AEMO
AUSTRALIAN ENERGY MARKET OPERATOR

Progress on innovations and improvements to AEMOs maximum demand forecasts

February 2018

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Agenda

1. Purpose
2. List of improvements planned for 2019
    - Progress update on initiatives presented in the Forecast Accuracy Report
3. Maximum demand modelling improvements
    - New method for calculating auxiliary load at time of maximum and minimum demand
    - Improved maximum demand model specification to be used in the ESOO 2019
    - Improved simulation engine using Apache Spark
        - Produce Monthly, Seasonal and Annual forecasts
    - Study multiple weather stations within regions
    - Ensemble approach for forecasting maximum demand
        - Weekly Generalized Extreme Value model simulation
        - Annual Generalized Extreme Value model

Purpose

1. Inform stakeholders on the progress on AEMO’s modelling improvement for maximum and minimum demand.
2. To be transparent and accountable for the continuous improvement in AEMO maximum and minimum demand forecasts

Forecast Accuracy Report
List of improvements planned for 2019

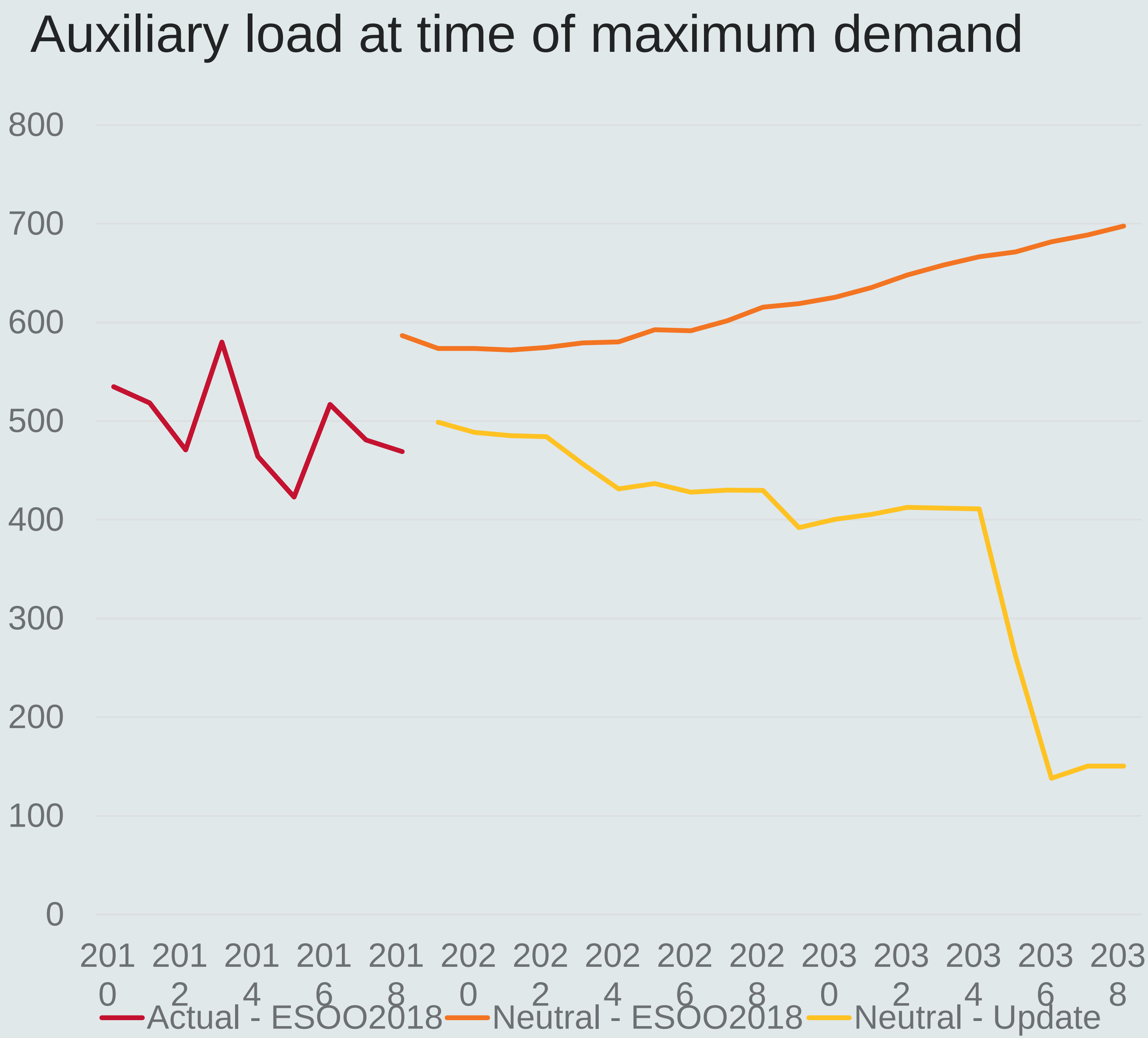
Observations	Action already taken in 2018	Actions to be taken in 2019	Progress
Maximum demand			
Improve ability to explain forecast differences	Increased information provided in this Forecast Accuracy Report, and consulted with industry on new performance metrics that could be used to measure accuracy of probabilistic forecasts.	Retain more modelling data so POE outcomes can be explained for a number of variables beyond temperature. This includes the impact of heatwaves, months and type of day.	**Being delivered through new simulation engine – 90% complete**
Forecast values fluctuate between forecast years	Doubled simulations to smooth forecasts between years.	Same as 2018 or even more simulations.	**Being delivered through new simulation engine, aiming for 2000 - 5000 sims - 90% complete**
Need to better understand interaction of multiple weather variables, including subregional weather	Improved modelling of climate change -particularly extreme temperature and heatwave trends.	Further improvements to model formulation, considering other combinations of weather variables, enabled by greater access to climate and weather data.	**Initial analysis complete**
Poor distribution alignment in New South Wales and Tasmania	Reformulated model – POE spread now more representative of historical values.	Continuous review of model formulation.	**New model specification developed – will be implemented in ESOO 2019**
Minimum demand			
Minimum demand forecasts too low across all regions, particularly Victoria and South Australia	Started forecast performance monitoring of minimum demand. Reviewed forecasts of rooftop PV and PVNSG.	Further improvement to model formulation with emphasis on minimum demand periods. Meter data analysis to glean any behavioural change impacts.	**New model specification developed – will be implemented in ESOO 2019**
Only checks for minimum demand summer and winter	No change.	Check for occurrence of minimum demand in forecast shoulder months.	**Being delivered through new simulation engine, that produce results for shoulder periods - 90% complete**

