AEMO CONNECTION POINT FORECASTING METHODOLOGY

FORECASTING MAXIMUM ELECTRICITY DEMAND IN THE NATIONAL ELECTRICITY MARKET

Published: **July 2016**

AEMO
AUSTRALIAN ENERGY MARKET OPERATOR

IMPORTANT NOTICE

Purpose

AEMO has prepared this document to provide information about its transmission connection point forecasting methodology for the National Electricity Market (NEM), as at the date of publication.

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Version control

Version	Release date	Changes
1	29/7/2016	The original connection point forecasting methodology was produced by ACIL Allen, and published in 2013. A number of subsequent improvements have been made to the methodology, and have been documented in each connection point forecasting report. This version is the first version of a consolidated AEMO Connection Point Forecasting Methodology, including elements of the original ACIL Allen methodology and subsequent improvements.

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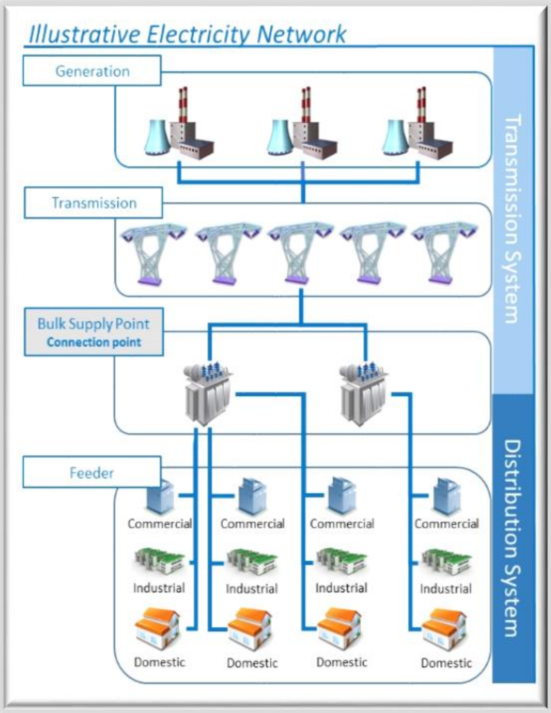
1. INTRODUCTION

In its role as independent market and system operator, AEMO develops maximum demand (MD) forecasts for each transmission connection point, to provide a higher level of detail than AEMO's *National Electricity Forecasting Report* (NEFR) about changes in demand and observations on local trends.

Together with the regional level maximum demand forecasts published in the NEFR, the transmission connection point forecasts provide an independent and transparent view of electricity demand in the National Electricity Market (NEM), supporting efficient network investment and policy decisions for the long-term benefit of consumers.

1.1 Connection point definition



AEMO's definition of a transmission connection point is the physical point at which the assets owned by a transmission network service provider (TNSP) meet the assets owned by a distribution network service provider (DNSP), as illustrated (right).

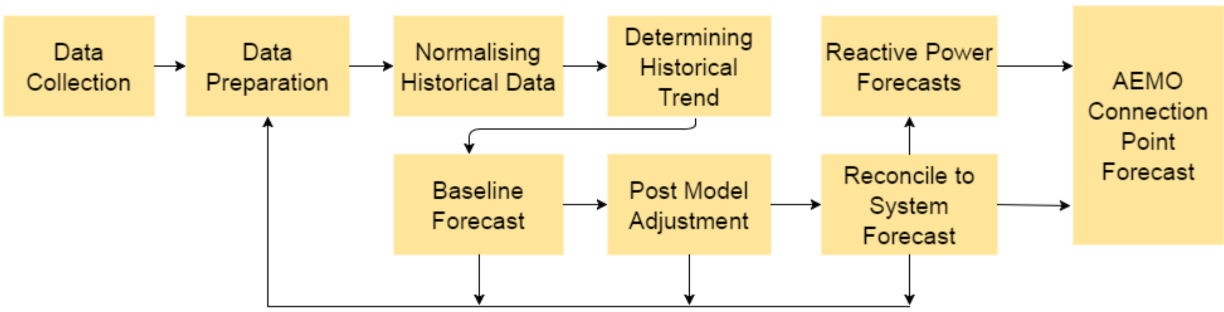
These may also be known as bulk supply points (BSPs), terminal stations, or exit points, and in the NEM's market metering and settlements processes they are called transmission node identities (TNIs).[1]

Connection points may be connected to one another at the distribution network level. In situations where this interconnectivity is extensive, AEMO develops a forecast for the aggregated load.

1.2 Methodology outline

AEMO's Connection Point Forecasting Methodology has nine steps, outlined in Figure 1. Each of the steps is explained in detail in this methodology document. A detailed flowchart focussing on the key steps is included in Appendix A.

Figure 1 AEMO Connection Point forecasting methodology



[1] For a complete list of TNIs, refer to *List of regional boundaries and Marginal Loss Factors for the 2016–17 financial year*. Available at: http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Security-and-reliability/Loss-factor-and-regional-boundaries.

1.3 Forecast scope

In general, the connection point forecasts prepared by AEMO:

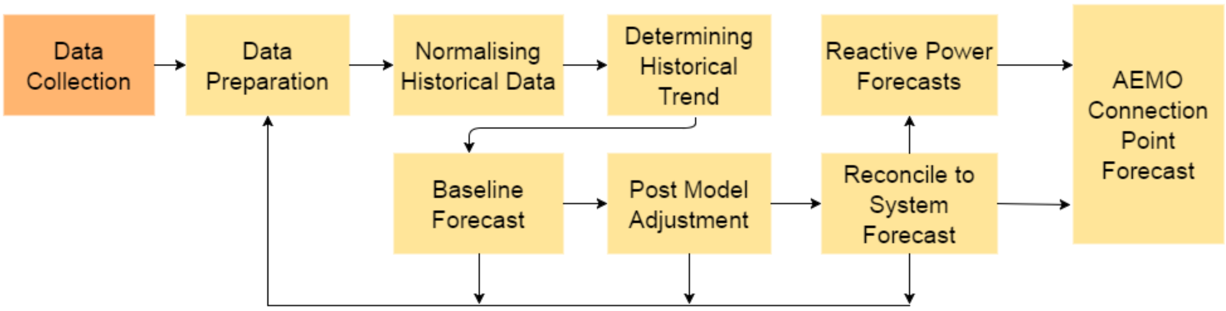
- Apply to active power in megawatts (MW) at each connection point (see Section 2.8 for information about reactive power estimates).
- Exclude transmission system losses and power station auxiliary loads.

Where there is just one customer at a connection point, AEMO only publishes forecasts if the customer has given permission.

2. METHODOLOGY

AEMO's connection point forecasting methodology is designed for forecasting maximum electricity demand. At the core of the methodology, forecasting is based on the trend in historical maximum demands levels that have had the effects of weather and structural changes removed. Once the trend is projected into the future, as a baseline forecast, post model adjustments are made to account for drivers influencing future demand that are not already included in the baseline. Finally, the forecasts are reconciled to a system-level forecast to incorporate effects of other drivers not already explicitly accounted for, such as forecast population growth, changes in electricity prices, the impact of energy efficiency in appliances and buildings, and the uptake of rooftop photovoltaic (PV).

2.1 Data collection



Data used in the connection point forecasting process can be grouped into three categories:

- Measured data: including electricity demand, and minimum and maximum daily temperatures.
- Modelled data: obtained from parallel modelling processes (undertaken by AEMO or external parties).
- Descriptive data: provided to AEMO from Distribution Network Service Providers (DNSPs) via an annual data collection exercise before the start of the forecasting process.

The following tables outline the key sources of data used to develop the connection point forecasts and the methodology step associated with the data. For further details on application of the data, see the relevant section of the methodology document.

Table 1 Measured data

Category	Description	Source	Used in
TNI Demand	Half-hourly MW demand, metered at transmission side of each connection point	AEMO	Data Preparation
Generation	Half-hourly MW output from generators connected to the distribution network	AEMO	Data Preparation
NMI Demand	Half-hourly MW demand for large industrial loads	AEMO	Data Preparation
Reactive Power	MVAr data, generally from SCADA feeds from transmission network transformers	AEMO	Reactive Power
Historical Installed Capacity of Rooftop PV	Capacity and installation date of rooftop PV systems, grouped by postcode Capacity of rooftop PV systems installed, grouped by connection point	CER DNSPs	Data Preparation, Post Model Adjustments
Number of meters	Number of NMIs registered at each connection point, grouped by TNI and postcode	AEMO	Post Model Adjustments
Weather	Daily maximum and minimum temperatures at selected weather stations	BOM	Data Preparation, Normalisation

* Note one PV data source is used to determine installed capacity, with the secondary source used as validation.

