 2020)



Forecast improvement program

Major improvements already implemented

PV forecasts

Developed automated processes to prepare rooftop PV and PVNSG capacity actuals and generation estimates from the CER. Developed more timely estimates of solar irradiance and normalized rooftop PV generation.

Max and min demand forecast methodology

Developed and implemented a multi-model ensemble for forecasting maximum and minimum demand.

Improvement of demand traces

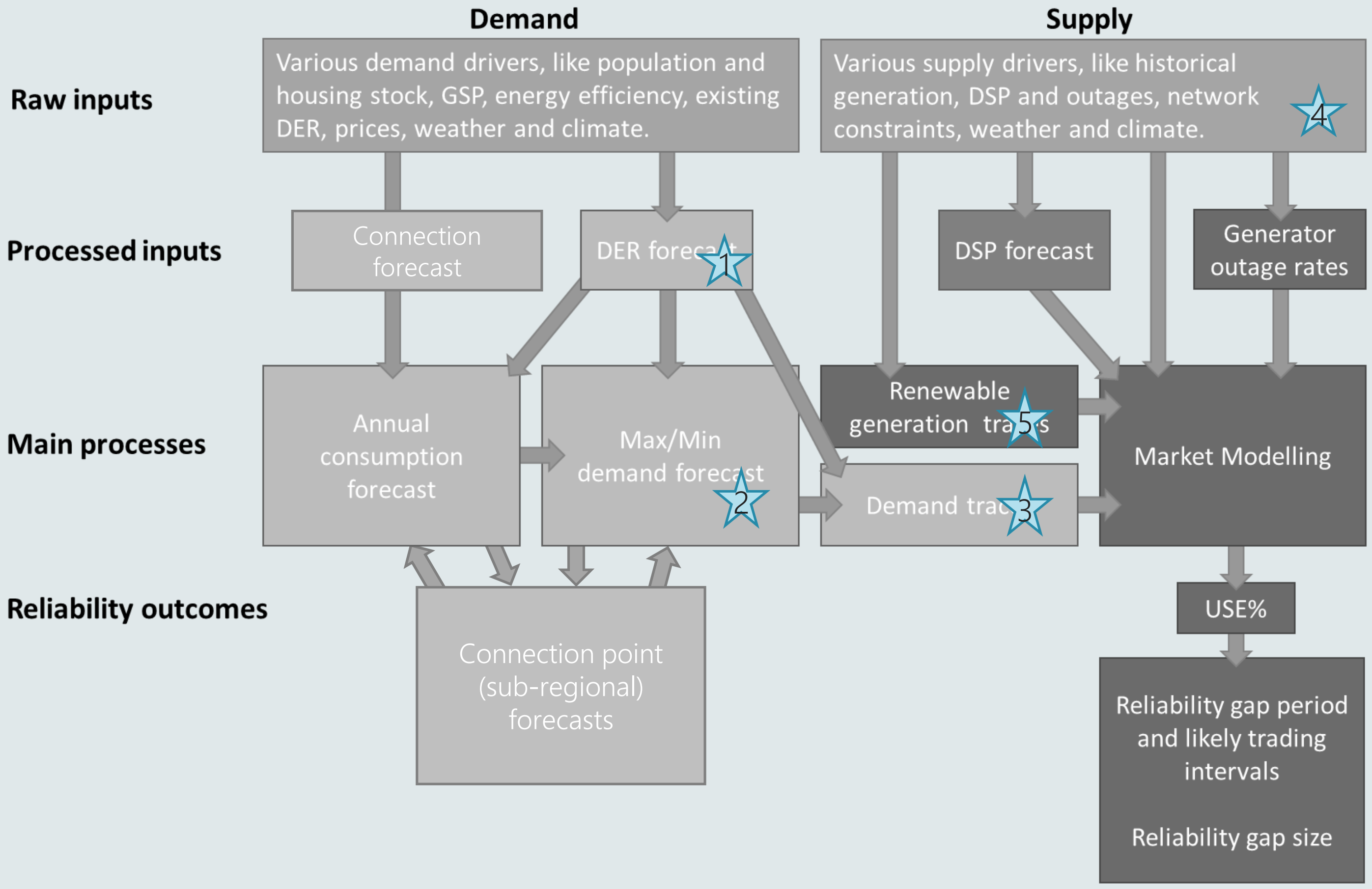
Improved the shape of demand traces for operational management of outage scheduling and the months at risk to be identified in any RRO reliability instrument.

Generator new entrant modelling

Adjusted criteria such that Com* projects were assumed to be delayed until after the T-1 RRO window.

Renewable generation traces

Developed VRE generation traces directly from weather estimates using power curves in addition to history.



Forecast improvement program

Highest priority improvements

Operational energy consumption forecast methodology

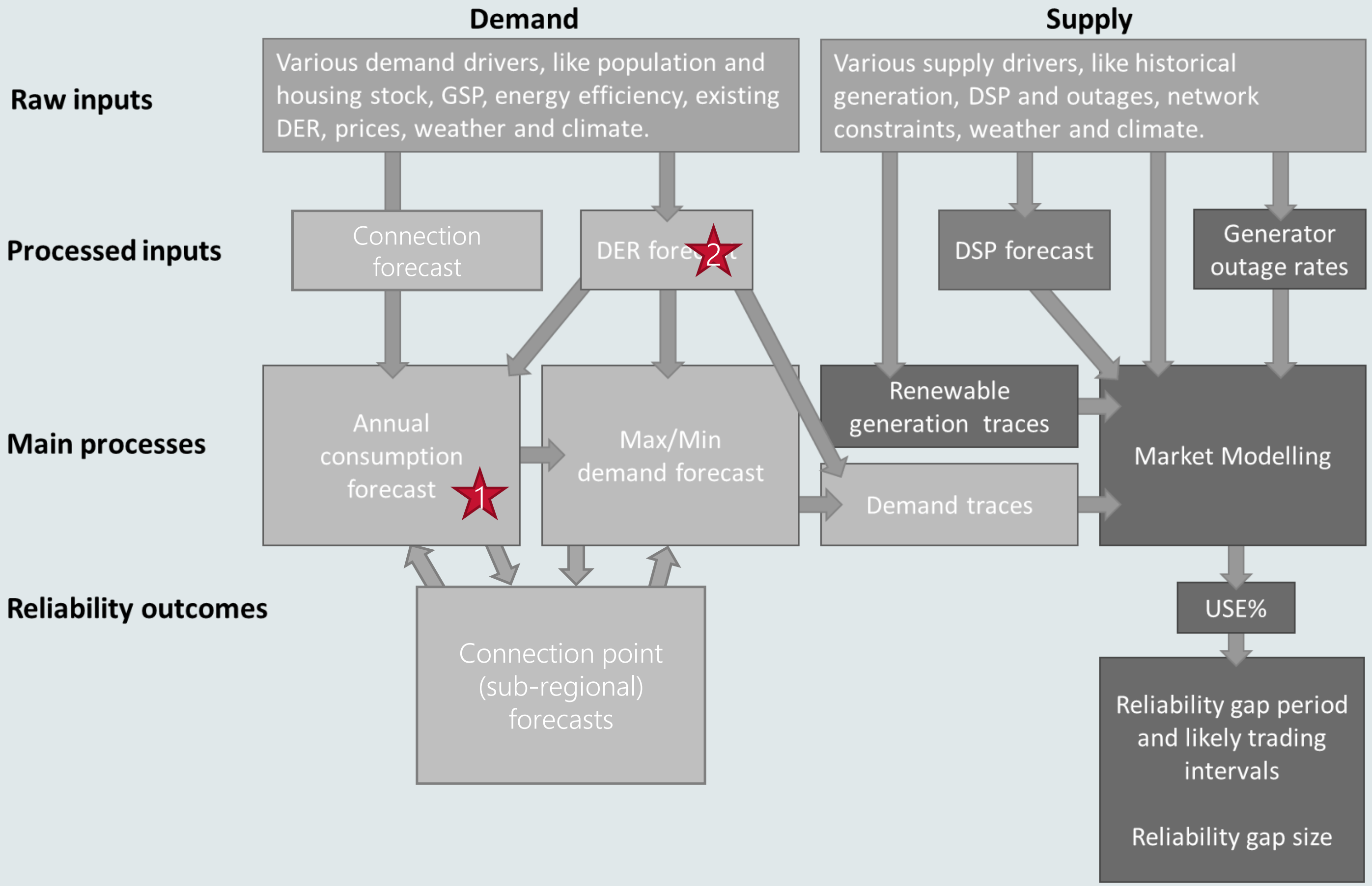
Develop multi-model ensembles of energy consumption per region, with focus on the next few years, considering both the existing component based model and shorter-term monthly time-series models.