New method for calculating auxiliary load at time of Minimum and Maximum demand

Improved maximum demand model specification

Previously used average percentage of auxiliary load

New process uses auxiliary load at time of maximum demand conditions



Improved maximum demand model specification

Improved maximum demand model specification

- Explored different explanatory variables and transformation of explanatory variables
- Explored different model specifications

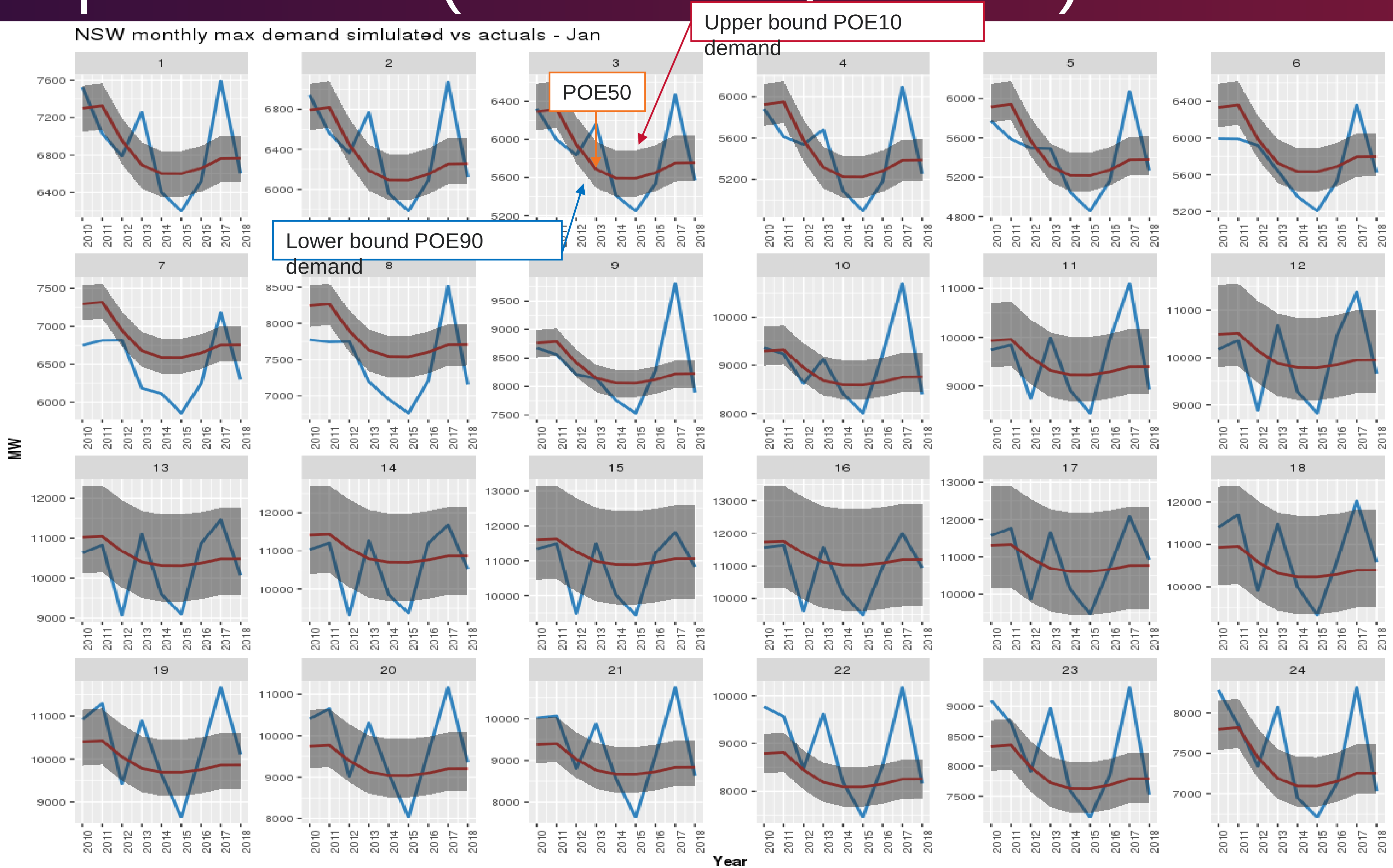
Exploratory Data Analysis (EDA):

- Found the optimal rolling average hours for instant half-hourly temperature and daily temperature
- Assessed the correlation between instantaneous temperature and daily temperature looking for multicollinearity using Variance Inflation Factor
- Graphically inspected instantaneous temperature, daily temperature and demand and other variables

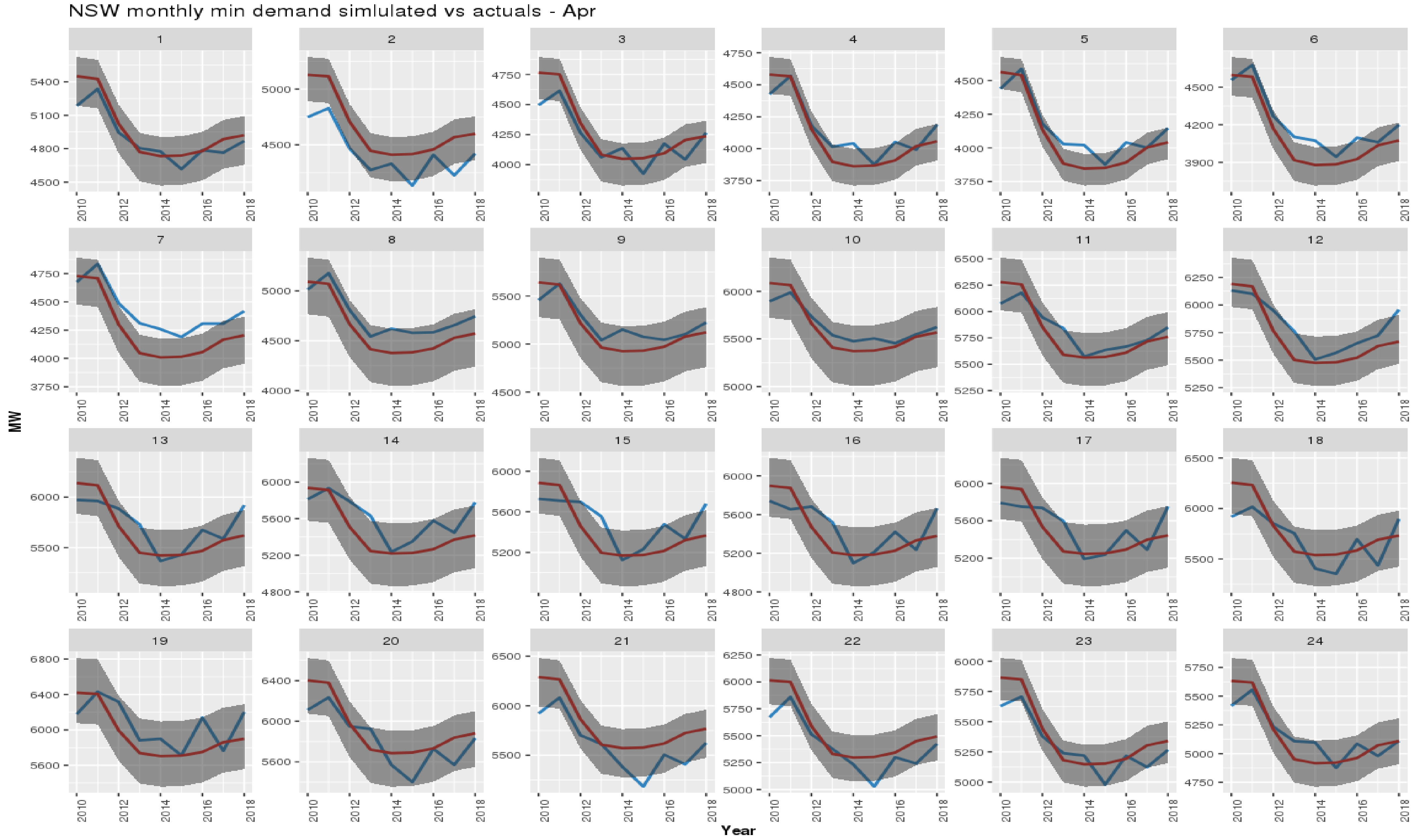
The model selection process includes:

- Demand and explainers of demand may not be linear. Transformed demand and covariates using machine driven Box-Cox allowing the model to take log-log, power or linear form
- Applied a General to Specific algorithm to select the variables that best explain demand trading off between variance and bias (LASSO)
- Performed Out-of-sample assessment: Using bias-variance trade-offs to choose a model that both accurately captures the regularities in its training data, but also generalises well to unseen out-of-sample test data
- Refit the selected covariates from LASSO and re-fit the model using Maximum Likelihood Estimation
- Validate the simulated demands are within reasonable bounds

Improved maximum demand model specification (one model per hour)



Improved minimum demand model specification



Improved simulation engine

Improved simulation engine

1. Move the simulation from running on local machine to cloud computer using Apache Spark on an Azure insights cluster
2. Cloud computing platform with scalable distributed processing allows AEMO to scale up the number of simulations
3. Benefits:
   - Reduce simulation bounce – current simulation bounce is around 0.5% (i.e. ± 70 MW for NSW). This is greater at the end of the forecast horizon due to increased impact of PV, PVNSG, ESS and EV
   - Run monthly minimum/maximum demand forecast
   - Persist a greater amount of simulation results providing enhanced insights into conditions driving minimum/maximum demand outcomes, and improving forecast accuracy assessments

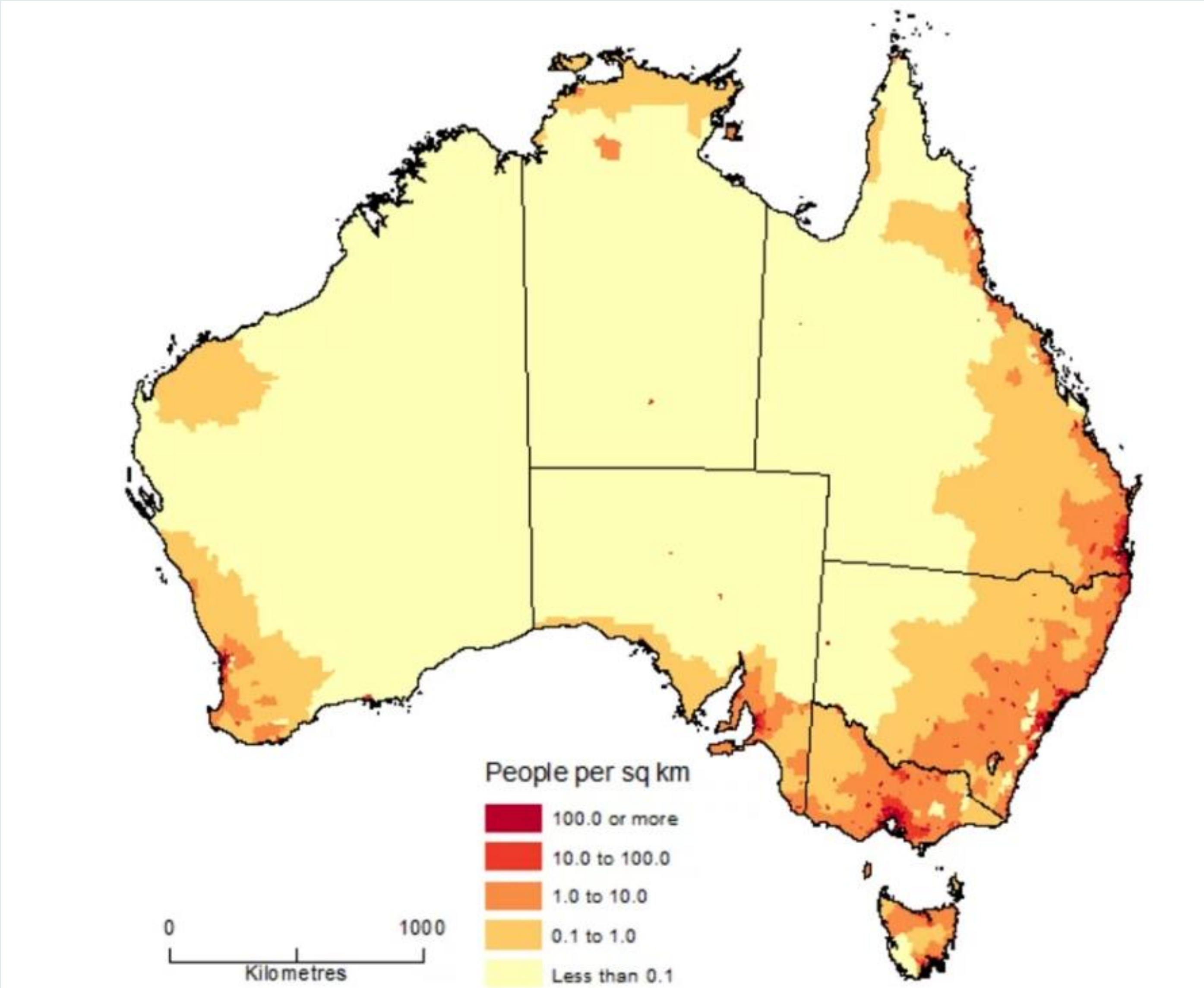
Multiple weather stations

Multiple weather stations

Population density doesn't always reflect the demand distribution that's related to weather

Max demand is driven by weather whereas min demand driven by lack of extreme weather