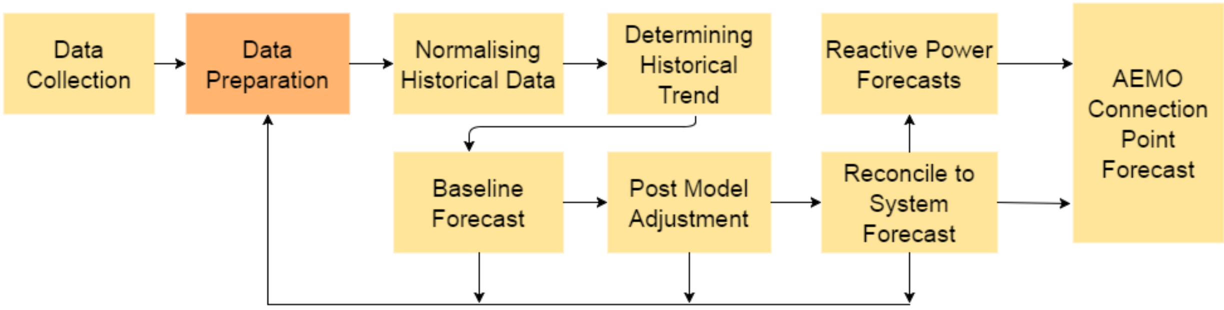
Table 2 Modelled data

Category	Description	Source	Step
Population	Population projections by sub-region	State governments	Baseline Forecast
PV Traces	Model data predicting PV output at connection point locations	AEMO (NEFR)	Data Preparation
Regional Forecast	Maximum demand forecasts by NEM region	AEMO (NEFR)	Reconcile to System Forecast
Regional Forecast of Installed Rooftop PV Capacity	Regional Forecast of Installed Rooftop PV Capacity	AEMO (NEFR)	Post Model Adjustments
Energy Efficiency	Forecast impact of energy efficiency on maximum demand, by NEM region	AEMO (NEFR)	Post Model Adjustments
DNSP Forecast	Maximum demand forecast, grouped by connection point	DNSPs	Verification of results

Table 3 Descriptive data

Category	Description	Source	Used in
Embedded Generation	Capacity, NMI and related connection point of embedded generators	AEMO	Data Preparation
Block, Transfer and Shed Loads	Detail on historical and future step changes to load at each connection point	AEMO, DNSPs	Data Preparation
Demand Mix	Quantity of customers at each connection point, split by category (residential/commercial/industrial/agricultural)	DNSPs	Determining historical trend, Post Model Adjustments
Development Plans	Description of any recent or upcoming changes to network configuration	DNSPs	Data Preparation, verification of results
Meshed Networks	Description of any sections of the network that are meshed (connection points linked on distribution network side)	TNSP, DNSPs	Data Preparation

2.2 Data preparation



Data preparation includes three main stages, with a number of sub-steps. An outline is as follows:

1. Developing the underlying demand trace by:
   a. Removing the effect of embedded generation from the connection point load trace.
   b. Removing the effect of industrial loads from the connection point load trace.
   c. Removing the effect of rooftop photovoltaic (PV) generation from the connection point load trace.
2. Making historical adjustments to the data to account for block loads and transfers.
3. Converting half-hourly data to daily data.

2.2.1 Developing underlying residential/commercial historical demand trace

Historical load data at each connection point is used as the starting point for determining underlying demand, which is the basis of AEMO’s connection point forecasts. This is generally collected from AEMO’s databases, including TNI, National Meter Identifier (NMI), and/or Supervisory Control and Data Acquisition (SCADA) data.

Once historical load data has been collected for each connection point, AEMO undertakes the following steps to remove the effect of embedded generators, industrial loads, and rooftop PV from the traces.

Embedded generators

Embedded generators are generators that are connected to the distribution network and reduce the load as measured at a connection point. Half-hourly data for embedded generators is sourced from AEMO’s databases.

To determine the load at the connection point without the effect of the embedded generator, the generation is added back to the measured connection point load.

Connection point forecasting uses a list of embedded generators consistent with the regional forecasts in the NEFR. However, in some cases additional generators may be included if they are likely to have a significant impact on the demand forecast at a connection point. The list only includes generators that have a dedicated meter, separate from customer load.

Embedded industrial loads

Embedded industrial loads are industrial loads that are connected to the distribution network and increase the load as measured at a connection point.

To determine the load at the connection point without the effect of the embedded industrial load, the load is removed from the measured connection point load. Each industrial load is modelled separately and added back to the connection point forecast as a post model adjustment.

Distributed rooftop PV generation

Historical rooftop PV generation at half-hourly intervals is estimated using the historical installed capacity of rooftop PV systems at each connection point, which is produced from one of the two following sources:

- Data provided by the relevant DNSP.
- Data from the Clean Energy Regulator (CER).

Using these data sources, the amount of installed rooftop PV at each connection point, on a monthly basis, is determined.

Monthly installed capacity data from the CER is received on a postcode basis and converted to a connection point basis using AEMO data by:

1. Calculating the percentage of retail NMIs in each postcode associated with each connection point.
2. Allocating the CER rooftop PV installed capacity to connection points, based on percentages calculated in step 1.

Once the installed rooftop PV capacity has been determined, a half-hourly rooftop PV generation trace is developed for each month where historical data was required.

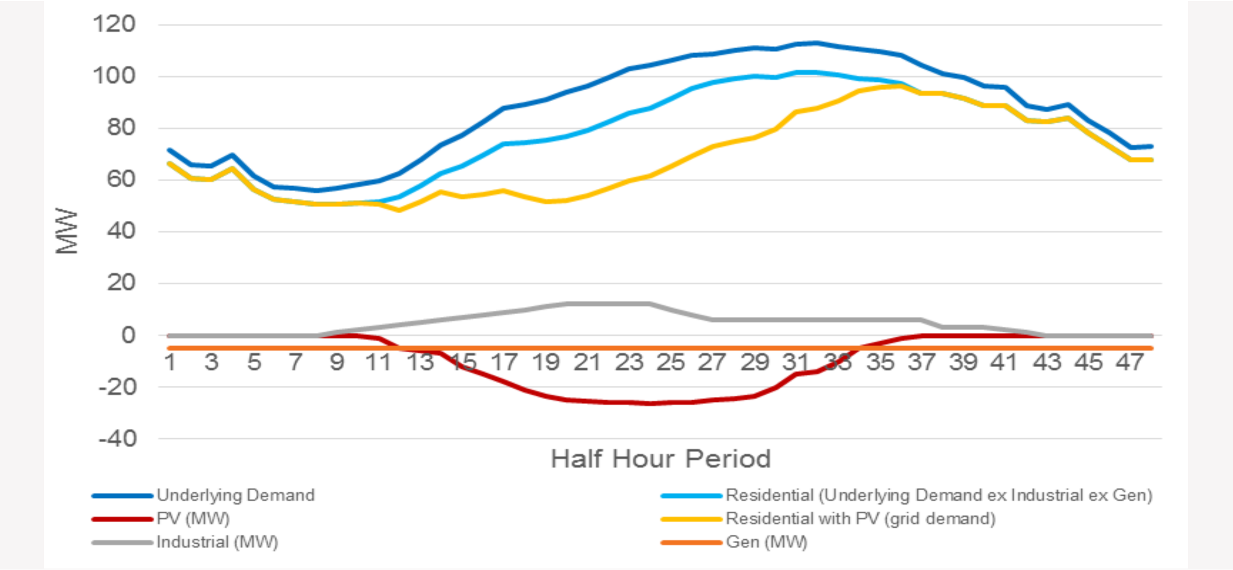
The half-hourly rooftop PV generation trace is developed as follows:

1. Preparing a half-hourly normalised generation trace[2], using the University of Melbourne (UoM)/AEMO rooftop PV generation model.[3]
2. Multiplying the normalised generation trace by the installed capacity for the relevant month and connection point.

To determine the load at the connection point without the effect of the rooftop PV generation, the generation is added back to the measured connection point load, as demonstrated in Figure 2.

[2] The normalised trace has values between 0 and 1 for each half hourly interval. A value of 1 indicates the distributed rooftop PV systems at that connection point are generating at their rated capacity, and 0 indicates no generation from rooftop PV systems.
[3] Methodology Summary – NEM Rooftop PV Generation Model. Available at: http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/National-Electricity-Forecasting-Report.

Figure 2 Example of load traces by component used to develop underlying demand trace

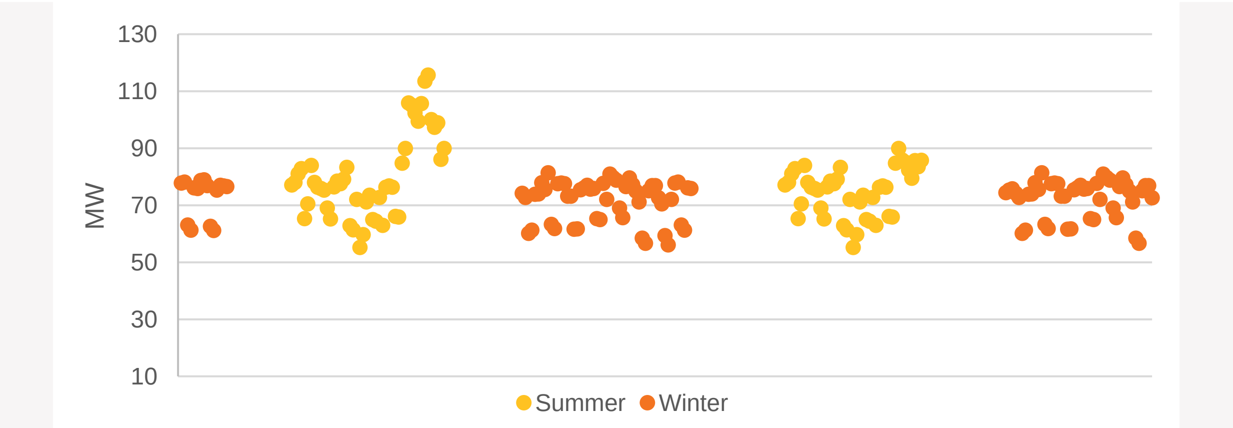


2.2.2 Historical adjustments

In the historical data, there will often be evidence of load transfers and block loads (step changes in demand caused either by large customers connecting or changing demand patterns) which have a significant impact on the maximum demand trend at the connection point level. Information on some historical block loads and transfers is provided by the relevant DNSP, where available, and additional block loads and transfers are detected through visualisation of the historical data.