Energy forecasts are a key input to max/min forecasts and demand traces. The improvements are therefore expected to result in better reliability assessments.

PV forecasts

Use the DER register and work more closely with the CER to ensure insights from historical installations are captured in short-term trends, possibly at lower spatial granularity.

PV forecasts are a key input to energy forecasts, max/min forecasts and demand traces. The improvements are therefore expected to result in better reliability assessments.



Forecast improvement program

Lower priority improvements

Generator derating in response to summer heat

AEMO will apply two summer capacity ratings to better capture available capacity at differing temperatures.

Customer connection forecast methodology

AEMO now has 5+ years of connections history for all regions, so a new connections model is being developed that incorporates greater visibility and consideration of the history and dwelling type characteristics.

Forecasting portal

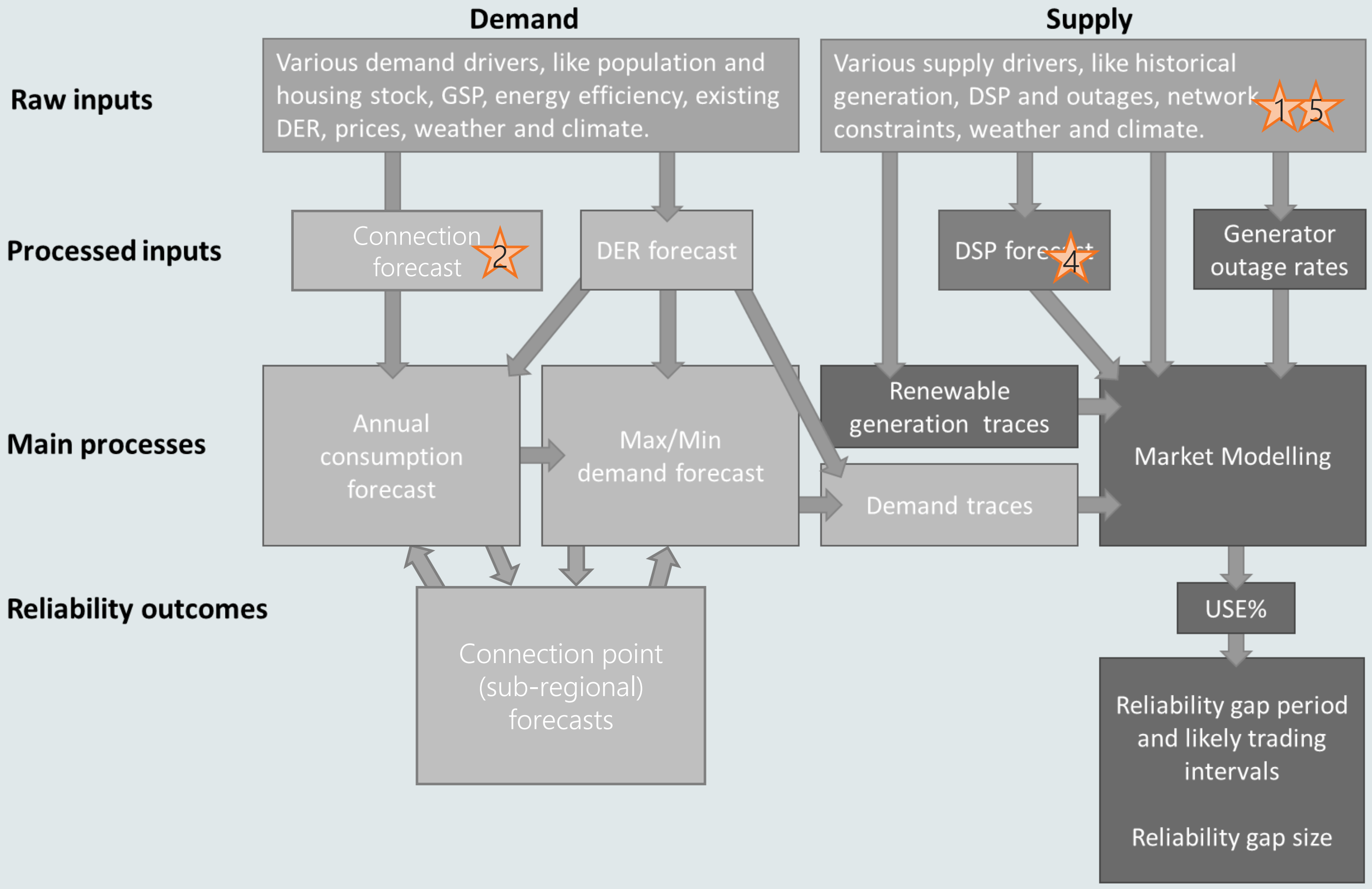
Publish shoulder seasonal minimums in addition to summer/winter

Demand side participation

Include responses from peaking type non-scheduled generators

Auxiliary load

Estimations of auxiliary load will be requested from generators directly through the GenInfo data collection process.



Forecast improvement program

Investigations

Weather and climate data

Investigate the use of reanalysis weather and climate data for customer demand, generator supply and line rating traces.

Loss factor forecasting

Investigate the use of metering and marginal loss factor data for loss factor forecasting

Enhanced use of metering data

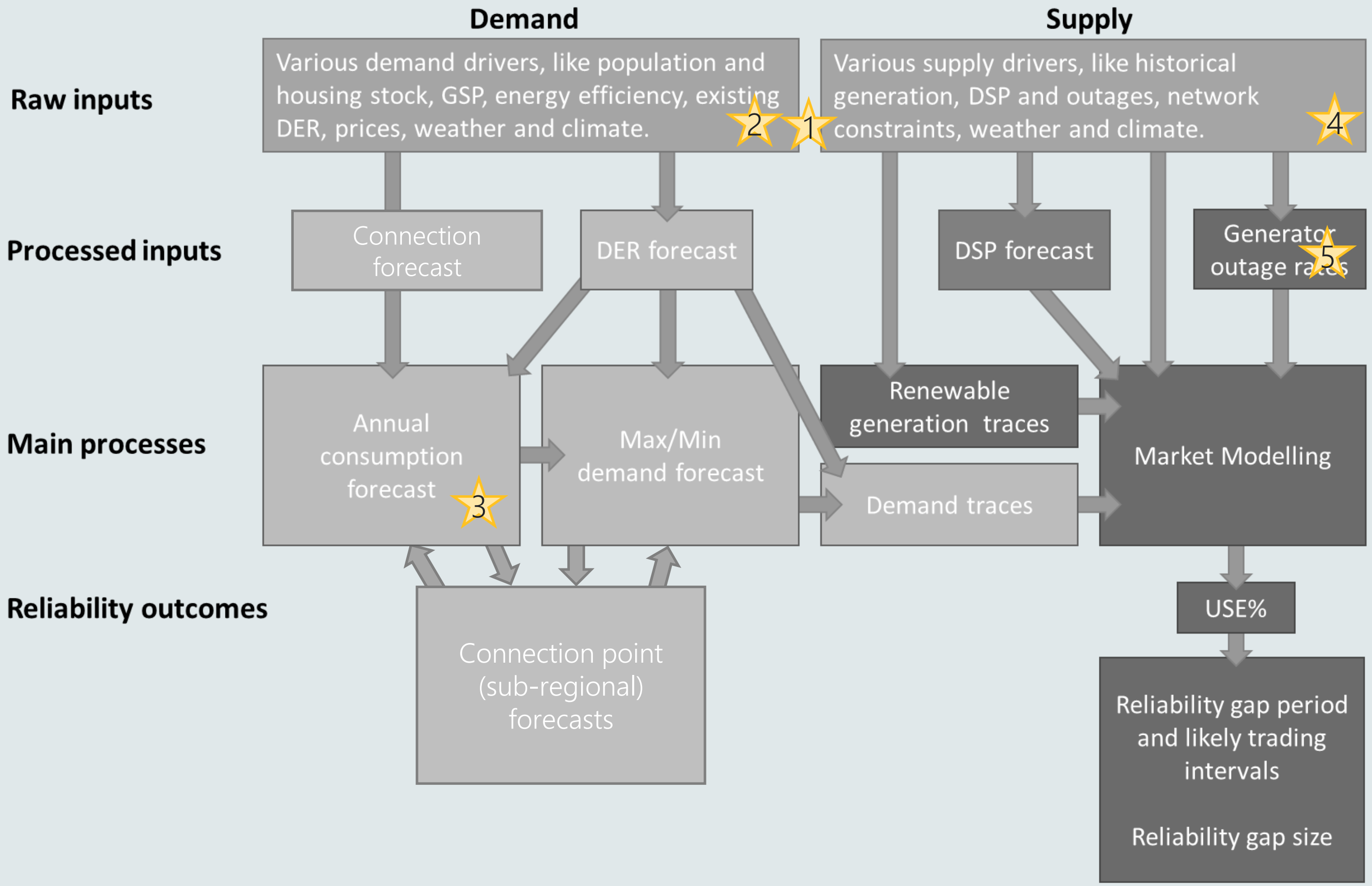
Increase measurement and verification of input components and customer segments using metering data