Australian population density heat map

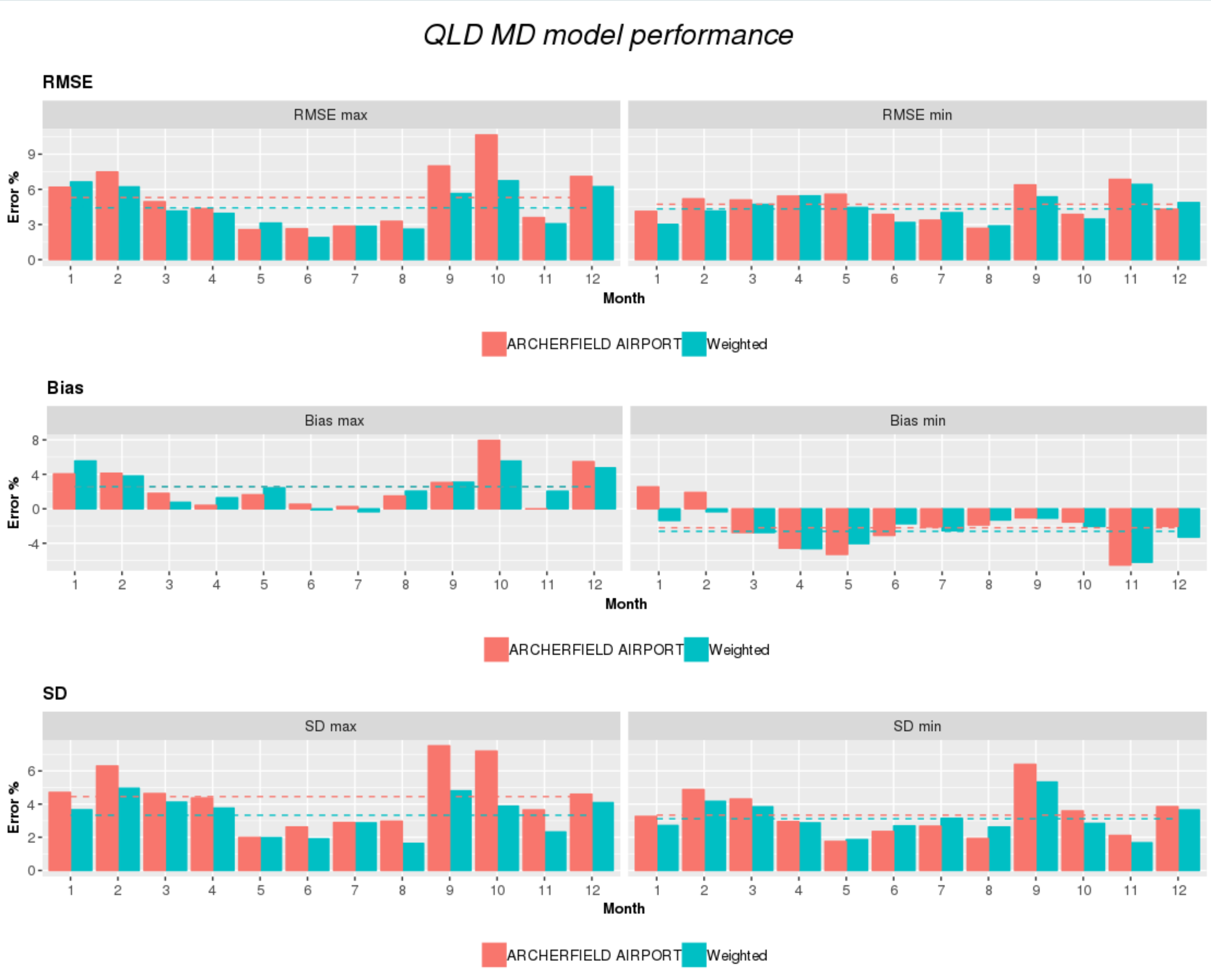


Study into multiple weather stations

Region	Weather station weightings		Population	
NSW	Penrith	30%	Sydney	76%
	Sydney Airport	45%		
			Canberra	9%
	Cessnock/ Williamtown	25%	Newcastle	15%
Vic	Melbourne Olympic Park	15%	Melbourne	85%
	Melbourne Airport	76%		
	Essendon Airport	6%		
	Stanwell	4%	Vic North	6%
			Geelong	9%
SA	Kent town	32%	Adelaide	76%
	Strathalbyn	16%		
	Edinburgh	22%		
	Mt Gambier	30%	Mt Gambier	2%
Qld	Archerfield	14%	Brisbane	59%
	Brisbane	58%		
	Toowoomba	14%		
			Gold Coast / Sunshine Coast	24%
	Cairns	14%	Rockhampton/ Townsville	17%

