

## AEMO Connection Point Forecasting methodology

2020 Overview

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## 2020 connection point forecasting methodology

The following materials and examples provide a high level overview of the approach and methodology undertaken for the 2020 Connection Point Forecasts.

The materials presented complement the existing connection point forecasting methodology\* and provide further refinements with respect to:

- Minimum demand
- Behind the meter technologies
- Electric vehicles
- PV systems
- Consumption patterns

An update to the Connection Point Forecasting methodology document will be published in Q1 2021 providing further details and information based on the materials presented below.

For further information or clarifications please contact **Energy.forecasting@aemo.com.au**.



# Background: decreasing minimum demand impacts power system stability



An example of summer minimum demand at a CP in Victoria

- Connection Points are the physical points at which Transmission assets meet Distribution assets
- Previously AEMO only forecast maximum demand
- Understanding minimum demand is essential for Network Planning. Unmanaged lower demand will lead to over voltage events and thus need to be addressed.
- The challenge in forecasting minimum demand is that the timing of the minimum can shift significantly with society and technology.



## Transition point: minimum demand time shifts from night to day

As minimum demand transitions from consistently occurring at night, our forecasting methodology must model multiple times of day (defined periods) and select the minimum.



Typical residential Connection Point minimum transition



### The goals

### Consistency with the Produce both minimum Nationally applicable regional forecast and maximum demand Account for transition of Account for behind the Account for spatial the timing of minimum demand drivers and meter technologies on demand in a demand at different reducing the reliance on computationally efficient reconciliation parts of the day way



## Improved CP forecasting methodology supports minimum demand forecasts



### Data preparation



- Data cleansing
- The historical underlying demand data is created by removing the impact of rooftop PV (PV), large-scale PV (PVNSG), embedded generation, and industrial loads.
- The data is corrected for historical load transfers and block loads, outages, etc.



### Train underlying demand model



- A half-hourly regression model is trained to capture the relationship between underlying demand and weather for each CP in each individual defined period.
  - Instantaneous air temperature
  - Lagging/Leading moving average temperature
  - Is holiday/Is weekend/Is Christmas Period
  - half-hour of the day
  - Month of the year
  - Interactions
- LASSO regularization algorithm derives a parsimonious model through a K-fold cross validation algorithm. This provides the "optimal" candidate model specification for a connection point given all available variables.
- Modelling the demand of all the half-hours which lie within each defined period allows determining both maximum and minimums through the same simulation process.



## Train models of LIL and embedded generators



- PV norm gen from consultants
- Wind norm gen is modelled
- Normalised contribution factors of other non-operational embedded generators are modelled
  - Explanatory variables includes calendar variables such as month of the year, day of the week, and half-hour of the day.
- MW contributions of industrial loads are modelled
  - Explanatory variables includes calendar variables such as month of the year, day of the week, and half-hour of the day.



### Simulate weather & dependent variables



For each simulated time in each defined period in the base year, predict:

- Underlying demand using regression model
  - 12 years of historical temperature measurements
- Wind and PV generation
- Large Industrial Load
- Estimated generation of other non-operational embedded generators

Residuals from the model of underlying demand are sampled to generate hundreds of additional weather-dependent scenarios.



### Starting point POEs and contribution factors



For Operational Demand in each Defined Period and Season:

- Find min/max in each simulated year
- Determine POEs from distribution of min/max
- Select "Starting Point POEs" (e.g. POE10,50,90)
- From the corresponding simulated events, find contribution factors of:
  - PV and wind normalized generation
  - •
  - Other embedded generation





### Forecast demand growth



CP demand growth is linked to:

- A spatial population forecast (typically LGA), paving the way for factoring in customer composition (residential, business, industrial, agricultural).
- Spatial DER (e.g. EV, battery, PV and PVNSG) projections at postcode level.



### Forecast



For each CP, starting point POE, season and future year:

- Grow contributions to demand in each Defined Period
- Find min/max across Defined Periods
- This is the "non-coincident" min/max

### Reconcile to regional demand



- Only "coincident" forecasts are reconciled to regional forecasts.
- For each CP, "coincident" forecast occurs in the same defined period (e.g. summer mid-afternoon) as the regional min/max.
- Reconcile: scale the "coincident" forecasts so they sum to regional min/max



### Reactive power





The compromise:

- Forecast change in reactive power driven by penetration of inverter-based generation.
- Assume inverter-based generation has a power factor of 1.
- Operational (non-inverter based) demand has a • power factor equivalent to the current weighted average starting power factor.
- A downward trend for power factor

### Not treated:

- Network management of voltage.
- Network MVAr generation under low load levels.



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