Generator new entrant modelling

Monitor the performance of Generation Information commercial use dates and adjust process to accurately reflect generator commissioning.

Generator outage rates

Undertaking an international review to examine the evidence of trends in forced outage rates of ageing coal generation.



Forecast improvement program

Connection point forecast improvements

Sub-regional model inputs

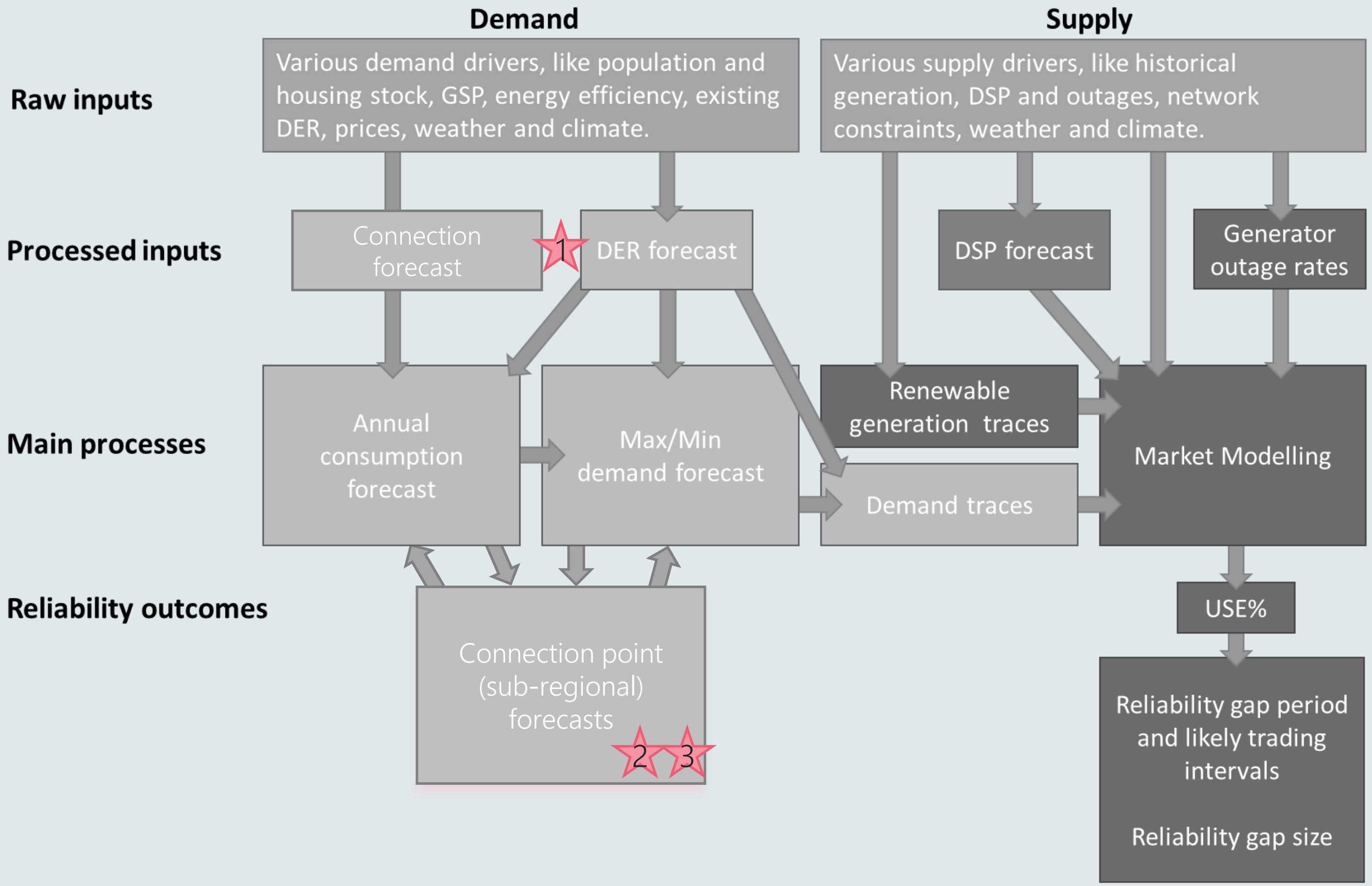
Use the DER register and enhanced PV and connections forecasts to develop sub-regional component forecasts

Minimum demand forecasts

Data quality issues have hampered efforts to deploy to date. Further work to clean connection point data will accompany minimum demand model deployment.

Industrial connection points understate variability

Explore adaptation of regional industrial estimation methods through the sampling of historical variability.



Major improvements already implemented

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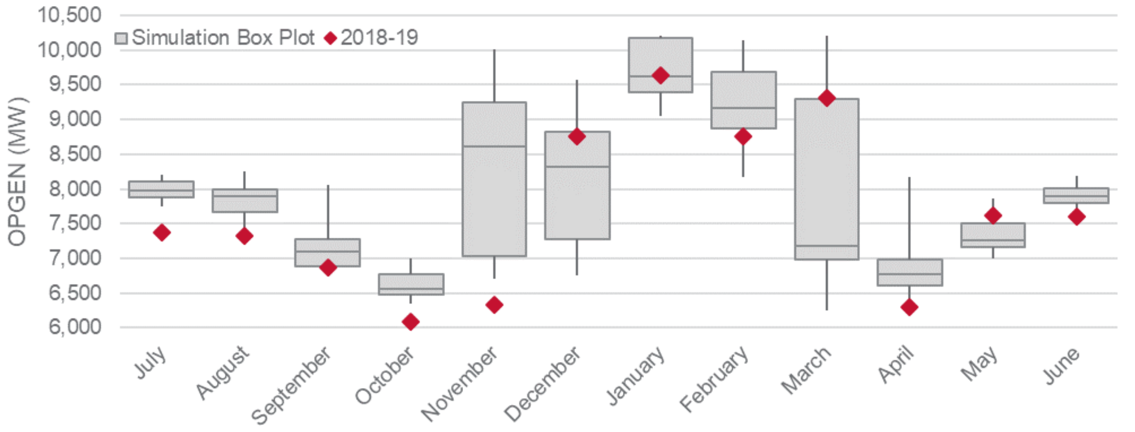
Generator new entrant modelling

- AEMO has adjusted the criteria for Com* assuming they will be delayed until after the T-1 RRO window.
- Should this method have been used in the 2018 ESOO, the difference between forecast and actual capacity would have been 29 MW instead of 996 MW.
- AEMO will continue to monitor and adjust approach if appropriate.

Demand traces

- New method developed for the 2019 ESOO, that scales historical demand traces to fit forecast:
  - energy,
  - max and min demand, and
  - embedded technology.
- The updated method better captures the shape of the demand curve, particularly in summer and shoulder where the temperature is not extreme.
- The accuracy observed in the demand traces is consistent with the accuracy observed in the energy consumption and extreme demand forecasts.
- While some monthly events remain outside the simulation bounds for both models, the difference is reduced with the updated method.