Figure 3 shows an example of detecting the presence of a block load visually. In this figure it is apparent that in the first historical summer, a temporary increase is present in the second half of the season. Upon observing an event such as this, and verifying that it is atypical using other information (DNSP advice, weather data and network knowledge), an adjustment is made in the historical data to remove the impact.

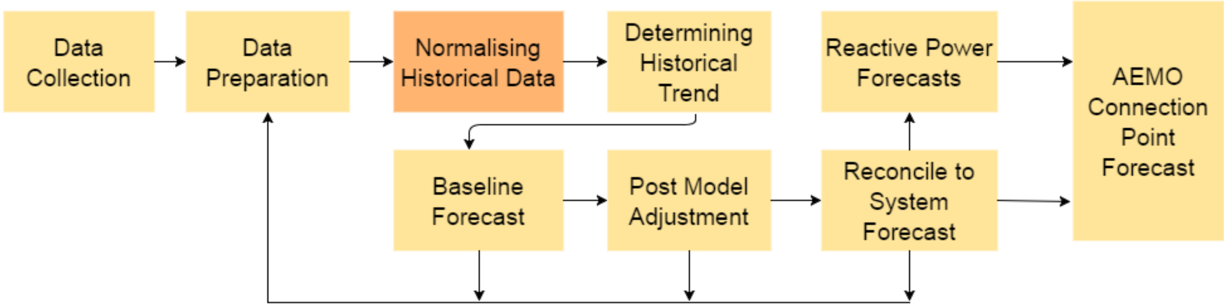
Figure 3 Visual detection of block load



2.2.3 Developing daily data

When the data preparation steps outlined above have been completed, daily maximum demand values are calculated for each connection point. These values are used in the subsequent modelling stages.

2.3 Normalising historical data



Electricity demand is highly influenced by weather, but, as weather varies yearly, it is necessary to maintain consistency of comparison through a process known as weather normalisation.

The normalisation process can be broken down into the following main steps and sub-steps, with this process applied to each year and season (summer and winter) for each connection point.

1. Extract appropriate data for model.
2. Apply exclusions to demand.
3. Fit a linear method to the data.
4. Apply weather normalisation.

2.3.1 Extracting data set

A linear regression model is built for each historical year and season, for each connection point.

The data required to develop this model is the daily maximum demand, maximum temperature, and minimum temperature from the year and season being assessed, as well as the adjacent years (or two adjacent years, in the case of the first and last historical year).

For example:

- To develop a linear regression for the 2013 summer of a particular connection point, demand and temperature data would be extracted from the summers of 2012, 2013, and 2014 from that connection point and associated weather station.
- To develop a model for the last historical year, for example summer of 2016, then the demand and temperature data would be extracted for the summers of 2014, 2015, and 2016.

Weather station selection

It is necessary to select daily maximum and minimum temperature data from a weather station that is most appropriate to the connection point being examined.

The aspects that identify the suitability of a weather station include:

- Demand–weather relationship (R-squared value of linear fit with maximum temperature).
- 90% of weather data should be present.
- 30 years of historical weather data is available if possible and station is currently operating.
- Distance from weather station to connection point, used as indicative of representativeness.

These factors, together with the forecaster’s qualitative assessment, are used to determine the most suitable weather station for a given connection point.

2.3.2 Exclusions

The following exclusions are applied to the model data set before fitting a linear regression.

Days

Truncation of the data set to exclude daily maximum demand from weekends, public holidays, and the Christmas period is applied.

Mild temperatures

A plot of maximum demand and temperature is prepared and used as a visual aid to filter the data set prior to fitting a linear regression.

Demand points at mild temperatures are removed from the data set as demand at these times appear uncorrelated with temperature.

Note that in winter and often in Tasmania in summer it will be higher temperatures that are filtered because maximum demand occurs during cold weather.

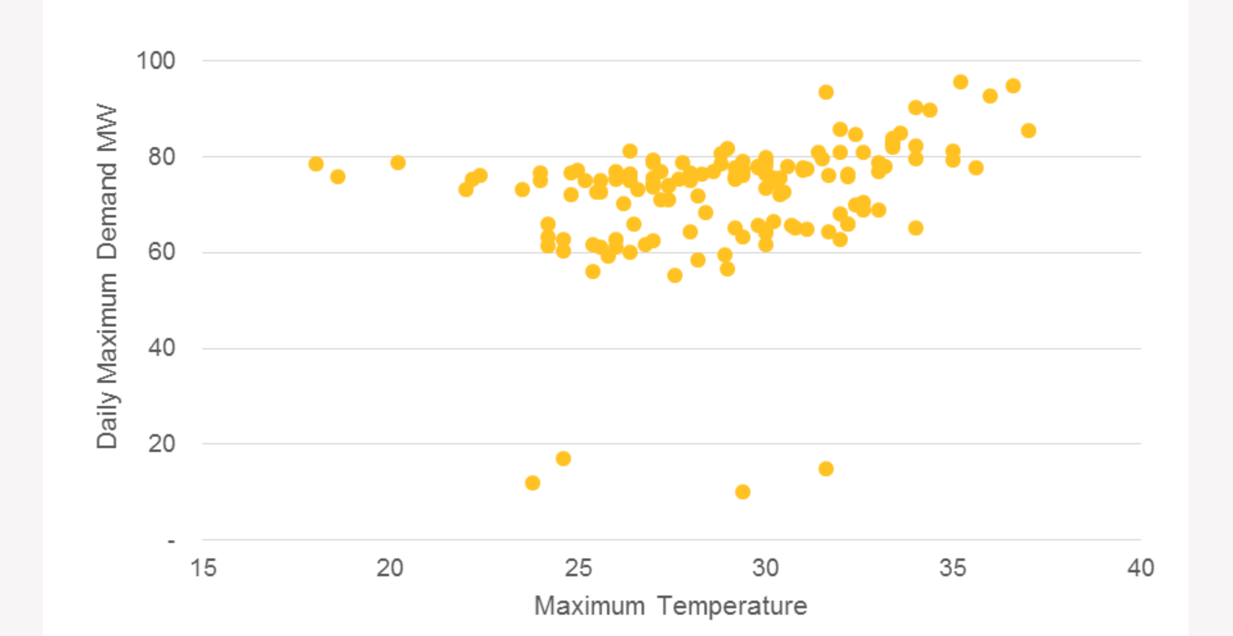
Unusual demands

There may be reasons to remove other data points for a more realistic relationship between maximum demand and weather. These can include discrepancies occurring as a result of load switching or outages at a connection point.

The figures below show the exclusion steps discussed above.

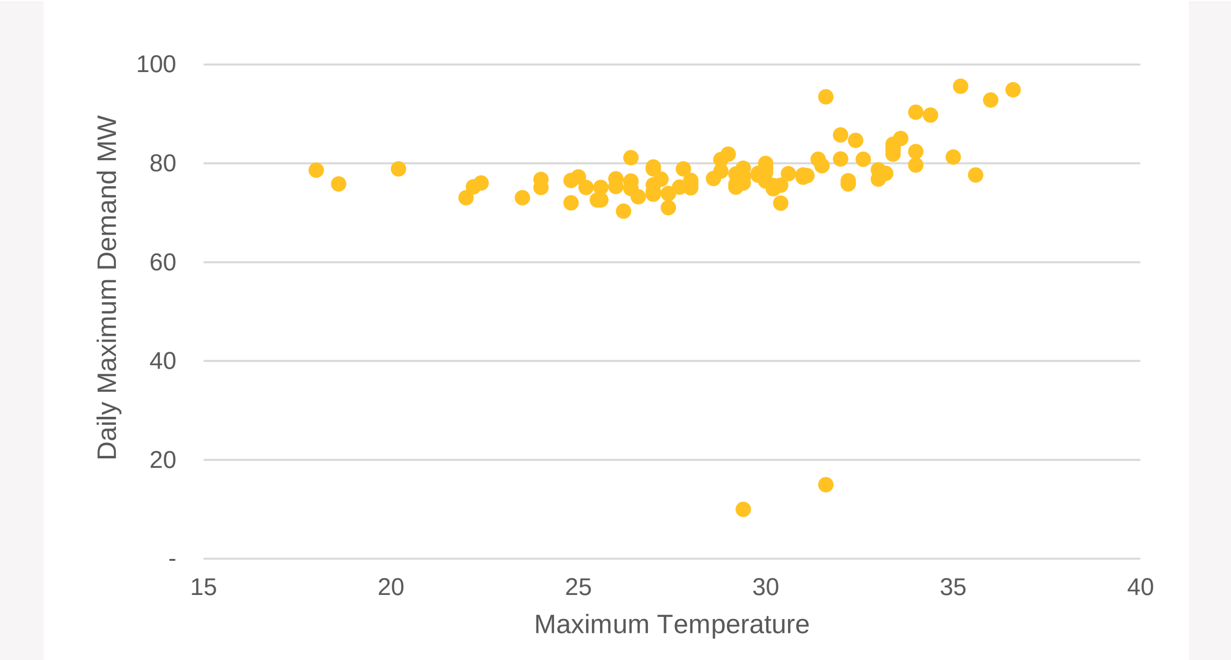
Figure 4 shows the original daily data set for a single season – maximum demand and maximum temperature data obtained from the data extraction stage.

Figure 4 Daily maximum demand vs maximum temperature original data



In Figure 5, an exclusion was applied to remove the data points from weekends, holidays, and during the Christmas period.

Figure 5 Weekends, holidays, and Christmas period removed



Demand during low temperatures is poorly correlated with maximum temperature. To improve the linear relationship at the high demand end of the spectrum, days with low temperatures will be excluded in this example (days with maximum temperature below 27 degrees were removed). The result is shown in Figure 6.