Study into multiple weather stations

Queensland performance

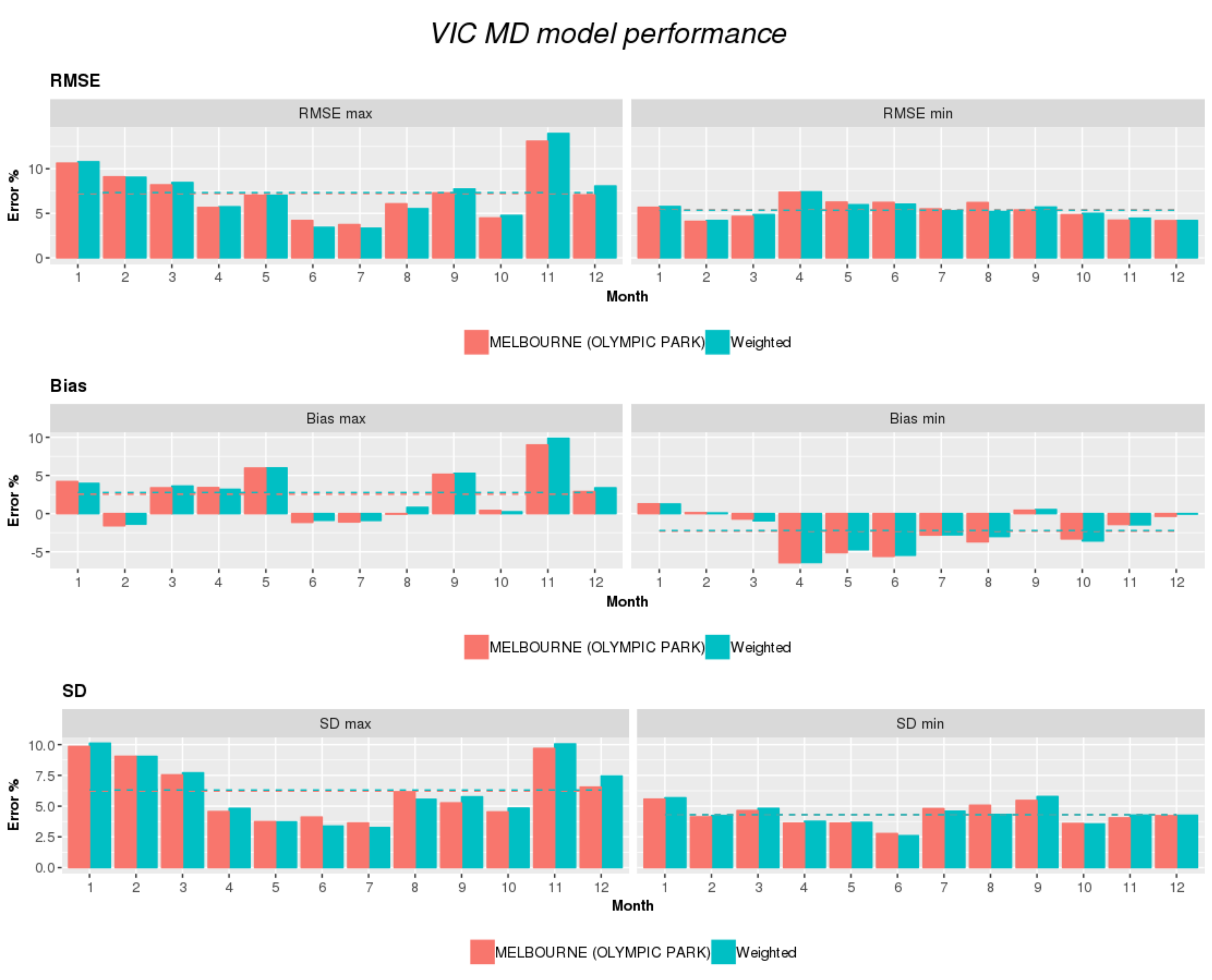


- Using multiple weather stations in Queensland improved forecast accuracy.

- RMSE – Root Mean Squared Error measure of distance between observations and predictions
- Bias – Measure for under or over forecasting. Closer to zero is better
- SD – Standard Deviation measure of the spread of the data

Study into multiple weather stations

Victoria performance



- Using multiple weather stations in Victoria (and all regions but Queensland) showed now improvement in forecast accuracy.

- RMSE – Root Mean Squared Error measure of distance between observations and predictions
- Bias – Measure for under or over forecasting
- SD – Standard Deviation measure of spread