Victoria 2018 simulated monthly maximum demand with actuals



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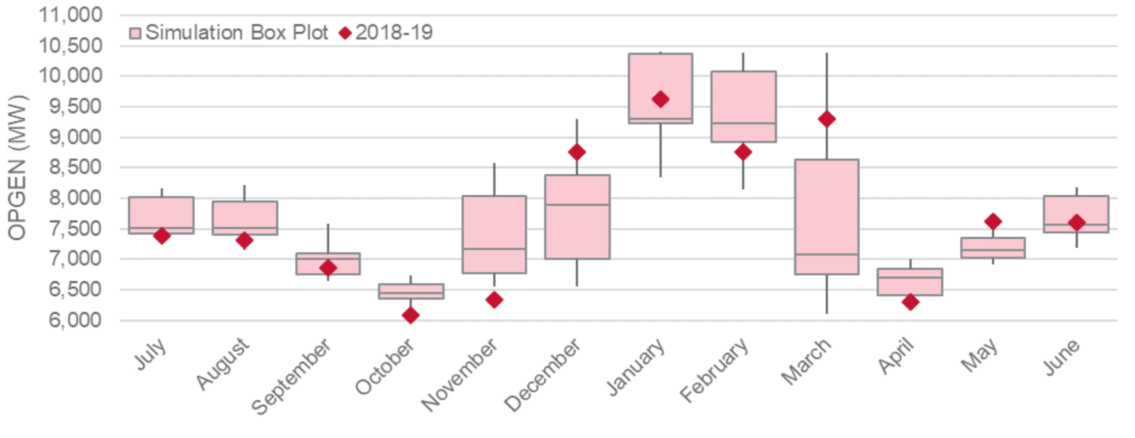

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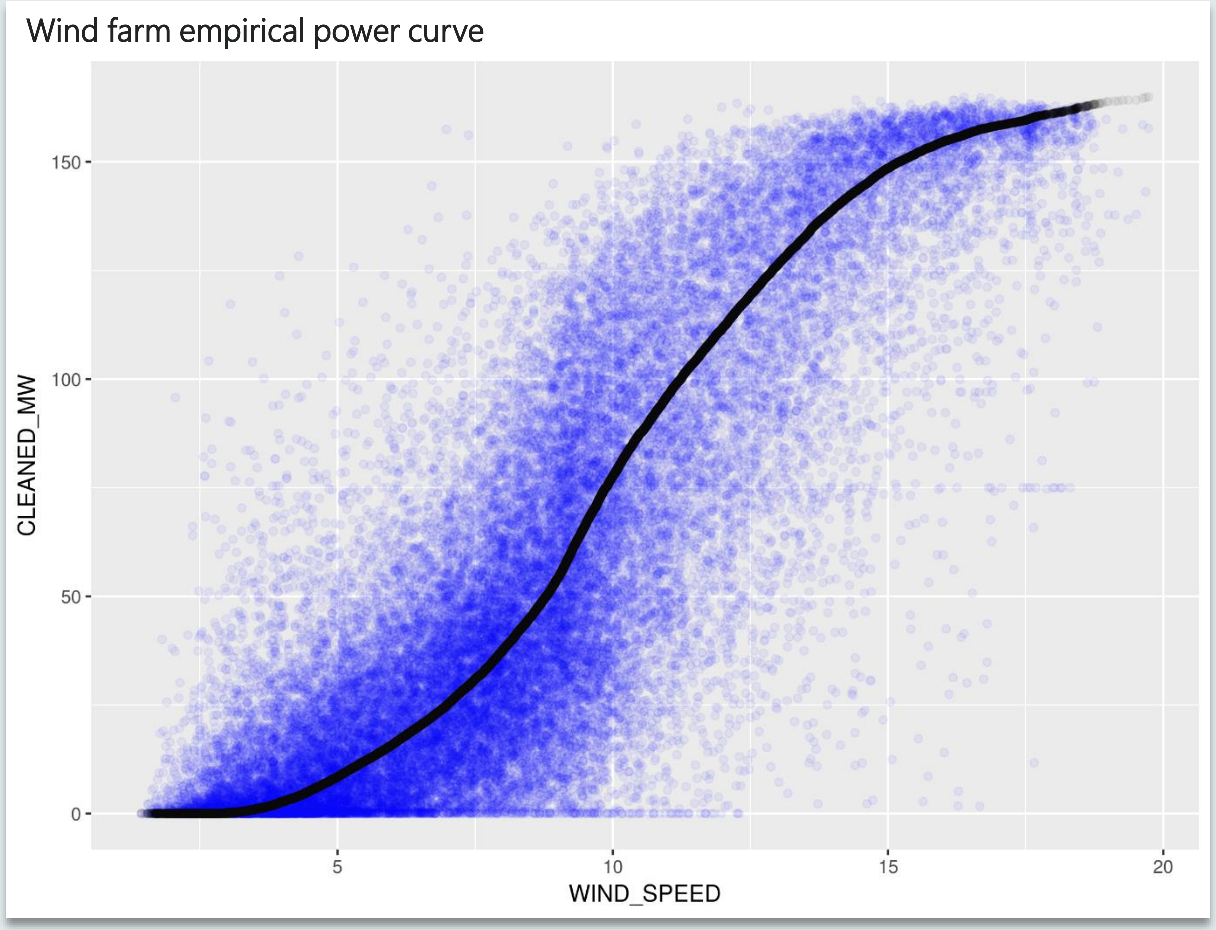
VRE traces

Historical VRE traces are often not suitable for direct use due to:

- The facility being new
- Commissioning hold points reducing output
- Network constraints reducing output
- Market responsive behaviour

For the 2019 ESOO, AEMO developed most generation traces for VRE using power curves estimated from empirical relationships

Further investigations are ongoing regarding the use of historical reanalysis and downscaled climate data to derive more accurate and weather varied VRE traces.



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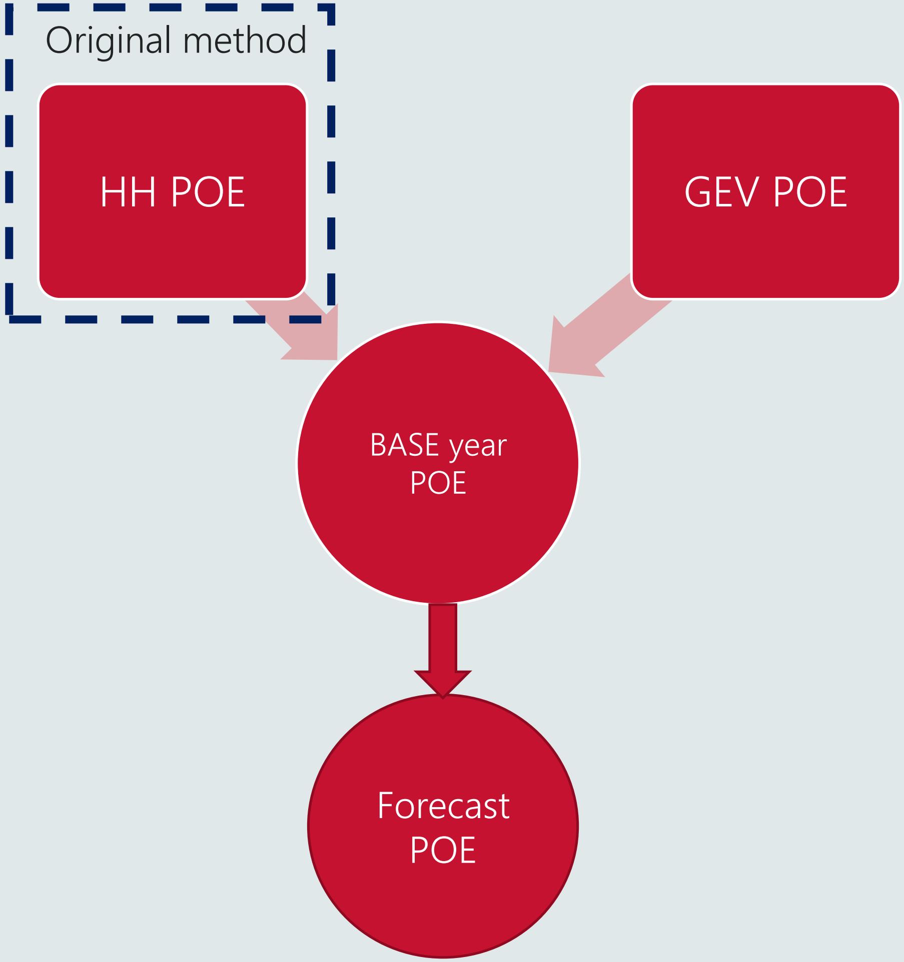
Maximum and minimum demand forecast methodology

- AEMO has implemented several modelling techniques that are used together as an ensemble.
- In 2018 and before, AEMO used a single half hourly demand model that was simulated to sample the range of maximums and minimums.
- In 2019, AEMO has tested an additional demand model that was considered alongside the half hourly model:
  - Half-hourly demand model (original model)
  - Weekly Generalised Extreme Value (GEV) model simulation

- The half-hourly model is better at forecasting the transition in timing of demand due to disruptive technology such as PV, battery systems and electric vehicles; higher resolution models have greater variability.
- The GEV model is better at forecasting short-term maximum demand (1-3 years ahead) but is unlikely to capture complex interactions between variables evident longer term.
- These models have been compared to develop an ensemble forecast, harnessing the strengths of each model over the forecast horizon. This approach was used for the 2019 ESOO.