Figure 6 Excluding low temperature demand points

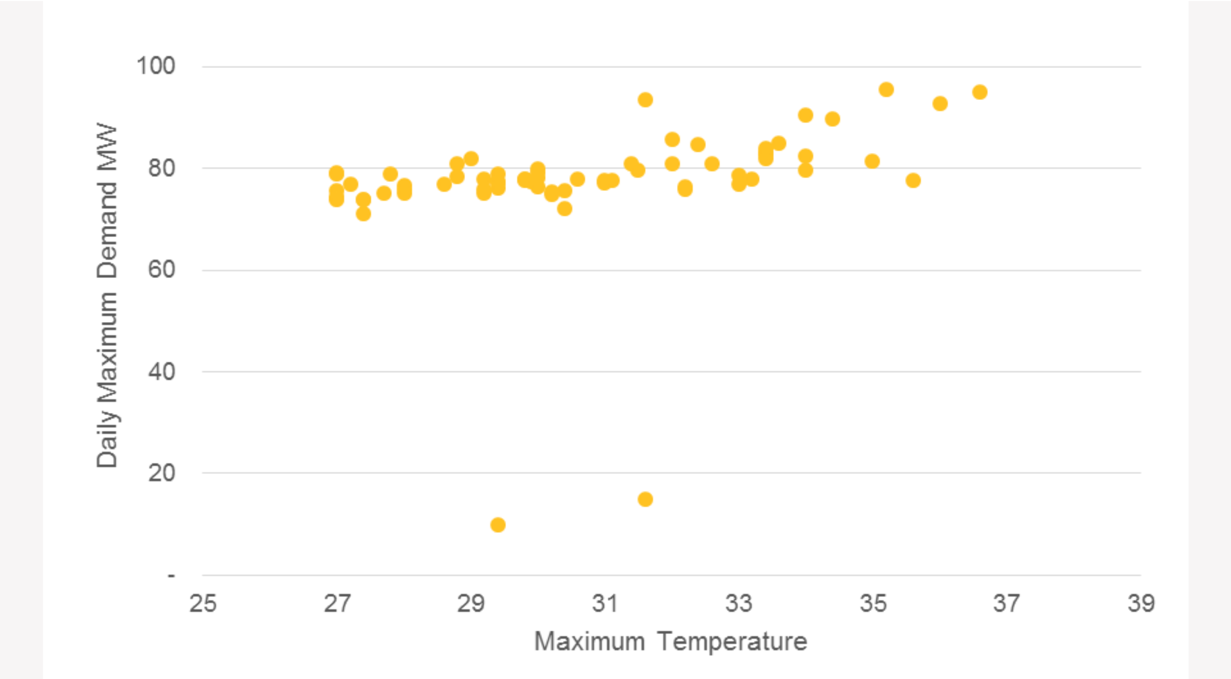
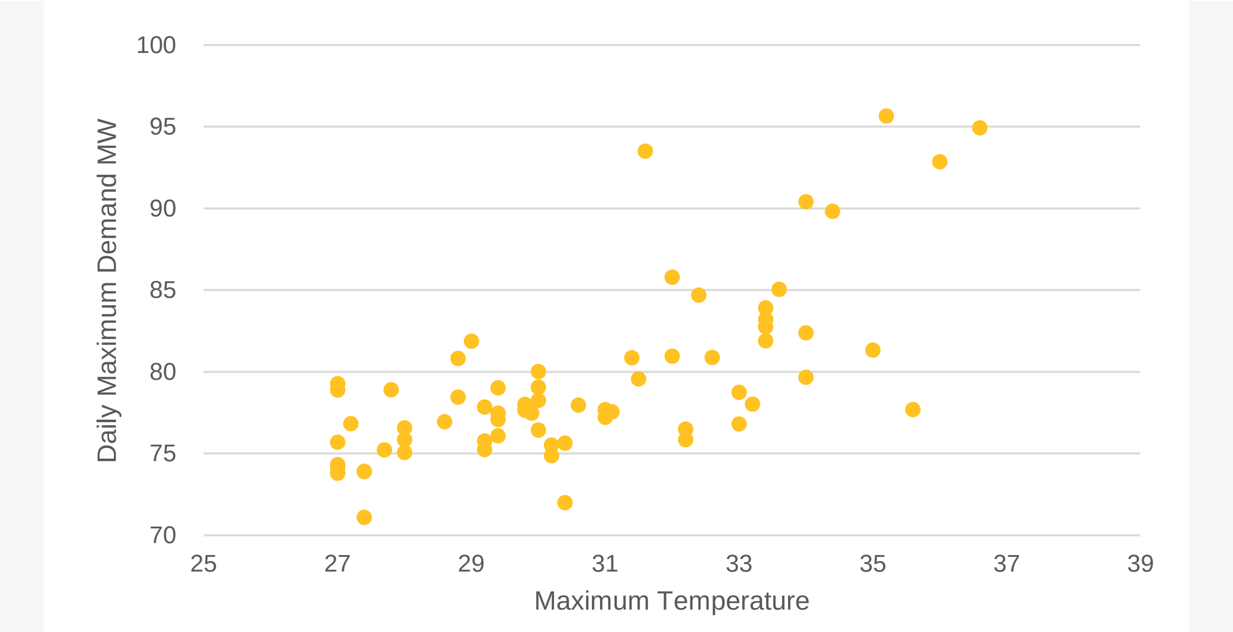


Figure 7 shows demand values after removing two atypical days which occurred because of an outage (seen in Figure 6 with demand below 20 MW). The inclusion of these outliers in the linear regression would reduce the quality of the regression fit. As such, it is appropriate to remove these points. This is an example of removing atypical events to improve the weather-demand relationship for maximum demand.

Figure 7 After removal of outage events



2.3.3 Model fitting

After the necessary exclusions are applied, the following linear model is fitted to the data.

$$MD_d = m \times Max\ Temp_d + n \times Min\ Temp_d + p \times Year1 + q \times Year2 + c + \varepsilon$$

Where

$$MD_d = maximum\ demand\ on\ day\ d$$

$$MaxTemp_d = maximum\ temperature\ on\ day\ d$$

$$MinTemp_d = minimum\ temperature\ on\ day\ d$$

$$Year1, Year2 = binary\ variables\ for\ data\ from\ adjacent\ years\ to\ the\ year\ examined$$

$$c = the\ y - intercept$$

$$\varepsilon = model\ error$$

The binary data-pooling variables *Year1* and *Year2* are used if the forecaster elects to pool demand data from a moving three-year window, when developing the relationship. If no pooling is selected by the forecaster, these variables have no effect.

The standard deviation of the residuals from the model fitting process is combined with a mean of zero to develop a normal distribution of residuals, used later during weather normalisation.

The R-squared term of the model fit is used to determine whether the connection point is weather sensitive (whether daily demand is associated with daily temperature) as shown in Table 4.

Table 4 Weather sensitivity test

R squared Value	Outcome
< 0.3	Not weather sensitive
≥ 0.3	Weather Sensitive

Connection points that are judged to be weather-insensitive are modelled using a constant model of the form:

$$MD_d = c + \varepsilon$$

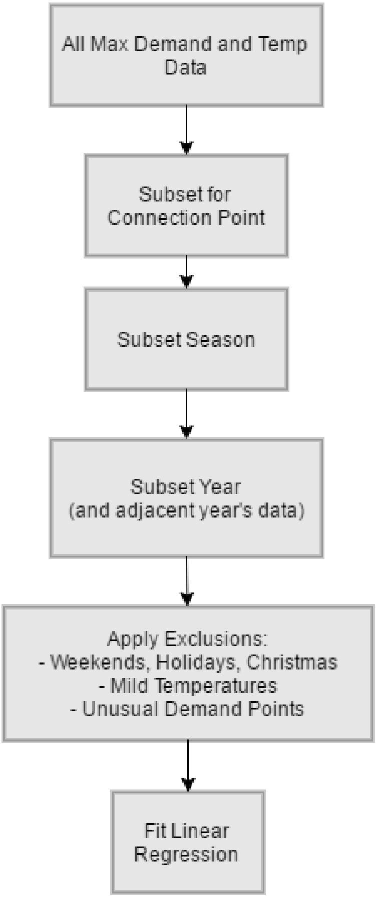
where

$$c = the\ y - intercept$$

$$\varepsilon = model\ error$$

Figure 8 summarises the steps in the data extraction, exclusion, and linear regression fitting stages.

Figure 8 Fitting the demand-weather relationship



2.3.4 Weather normalisation

The weather normalisation process is primarily used to remove the influence of year-to-year variability in weather and provide a distribution of possible maximum demands. Demand levels at the lower end of the distribution are more likely to be exceeded than demand levels at the higher end.

Each year and season of data for a connection point is weather normalised, therefore this section’s descriptions focus on weather normalising a single year and season.

Weather data

To apply weather normalisation, the full 30-year record of historical daily maximum and minimum temperature data is collected from the weather station selected for the connection point. The data for the season of interest is retained.

Simulating daily maximum demand

Using the model developed as shown in Section 2.3.3, each year of historical weather data is used to predict a set of daily maximum demands. A random error amount is drawn from the normal distribution of residuals (developed in Section 2.3.3) and added to the predictions. This accounts for demand variability not captured in the weather-demand relationship.

The process of drawing and adding error values is performed *n* times, such that there will be *n* sets of estimated daily demand data for chosen year in the historical weather data set. The highest daily demand in each set is retained as the maximum demand, such that there are n maximum demands for that year. The next year of historical weather data is used in the same process, and so on until all the weather data has been processed.