Ensemble of maximum demand models

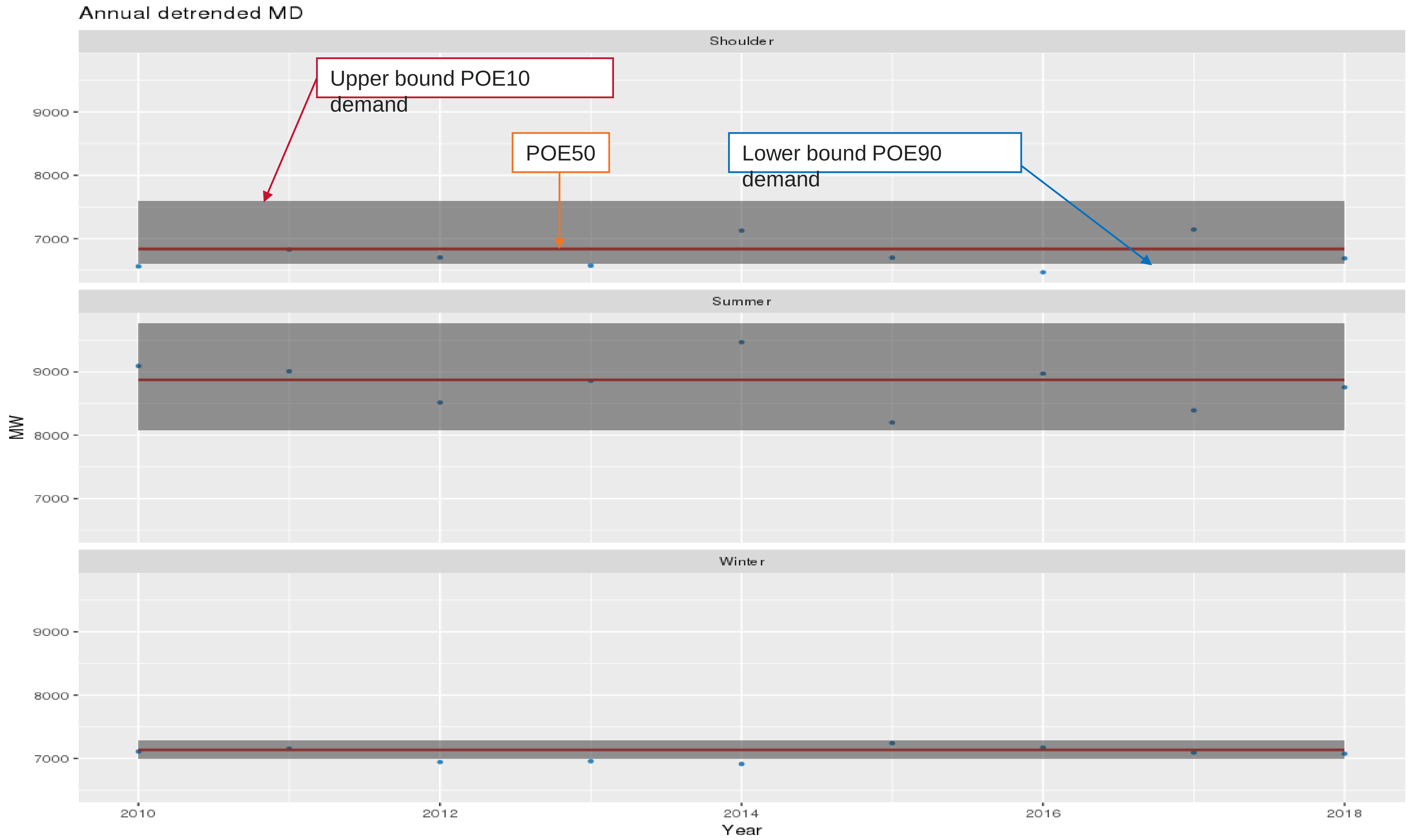
Ensemble of minimum/maximum demand models

- Developing a number of models for forecasting minimum and maximum demand.
  - Currently only have one minimum/maximum demand model.
  - The ensemble model approach will allow AEMO to cross check each model to assess performance and trade off between the strengths and weaknesses of each model.
- Still early but AEMO is experimenting with a Generalized Additive Models (GAM) from the Generalized Extreme Value (GEV) family of models.
- Develop an additional two minimum/maximum demand models for a total of three maximum demand models:
  - Half-hourly demand model (current model)
  - Weekly Generalized Extreme Value (GEV) model simulation
  - Annual Generalized Extreme Value model using GEV theory to mathematically stretch the distribution of daily maxima to annual maxima
- Benefits:
  - Half-hourly model is better at forecasting the transition in timing of demand due to disruptive technology (PV, Battery and EV) but higher resolution models have greater variability
  - GEV is better for forecasting short-term maximum demand (1-3 years ahead) but

Ensemble of maximum demand models

- The GEV is based on Extreme value theory to capture the distribution of rare events or the limit distribution of normalized maxima. The Maxima from an underlying normal distribution of an independent and identically distributed variable follows an extreme distribution that can be categorize as a Fréchet, Weibull or Gumbel distribution
- GEV model develop process:
  - The GEV model was fitted using weekly maxima as a function of PV capacity, customer number count (NMIs), calendar effect variables and can be with/without weather (experimenting with both splines and indicator variables)
  - Assess each variable’s significance and check residuals are random for the final selected model
  - Simulate the fitted GEV model for large number of times and calculate the POEs for summer/winter
  - Compare simulated base year POEs with detrended actual max demand

Ensemble of maximum demand models: Victoria



Methodology updates suggested in consultation

AEMO's recent consultation on the documentation of the methodology also resulted in a few suggestions for improvements to the methodology.

- Ability to provide further breakdown of maximum demand POE levels by segment, ie split residential and commercial.
  - AEMO currently lacks meter data required to do this split. However, a number of initiatives in the metering area could potentially allow this from 2021.
- Consider publishing monthly maximum demand forecasts rather than seasonal to help better planning of supply side outages, demand management activities, and improve accuracy of reliability assessments.
  - AEMO is actively pursuing this.

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