Process improvement detail

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Operational energy consumption forecast methodology

Types of Forecasting Methods

There are a variety of different forecasting methods[1]. Broadly, these can be classified[2,3] into:

- *Qualitative techniques* - use qualitative data (expert opinion, for example) and information about special events (e.g. changes in the economy, new technologies)
- *Time series analysis* - statistical techniques used when enough history (for example several years' electricity data) is available and when relationships and trends are both clear and relatively stable.
- *Component based models* - try to identify the underlying factors that might influence the variable that is being forecast. They express mathematically the relevant causal relationships and may also directly incorporate the results of a time series analysis.

AEMO forecasting use a combination of these approaches for long-term forecasting

1 Sander, and Reid (2012), *Operations Management: An Integrated Approach*, 5th Edition
2 Chambers, Mullick and Smith (1971) *How to Choose the Right Forecasting Technique*, Available at: https://hbr.org/1971/07/how-to-choose-the-right-forecasting-technique
3 Chase, C, 2013, *Demand-Driven Forecasting: A Structured Approach to Forecasting*, 2nd Edition

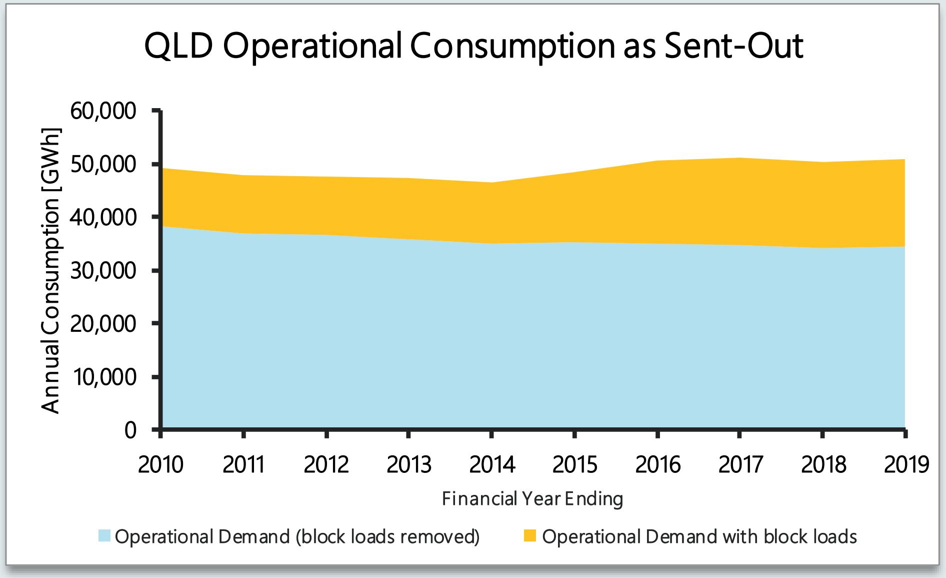
Development in AEMO forecasting methods

AEMO Long-term forecasting techniques have evolved over the last decade moving to component based models:

- Prior to 2012, forecasts were aggregated from information provided by TNSPs
- Beginning with the 2012 ESOO, forecasts of energy efficiency impact and rooftop PV uptake were included
- From 2016, the process segmented electricity usage into business and residential sectors. AEMO has also expanded its survey and interview process to obtain consumption patterns of large industrial users of energy
- The latest series of forecasts considers the introduction of electric vehicles, behind-the-meter batteries, and small non-scheduled PV systems.

Operational energy consumption forecast methodology
Improvement in historical data

- In the 2019 ESOO AEMO utilised meter data for the first time to isolate large energy users, enabling inspection of underlying long term trends, built upon knowledge built from surveys since 2016.
- The figure below displays how the isolation of block loads can reveal different underlying trends in consumption. Isolating long-term patterns from short-term events are established techniques to enhance insights from time-series data. [1]
- In preparation for the 2020 ESOO AEMO intends to utilise 10+ years of meter data along with different forecasting methods to focus both on accuracy and explainability for the various drivers.



1 Ellis, L, Reserve Bank Assistant Governor (Economic), 2019. Available at https://www.rba.gov.au/speeches/2019/sp-so-2019-10-04.html

Operational energy consumption forecast methodology
Model advantages and disadvantages

	Time Series	Component based models
Advantages	scalable	Better at predicting turning points
	work well for stable historical data	Accounts for the dynamics of a sytem
	can smooth out small random fluctuations	Good at reducing unexplained variance
	simple to understand and use	They are capable of supporting what-if analysis.
	systematic, requiring low data storage	More accurate short- and medium-term forecasts than time series methods alone.
	software packages readily variable	More accurate in long-term forecasts than short-term
	They are generally good at short-term forecasting (one to three periods into the future).	
Disadvantages	Require a large amount of historical data.	They require different types of data
	They adjust slowly to changes in historical data.	A good understanding/measurement of independent variables is required
	Less applicable when the forecast horizon is long and/or structural change anticipated in future.	Forecasting accuracy depends on a consistent relationship between independent and dependent (or influence) variables.
	Large fluctuations in data (such as structural shifts) can produce large errors	Takes much longer to develop models

Adapted from:
1 https://hbr.org/1971/07/how-to-choose-the-right-forecasting-technique
2 Chase, C, 2013, *Demand-Driven Forecasting: A Structured Approach to Forecasting*, 2nd Edition

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Operational energy consumption forecast methodology
Model applicability