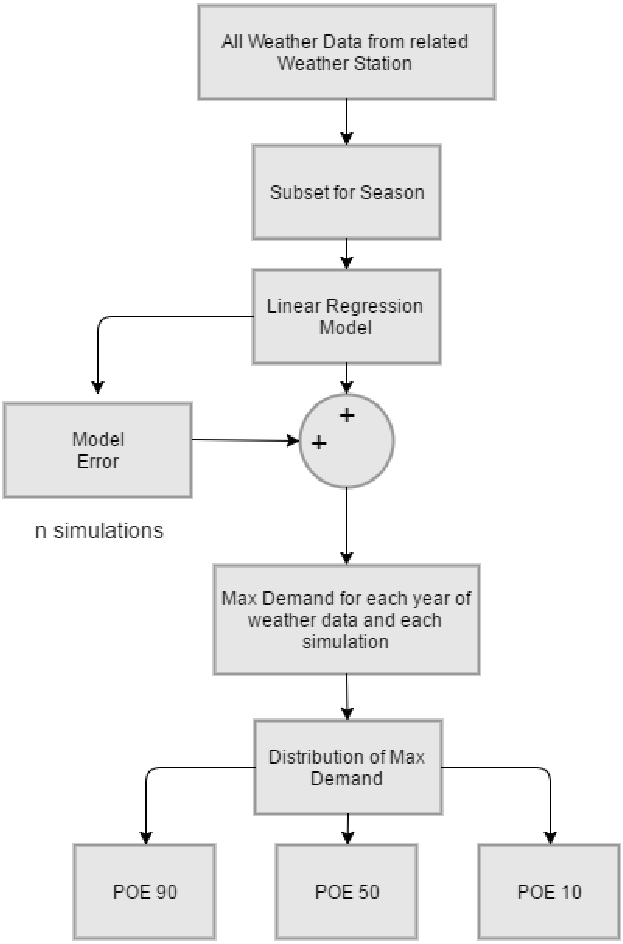
Connection points that are judged to be weather-insensitive are normalised using the predictions of the constant model and the same error sampling procedure as described.

Maximum demand distribution

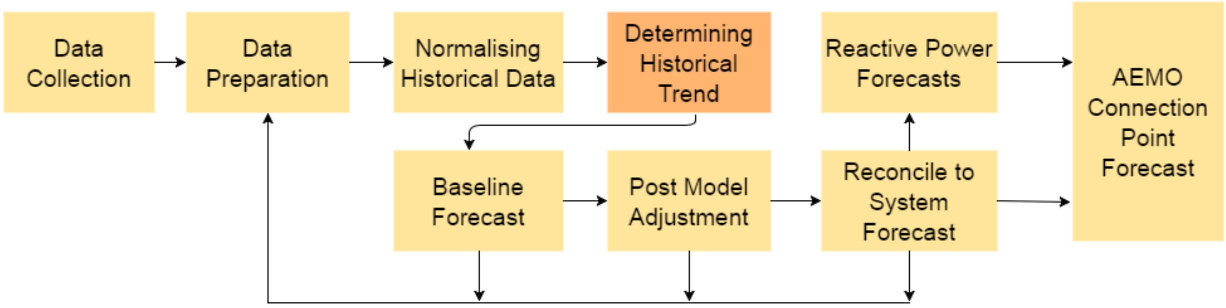
If 30 years of weather data are used in the simulation process, and 500 error sampling events are undertaken each time, then 15,000 maximum demands are produced. These form the maximum demand distribution. Using this distribution, the 10%, 50% and 90% probability of exceedance (POE) levels are obtained from the 90th, 50th, and 10th percentiles respectively.

Figure 9 summarises the process for weather normalisation to obtain the weather normalised maximum demand. AEMO's published forecasts apply to the 10% POE and 50% POE. The 90% POE level is used internally when assessing the distribution.

Figure 9 Weather normalisation



2.4 Determining historical trend



Having obtained the historical weather normalised maximum demand values for each historical demand year, the trend is used to predict future maximum demand at the 10% and 50% POE levels. Two types of trend are tested – a linear trend and a cubic trend.

2.4.1 Linear trend

A linear trend is fitted to the historical weather normalised maximum demand values over the historical years for a given connection point. This method is the default trend used to extrapolate and forecast demand into the future. However, as demand growth is not always linear, a cubic trend is also fitted and compared to the linear trend for goodness-of-fit.

2.4.2 Cubic trend

To fit the cubic trend a horizon year and horizon value are appended to the data set. If this is not done, over-extrapolation of the cubic trend occurs and can lead to non-intuitive forecasts. This horizon year and horizon value act to constrain the cubic trend so that realistic forecasts are produced.

Horizon year and horizon value

The horizon year is set to be a number of years after the end of the forecast period, typically between 10 and 20 years after the end of the forecast period.

A range of horizon values are tested to determine the cubic model to be used in forecasting. The range of horizon values are set to be centred on a value that is determined by the compound average growth rate of the historical data. In the case that the historical growth rate is observed to be decreasing, a threshold is applied to the position of the horizon value range to minimise the possibility of non-intuitive decreases in forecasts.

Cubic model

With a range of horizon values to test, individual cubic models of the form shown below are fitted to each horizon value together with the historical data. The base year is by default set to 1999.

$$\mathrm{MD} = \mathrm{m}\,t^3 + \mathrm{n}\,t^2 + \mathrm{p}\,t + c + \varepsilon$$

where

$$t = \log(year - baseYear)$$

$$c = the\ y - intercept$$

$$\varepsilon = model\ error$$

and,

$$m, n, p\ are\ coefficients$$

To determine which of these cubic models produces the best fit for the data, a Davidson-Mackinnon J-test is applied. This tests whether fitted values of the cubic model add statistically significant explanatory power to the linear model and, if so, the cubic model can be preferred over the linear model. From this, the most suitable horizon value and its corresponding cubic model is determined.

2.4.3 Selecting a linear or cubic trend

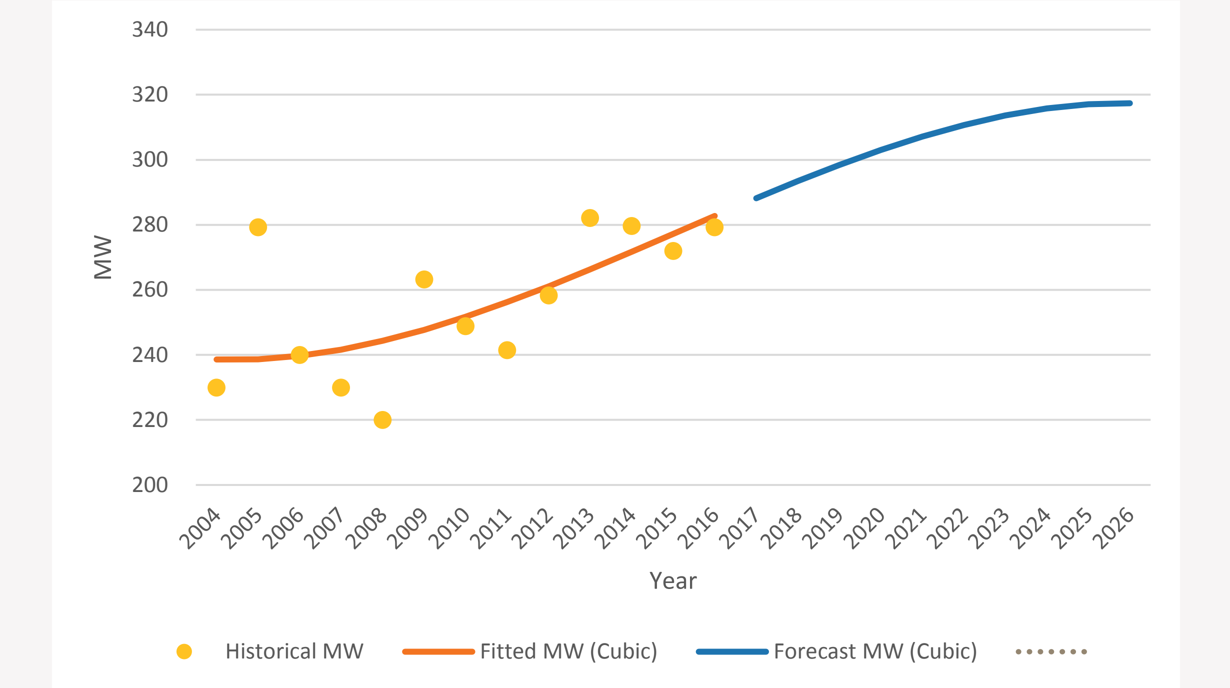
Two tests are applied to judge whether to adopt the cubic trend in preference to the linear trend:

1. Outlier test, which checks whether the last historical data point adds explanatory power when singled out with a binary dummy variable.
2. The J-test, as discussed in section 2.4.2.

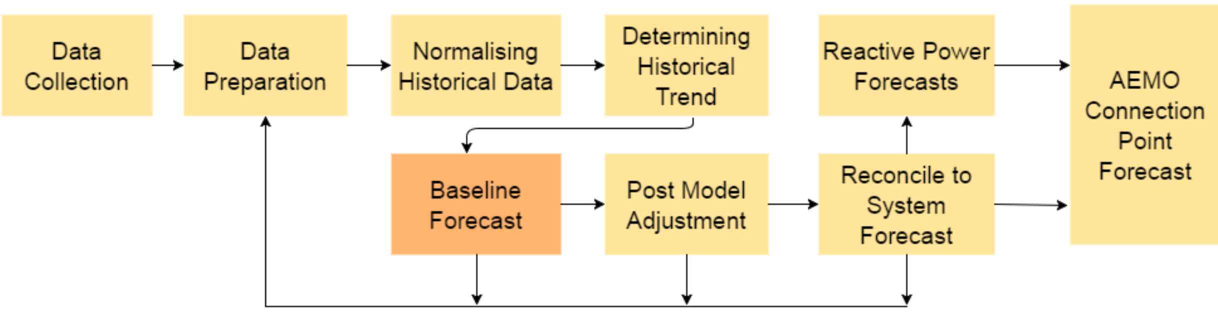
If either of the tests indicate that the linear model is to be rejected in preference of the cubic model then the cubic model is adopted.