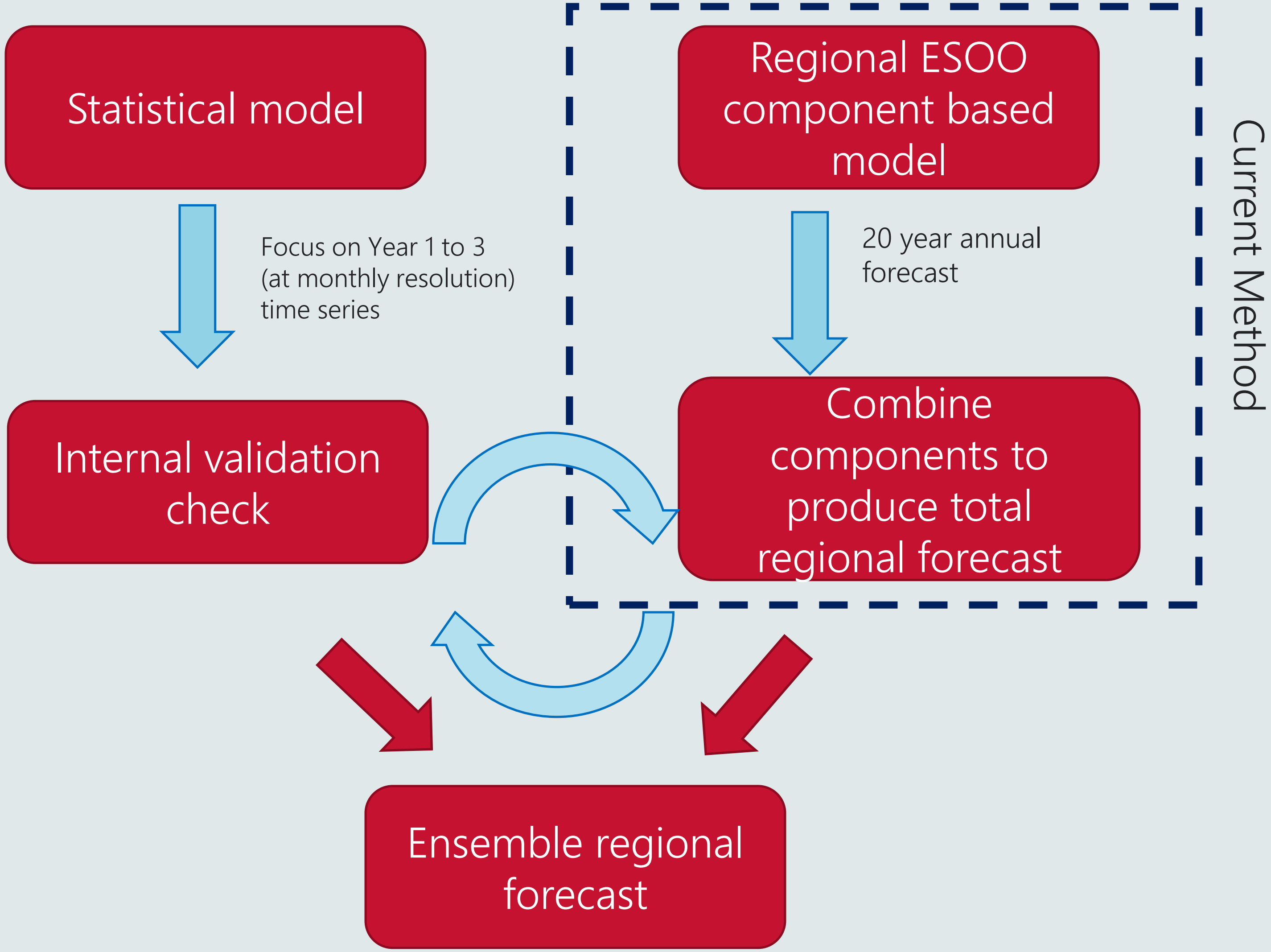
Segmenting electricity consumption and identifying the appropriate method can be focussed in four areas[1]:

- **Low impact, low forecastability:**
  - Low trend and low effect on consumption.
- **Low impact, high forecastability**:
  - Strong trend but low effect on consumption.
- **High value, low forecastability**:
  - For example, new technologies with very little historical data (EVs, batteries, new energy efficiency schemes).
- **High value, high forecastability**:
  - For example, seasonal heating/cooling fluctuations, strong historical trends (residential connections and PV installations).

1 Adapted from Chase, C, 2013, Chapter 3, *Demand-Driven Forecasting: A Structured Approach to Forecasting*, 2nd Edition

Operational energy consumption forecast methodology
Proposed ESOO consumption validation step

- Time-series analysis to be utilised to uncover demand patterns
- Develop a framework where the most appropriate method is applied for the situation both in terms of impact, data visibility and forecastability.



Operational energy consumption forecast methodology
Prototype results

Prototype time-series models have been developed to test the improvement in accuracy. These models were developed using data up to 2017-18, (excluding any data from 2018-19) to test the accuracy of 2018-19 consumption. The following reduction in error was identified when compared to the current component based models:

Forecasting performance comparison

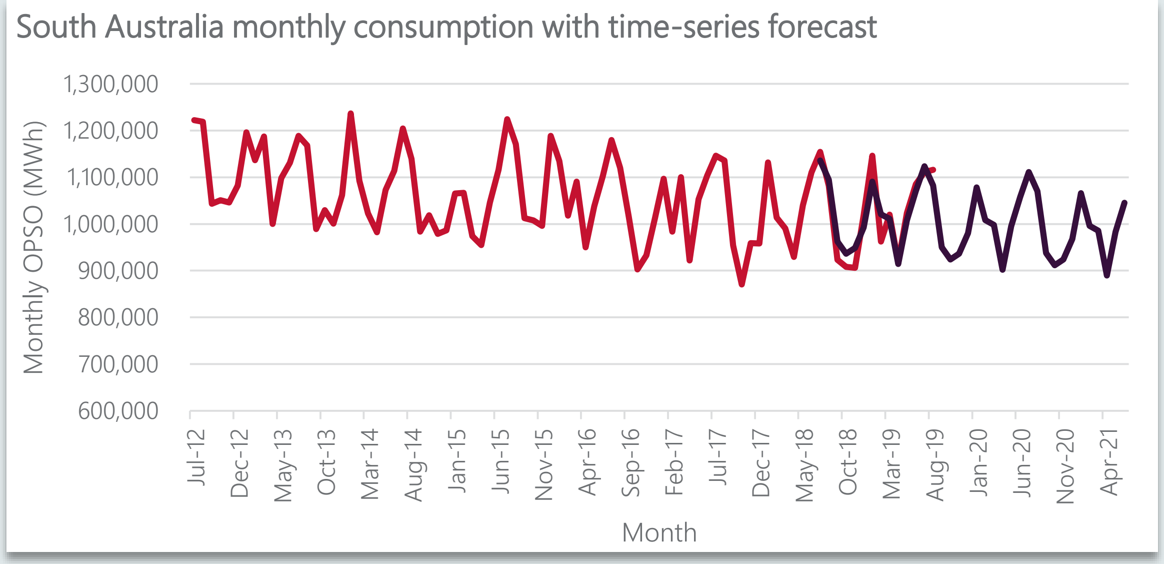
2018-19 year ahead forecast error	Actual performance	Prototype ensemble model performance
Mean Absolute Percentage Error	2.1%	1.0%

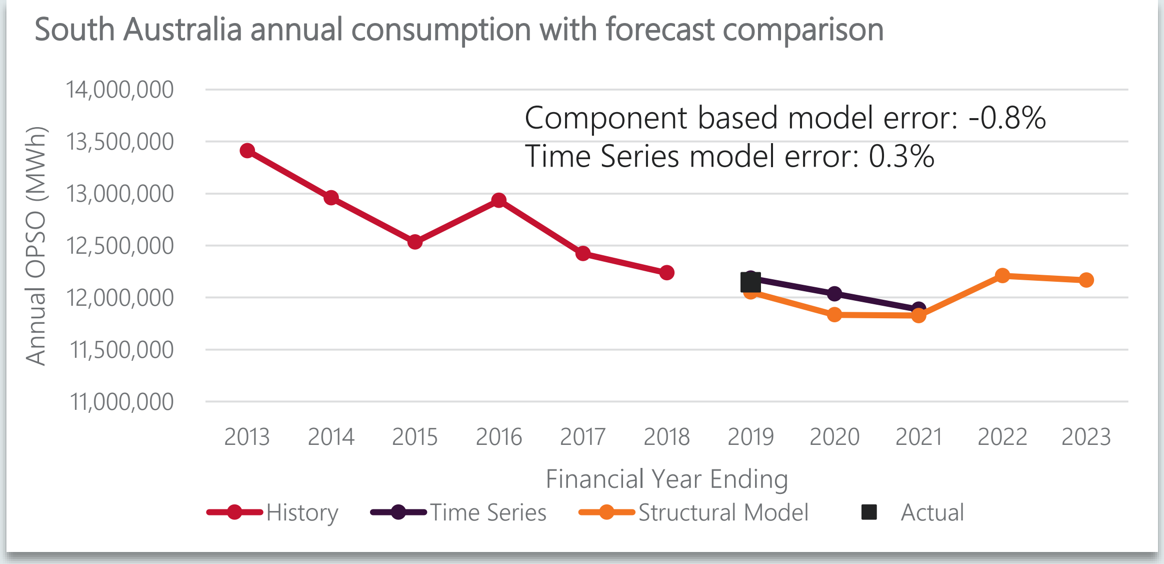
Framework for forming the ensemble will consider options such as:

- utilising the component based forecast only,
- baselining the component based forecast but retaining trend, or
- combining the two forecasts together.

Operational energy consumption forecast methodology

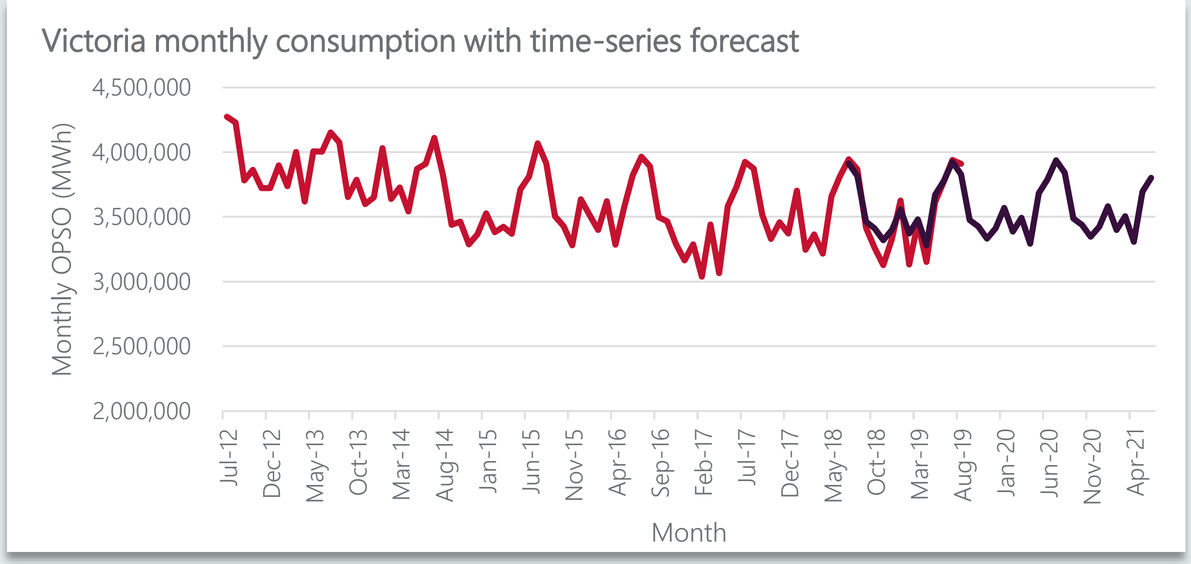
Prototype results – South Australia

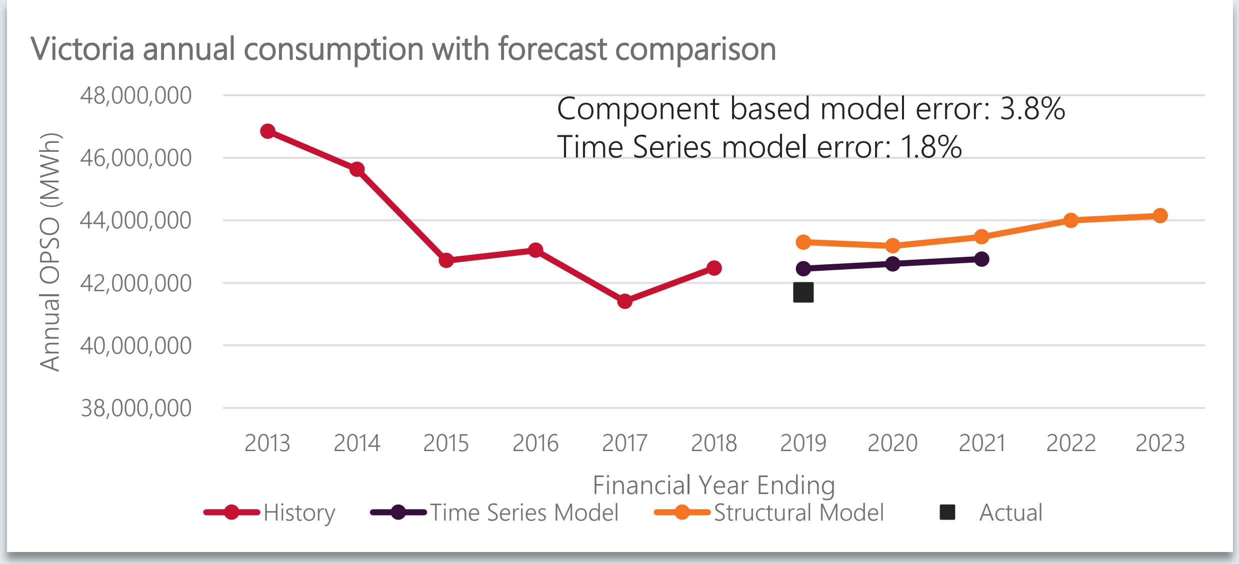




- A time-series forecast has been developed using STL (season, trend, irregular) decomposition, with a trend forecast using piecewise-linear regression. Monthly forecast values have been aggregated to form an annual forecast.
- Producing both a time series and component based model allows further comparison:
  - Both the component model and the STL model show similar three year trajectories (though with variations in the starting point for 18-19).
  - Differences in the gradient between the two models are then investigated to ensure that the variation is understood and explainable.
  - Actual consumption lay between both models, but the time-series model showed closer agreement with observed actuals.
- An ensemble of the two models can utilise the better short term accuracy of the time-series model while allowing the component based model to guide the long term projection.

Operational energy consumption forecast methodology
Prototype results - Victoria





- A time-series forecast has been developed using STL (season, trend, irregular) decomposition, with a trend forecast using piecewise-linear regression. Monthly forecast values have been aggregated to form an annual forecast.
- Producing both a time series and component based model allows further comparison :
  - Both the component model and the STL model show similar three year trajectories (though with variations in the starting point for 18-19).
  - Differences in the gradient between the two models are then investigated to ensure that the variation is understood and explainable.
  - Actual consumption fell below both models due to lower than expected consumption over summer 2018-19, but the time-series model showed closer agreement with observed actuals.
- An ensemble of the two models can utilise the better short term accuracy of the time-series model while allowing the component based model to guide the long term projection.

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PV forecasts

Rooftop PV and PVNSG are challenging to forecast, and remain a material driver of energy and demand forecast accuracy variance with short-term trends in installations and output still an area of focus in 2020

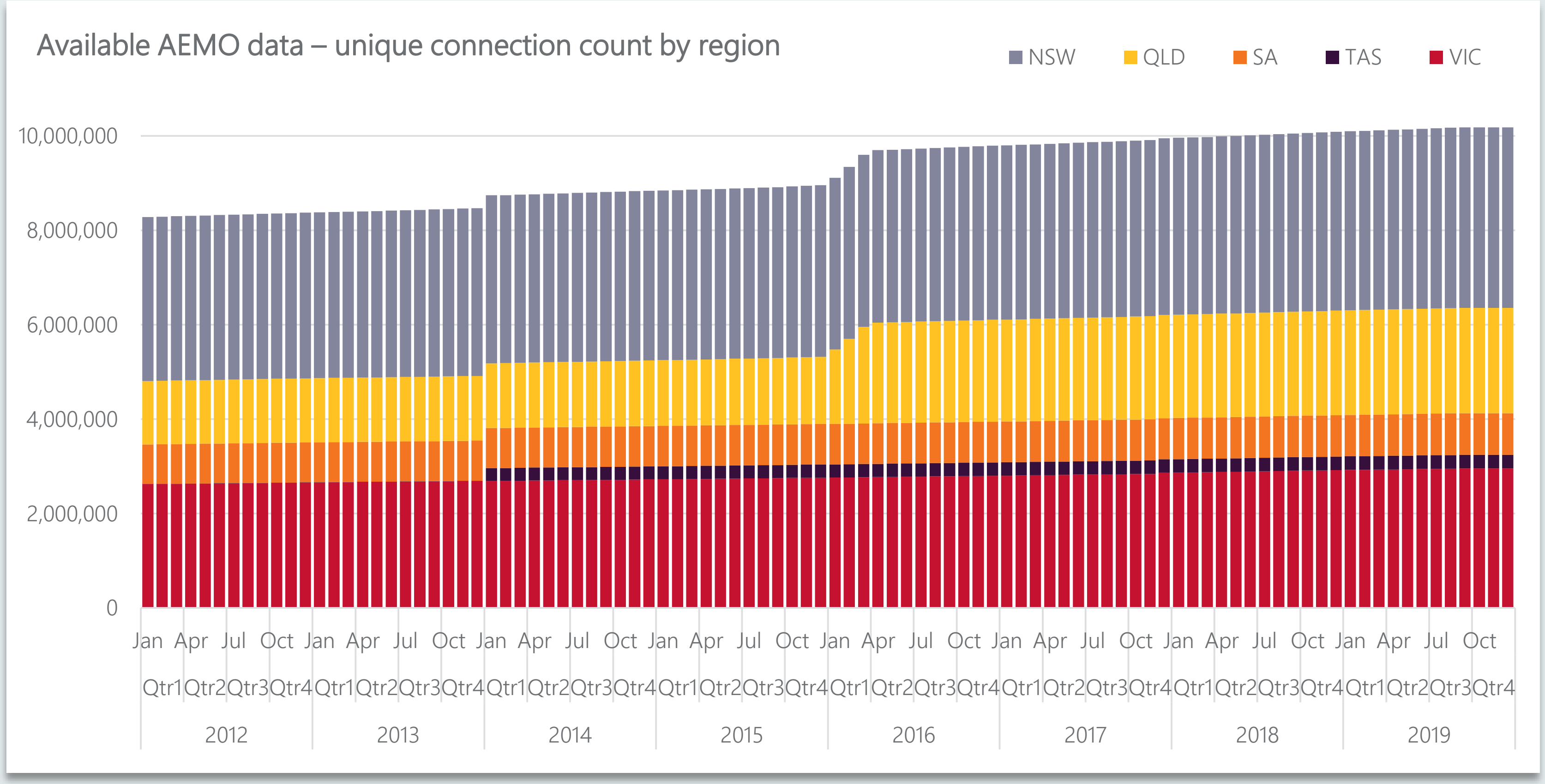
Specifically, AEMO intends to:

- Continue to acquire expert forecasts from multiple consultants.
- Utilise the DER register and work more closely with the CER and market participants on the development of cleaned historical spatial series.
- Work more closely with consultant forecasters to ensure insights from historical installations are captured in short-term trends, possibly at lower spatial granularity. This includes a requirement for consultants to provide AEMO their forecast accuracy and quality control processes to improve/ensure this is an area of focus.
- Continue to use scenarios to test the substantial uncertainty in long-term installation and system output rates.

Customer connection forecast

- The 2018 ESOO residential connection growth forecasts have not aligned well with actual growth. However, this did not have a material impact on year-ahead accuracy.

- AEMO has sufficient connections history for all regions, so a new connections model is being developed that incorporates greater visibility of the historical trend along with consideration of the history and dwelling type characteristics.



Connection point forecast improvements

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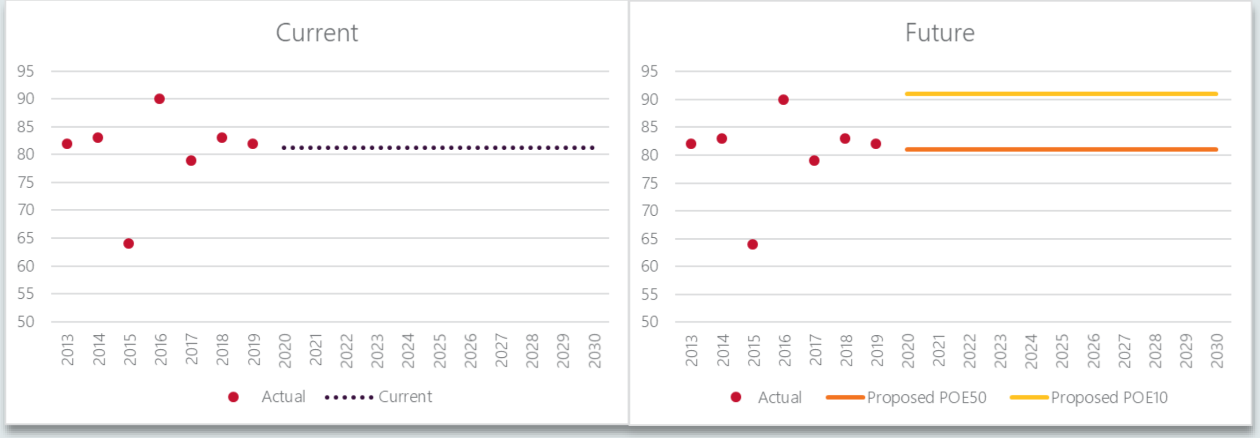
Connection point forecast improvements

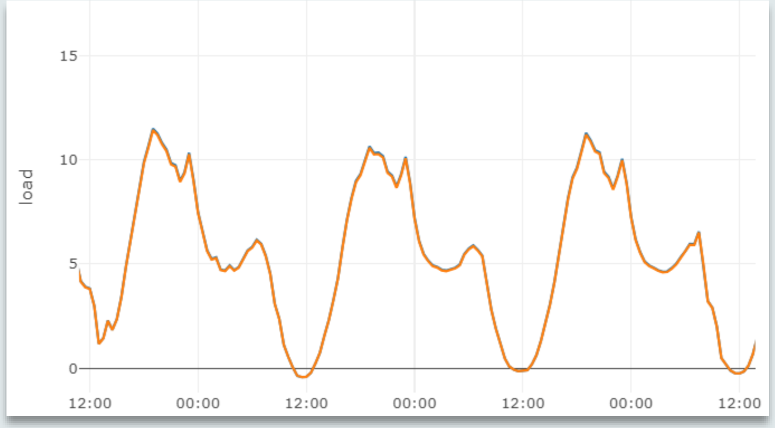
Industrial component variability in forecasts

- The industrial demand component is derived from historical data as a deterministic MW amount, with new block loads explicitly considered.
- Demand at the connection point can vary due to operational variations in industrial loads, therefore POEs should reflect this.



Minimum demand forecasting project

- The project will result in minimum demand forecasts at connection point, and depends on development of sub-regional input drivers.



Improved sub-regional model inputs

- Use the DER register and enhanced PV and connections forecasts to develop sub-regional component forecasts, informing regional forecasts and reflecting sub-regional demographics.

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Short form consultation

Please submit feedback to energy.forecasting@aemo.com.au

By Friday the 14th February 2020

You may comment on one, many or all of the proposed improvements

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Major improvements already implemented

PV forecasts

Developed automated processes to prepare rooftop PV and PVNSG capacity actuals and generation estimates from the CER. Developed more timely estimates of solar irradiance and normalized rooftop PV generation.

Max and min demand forecast methodology

Developed and implemented a multi-model ensemble for forecasting maximum and minimum demand.

Improvement of demand traces

Improved the shape of demand traces for operational management of outage scheduling and the months at risk to be identified in any RRO reliability instrument.

Generator new entrant modelling

Adjusted criteria such that Com* projects were assumed to be delayed until after the T-1 RRO window.

Renewable generation traces

Developed VRE generation traces directly from weather estimates using power curves in addition to history.

Highest priority improvements

Operational energy consumption forecast methodology

Develop multi-model ensembles of energy consumption per region considering both the existing component based model and shorter-term monthly time-series models.

PV forecasts

Use the DER register and work more closely with the CER to ensure insights from historical installations are captured in short-term trends, possibly at lower spatial granularity.

Lower priority improvements

Generator derating in response to summer heat

AEMO will apply two summer capacity ratings to better capture available capacity at differing temperatures.

A description of the methodology that will be applied in the 2020 ESOO to better model summer temperature derating was presented at the November FRG.

Customer connection forecast methodology

AEMO now has 5+ years of connections history for all regions, so a new connections model is being developed that incorporates greater visibility and consideration of the history and dwelling type characteristics.

Forecasting portal

Publish shoulder seasonal minimums in addition to summer/winter

Demand side participation

Include responses from peaking type non-scheduled generators

Auxiliary load

Estimations of auxiliary load will be requested from generators directly through the GenInfo data collection process.

Investigations

Weather and climate data

Investigate the use of reanalysis weather and climate data for customer demand, generator supply and line rating traces.

Loss factor forecasting

Investigate the use of metering and marginal loss factor data for loss factor forecasting

Enhanced use of metering data

Increase measurement and verification of input components and customer segments using metering data

Generator new entrant modelling

Monitor the performance of Generation Information commercial use dates and adjust process to accurately reflect generator commissioning.

Generator outage rates

Undertaking an international review to examine the evidence of trends in forced outage rates of ageing coal generation.

Connection point forecast improvements

Sub-regional model inputs

Use the DER register and enhanced PV and connections forecast to develop sub-regional component forecasts

Minimum demand forecasts

Data quality issues have hampered efforts to deploy to date. Further work to clean connection point data will accompany minimum demand model deployment.

Industrial connection points understate variability

Explore adaptation of regional industrial estimation methods through the sampling of historical variability.