Figure 10 shows an example of the cubic trend.

Figure 10 Cubic fit and forecast



2.5 Baseline forecast



2.5.1 Initial baseline forecast

After a trend-line has been fitted to the historical data, an initial baseline forecast is produced by extrapolating the historical trend through the forecast period. It is initial because the forecast is yet to undergo review. An alternate forecast may still be adopted.

2.5.2 Reviewing forecast

Before the baseline forecast is adopted, each connection point forecast is reviewed.

There may be many reasons the historical trend is not considered a reliable indication of future demand. Example situations include:

- Agricultural loads – variability in cropping practices, harvest times and volumes, and irrigation requirements can create variability in the historical trend.
- Pumping loads – pumping loads can often be switching on and off and are often driven by water availability and demand, thus creating variability in the historical trend.

- Recent historical data appear to trend differently to earlier data – Figure 11 shows an example where the historical data is seen to increase in recent years while decreasing in earlier historical years. A decreasing linear trend is fitted when it may be more appropriate to have the forecast flat or increasing.
- Crossing POEs – when 10% and 50% POE forecasts cross over. This is demonstrated in Figure 12.
- Limited historical data or new connection point – sometimes a historical trend cannot be developed.

If there is strong evidence to suggest that the forecast is not likely to provide a reasonable indication of future demand, an alternate forecast will be adopted (Section 2.5.3).

Figure 11 Increasing in recent years

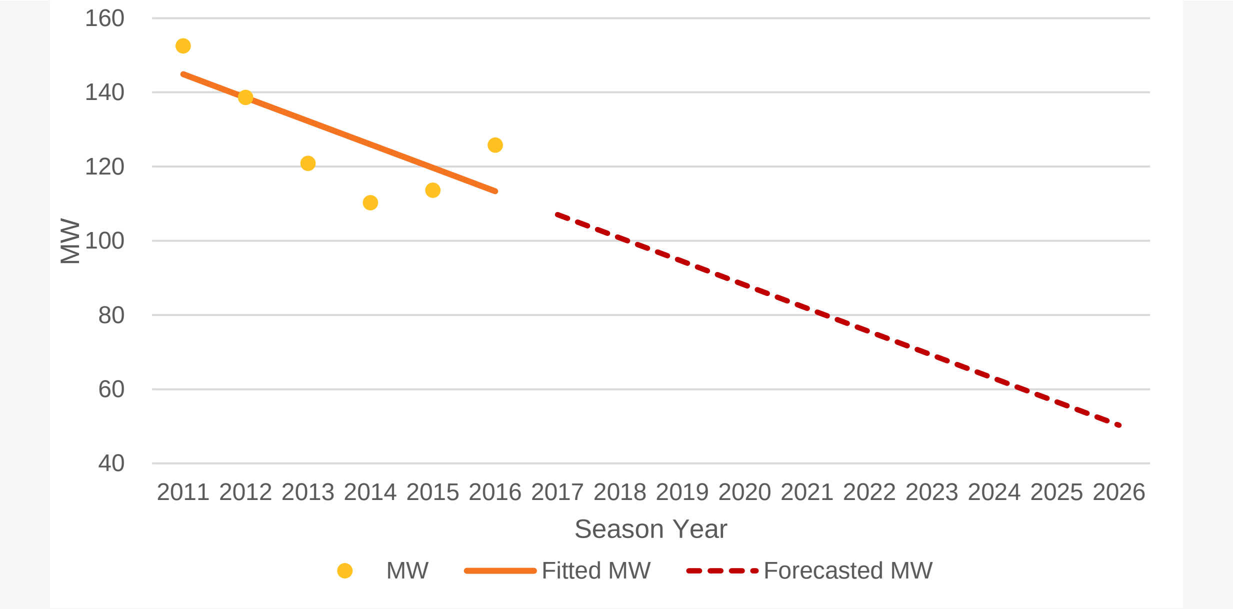
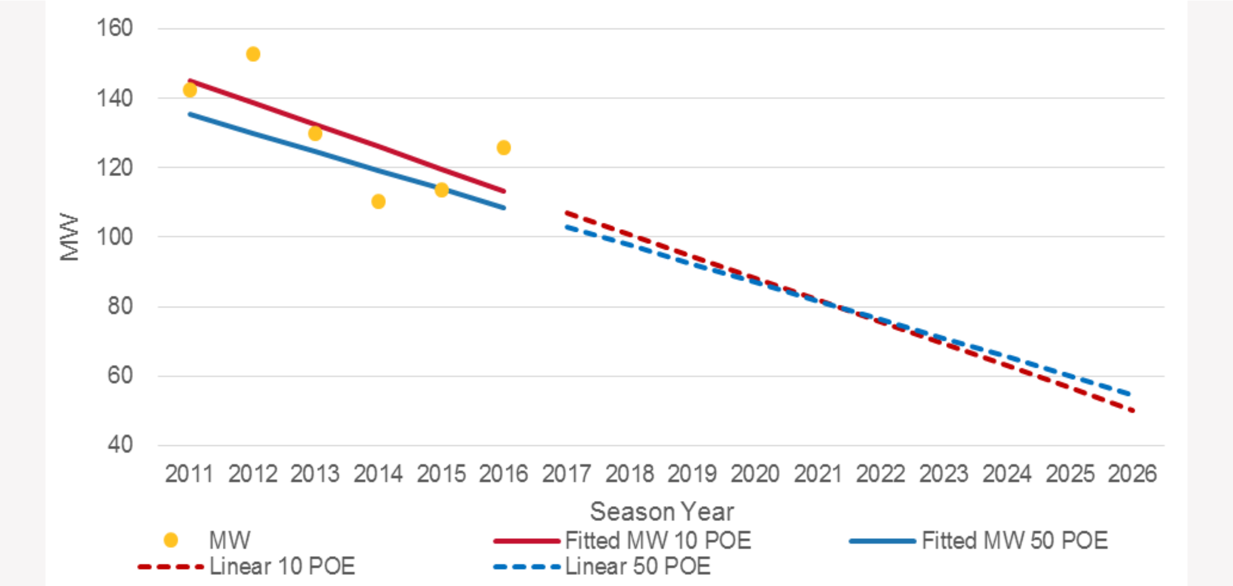


Figure 12 Crossing POE trends



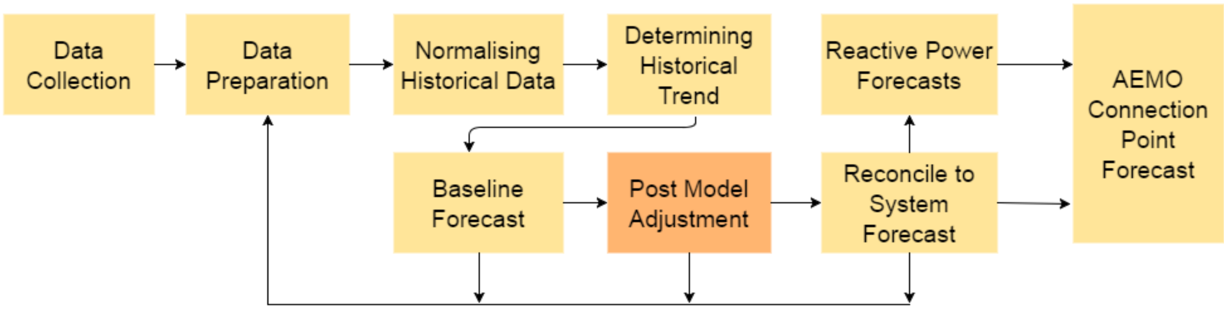
2.5.3 Adopting an alternate forecast

Selecting an appropriate alternate forecast requires an understanding of the connection point and the composition of the load. An alternate forecast can be:

- The alternate historical trend (linear or cubic) to the initial selection.
- A zero percent growth rate for industrial-dominated connection points.
- Growth in line with population growth for residential/commercial connection points.

If either a flat forecast (zero growth) or a forecast in line with population growth is deemed appropriate, a suitable starting point for the forecast needs to be selected. As a default, this will be the normalised values for the last historical year.

2.6 Post model adjustments



A number of post model adjustments are made to the forecasts to capture future changes in demand that are not accounted for in the baseline forecast.

The post model adjustments made are intended to account for the impact of the following:

- Distributed rooftop PV systems – the baseline forecast was produced using data with the effect of rooftop PV removed. Therefore, this effect needs to be added back to the forecast.
- Energy efficiency – an adjustment is made to each forecast in order to account for reductions in demand due to energy efficiency related policies, when modelled separately in the regional forecast.
- Block loads and transfers – additional loads that are highly likely to come on-line in the forecast period are added to the forecast.

2.6.1 Rooftop PV

The baseline forecasts produced assume that there is no distributed rooftop PV reducing grid demand.

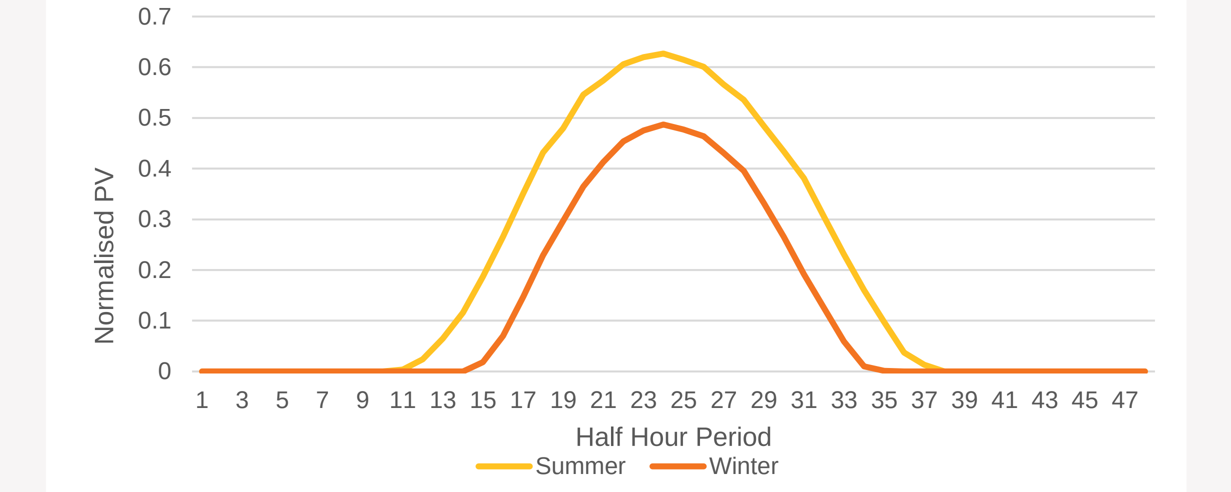
The rooftop PV adjustment is calculated in multiple steps as follows, for each connection point and season:

1. Produce a typical normalised rooftop PV generation trace for high demand days.
2. Determine a typical underlying demand trace for high demand days.
3. Prepare a forecast of rooftop PV installed capacity at each connection point.
4. Produce a typical peak demand day underlying demand trace for each forecast year, by scaling the typical underlying demand trace to the baseline forecast MD figures. Scale the normalised PV trace to the rooftop PV installed capacity at the connection point. Subtract the forecast rooftop PV trace from the forecast underlying demand trace, for each forecast year.
5. Calculate the new daily maximum demand, for each forecast year.

Determining rooftop PV generation trace on high demand days

The UoM/AEMO rooftop PV model provides a historical half-hourly time series of normalised distributed rooftop PV generation at each connection point. The top five demand days in each season are determined from the demand data and the rooftop PV generation on these days is grouped by half-hour intervals. A spline is then fitted to the resulting data set and the resulting profile, shown in Figure 13, is used as the connection point specific rooftop PV generation profile for high demand days.

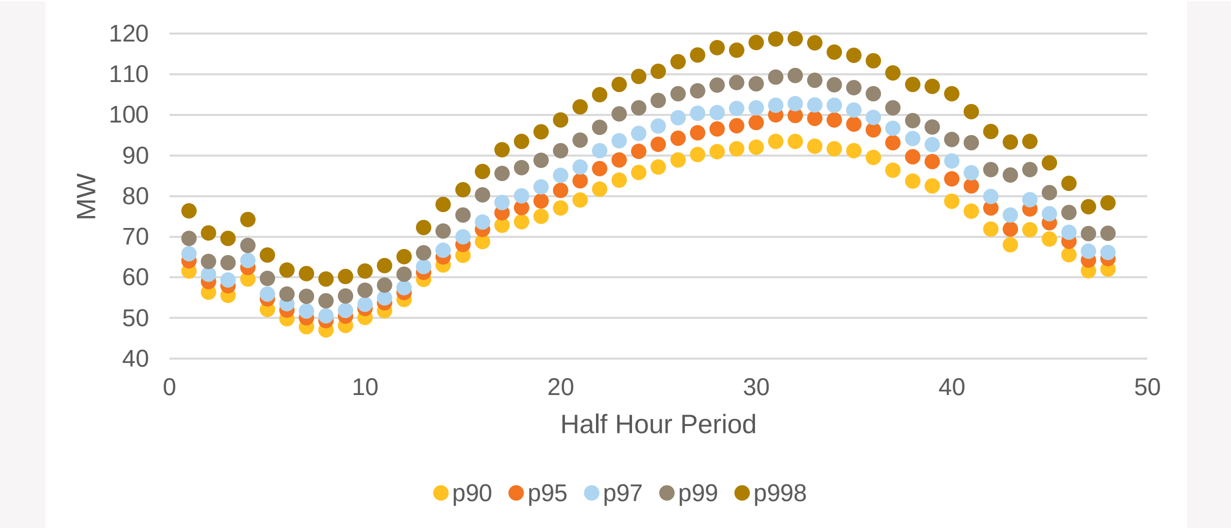
Figure 13 Normalised rooftop PV generation for high demand days



Typical underlying demand trace on high demand days

To produce the typical underlying demand trace, the adjusted demand data for the previous five years is grouped into half-hourly bins for each season (see example in Figure 14). From this data, the 99th percentile value from each bin is taken to represent the demand on a typical high demand day.

Figure 14 Historical underlying demand, grouped into half-hourly bins for summer



Installed rooftop PV capacity forecast

The regional forecast of installed capacity of rooftop PV is allocated across connection points, based on the most recent historical year's installed capacity at each connection point. For instance, if a particular connection point had 10% of the region's rooftop PV capacity in the most recent historical year, it is assumed it will have 10% of the region's distributed rooftop PV capacity throughout the forecast period. The breakdown of installed rooftop PV capacity by connection point is determined as in section 2.2.1.

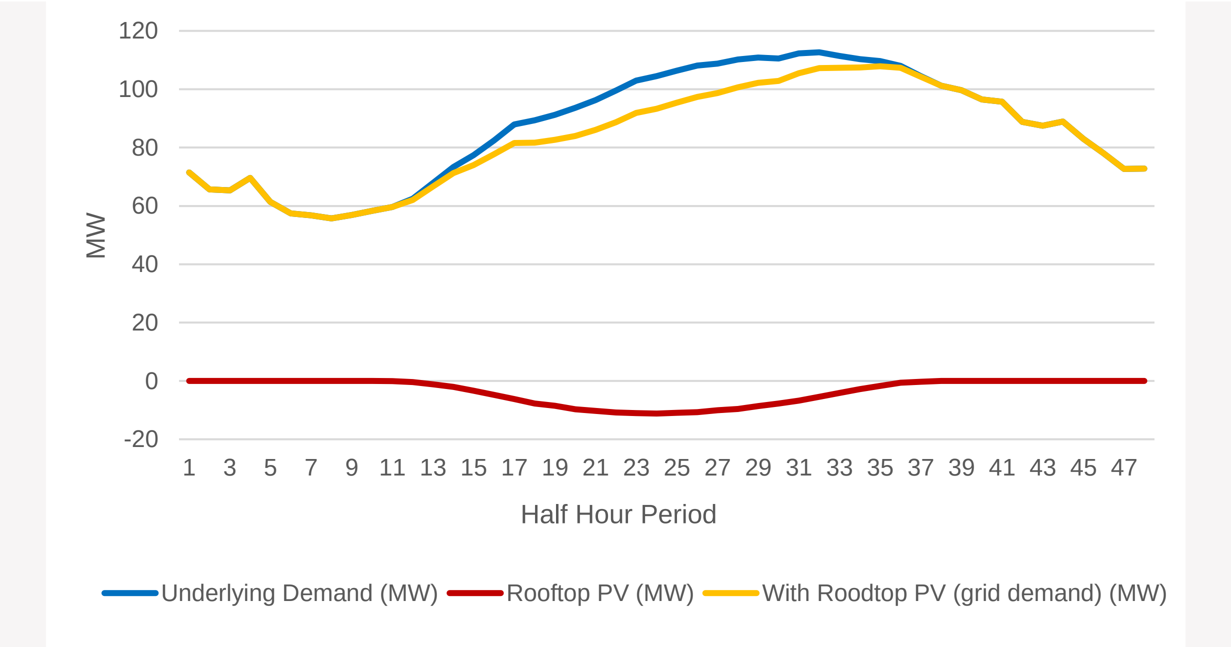
Calculating the rooftop PV adjustment

At each year in the forecast, the typical demand trace and the typical rooftop PV generation trace are scaled so that they are representative of the installed capacity and demand forecast for the year. The demand trace is scaled for each POE level forecast. The normalised rooftop PV trace is scaled using the forecast of rooftop PV installed capacity.

The rooftop PV generation (negative values) is added to the demand trace, producing the 'with rooftop PV (grid demand)' trace. The difference between the new maximum demand and the old maximum demand (without rooftop PV) is recorded as the adjustment.

Figure 15 demonstrates this process, whereby to produce the grid demand trace, the rooftop PV generation is deducted from the underlying demand trace.

Figure 15 Example daily profile of demand and rooftop PV generation



2.6.2 Energy efficiency

The energy efficiency adjustment is based on forecast impact of energy efficiency on maximum demand, by NEM region, disaggregated to the connection points. Energy efficiency allocation to the connection point is based on numbers of commercial, residential, and industrial customers at each connection point. This adjustment is made when the regional forecast provides the energy efficiency impact separately. If not separate, but still modelled in the regional forecast, then the impact of energy efficiency is allocated during reconciliation.

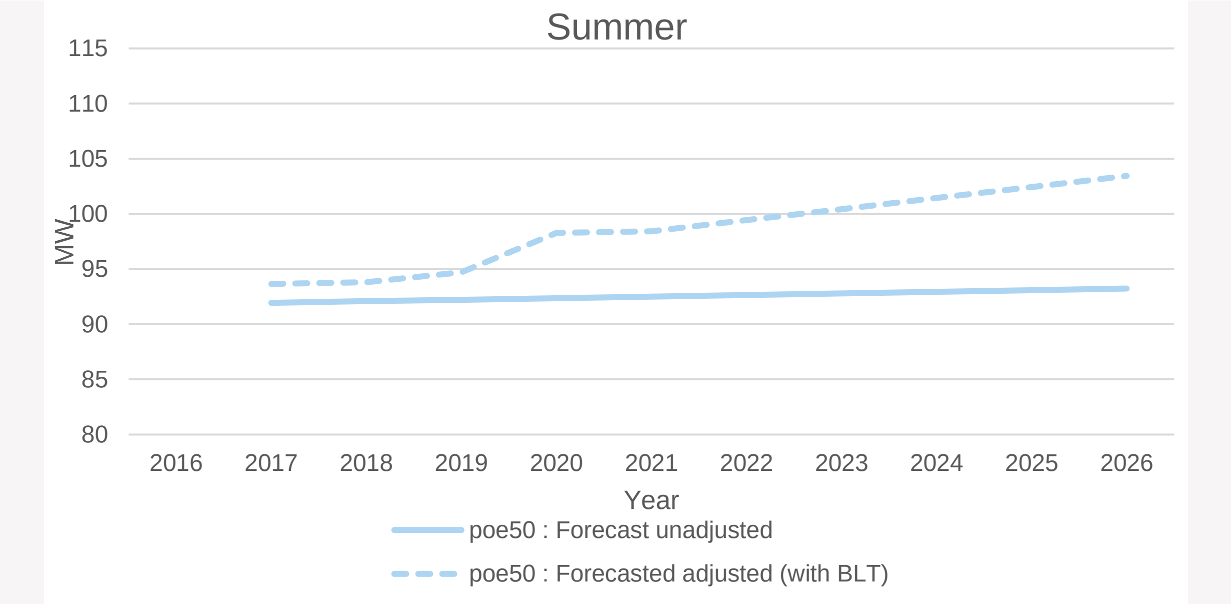
The number of residential, commercial, and industrial consumers is estimated either from data provided by DNSPs, or standing data relating to NMIs in AEMO's databases.

2.6.3 Block loads and transfers

Information regarding new block loads and transfers between terminal stations is provided to AEMO by the relevant DNSPs. This is reviewed and applied to the forecast as an increase or decrease in the load at that connection point.

Figure 16 displays a baseline forecast prior to block loads being added and after block load is added in the year 2020.

Figure 16 Baseline and adjusted forecasts



2.6.4 Treatment of embedded generators

No post model adjustment is made for embedded generators, in effect assuming that embedded generators are not operating at times of connection point peak demand.

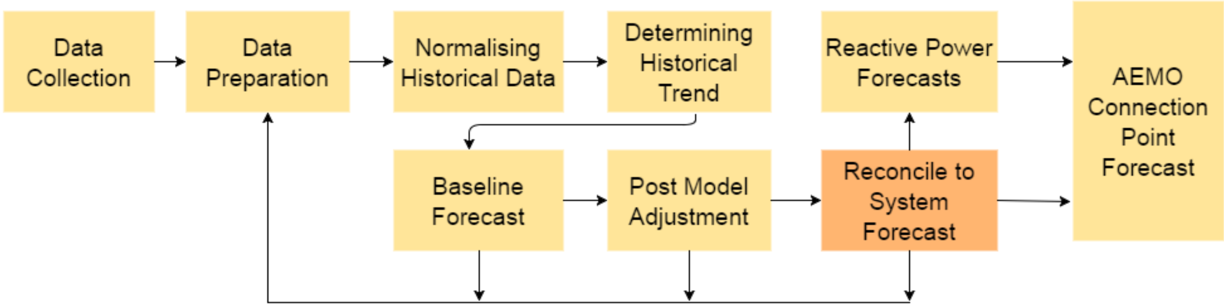
This consideration is made in the data preparation stage discussed in Section 2.2.1.

2.6.5 Order of processing post model adjustments

The order of processing post model adjustments is as follows:

1. Block loads and load transfers are applied to the baseline forecast.
2. Energy efficiency impacts are applied next.
3. Rooftop PV adjustments are made last so scaling of the demand trace is performed on the appropriate basis.

2.7 Reconcile to system forecast



In this stage the forecasts are reconciled to a regional forecast.

The methodology described in previous sections focuses on developing non-coincident forecasts for each connection point. They are non-coincident because they do not necessarily coincide with the time of the system peak. Coincident forecasts, on the other hand, represent the demand of the connection point coinciding with the time of the system peak. Both non-coincident and coincident connection point forecasts are reconciled.

2.7.1 Coincident connection point forecasts

The following steps are undertaken to produce coincident reconciled connection point forecasts, through reconciliation with the regional forecast:

1. Calculate diversity factors.
2. Calculate diversified coincident forecast.
3. Calculate coincident scaling factor.
4. Calculate coincident forecast.

Industrial loads are usually not included in the reconciliation process, because their drivers of demand are usually site-specific and already accounted for in the unreconciled forecast.

Calculate diversity factors

To estimate each connection point's demand at the time of the regional peak, diversity factors are calculated. A diversity factor is defined as

$$Diversity\ Factor = \frac{Demand\ at\ time\ of\ Regional\ Peak}{Peak\ demand}$$

and can be calculated for all types of load and seasons.

As an example, a connection point may have a peak demand of 100 MW, but a demand of 80 MW at the time of the regional peak demand. In this case the diversity factor would be 0.8.

Diversity factors are calculated from historical demand data, taking the average of the most recent five years where possible.

Calculate diversified co-incident forecast

After diversity factors are calculated, they are applied to the forecast. Table 5 provides an example.

Table 5 Example of diversified forecast

Year	Non-coincident connection point maximum demand forecast (MW)	Diversity Factor	Coincident (unreconciled) connection point forecast (MW)
2017	100	0.8	80.0
2018	102	0.8	81.6

Calculate coincident scaling factor and coincident forecast

The next step is to determine the scaling factor that needs to be applied to ensure that the sum of coincident connection point forecasts matches the coincident regional forecast. An example is shown in Table 6.

Each reconciled coincident connection point forecast is then calculated by scaling the diversified connection point forecast using the coincident scaling factor, as outlined in Table 7.

Table 6 Example of scaling factors

Year	Regional forecast (MW)	Sum of coincident (unreconciled) connection point forecast (MW)	Coincident Scaling Factor
2017	8,798	9,062	0.971
2018	8,868	9,028	0.982
2019	8,992	9,046	0.994
2020	9,082	9,028	1.006
2021	9,155	8,990	1.018
2022	9,228	8,952	1.031
2023	9,358	8,965	1.044
2024	9,451	8,941	1.057
2025	9,527	8,898	1.071
2026	9,584	8,836	1.085

* Scaling factors are calculated for each season and POE level. One common scaling factor is used for the region.

Table 7 Example of coincident forecast

Year	Coincident (unreconciled) connection point forecast (MW)	Coincident Scaling factor	Coincident (reconciled) connection point forecast (MW)
2017	80	0.971	77.7
2018	81.6	0.982	80.1
2019	83.2	0.994	82.7
2020	84.8	1.006	85.3
2021	86.8	1.018	88.4
2022	88.0	1.031	90.7
2023	89.6	1.044	93.5
2024	91.2	1.057	96.4
2025	92.8	1.071	99.4
2026	94.4	1.085	102.4

* Scaling factors are calculated for each season and POE level. One common scaling factor is used for the region.

2.7.2 Non-coincident connection point forecasts

The non-coincident connection point forecasts are reconciled to the growth rate of the regional forecast using an indexing approach.

Calculate growth indices

Growth indices are calculated for the regional forecast and the aggregate connection point forecasts, in reference to the first year. An example is in Table 8.

Table 8 Example of growth indices

Year	Regional forecast (MW)	Regional Forecast growth index	Sum of non-coincident connection point forecasts (MW)	Aggregate connection point forecast growth index
2017	8,798	1	10,069	1
2018	8,868	1.008	10,031	0.996
2019	8,992	1.022	10,035	0.997
2020	9,082	1.032	10,031	0.996
2021	9,155	1.041	9,989	0.992
2022	9,228	1.049	9,946	0.988
2023	9,358	1.064	9,960	0.989
2024	9,451	1.074	9,934	0.987
2025	9,527	1.083	9,886	0.982
2026	9,584	1.089	9,818	0.975

Calculate the non-coincident index ratio

An initial index ratio of the regional forecast growth index and the aggregate connection point forecast growth index is calculated as shown:

$$Initial\ Index\ Ratio = \frac{Regional\ forecast\ growth\ index}{Aggregate\ connection\ point\ forecast\ growth\ index}$$

To allow the growth rate of the connection point forecast to dominate in earlier forecast years and the regional forecast growth to dominate in later forecast years, a blending factor is applied. This gives a smooth transition from the short-term trend-based connection point forecast into the longer-term regional trend.

Using this blending factor the final index ratio is determined with the formula:

$$Index\ Ratio\ Applied = (Initial\ Index\ Ratio - 1) \times BlendingFactor + 1$$

This formula is applied to the results of Table 8 to produce the index ratios in Table 9.

Table 9 Example index ratios

Year	Regional Forecast growth index	Aggregate connection point forecast growth index	Initial Index Ratio	Blending Factor	Index Ratio
2017	1	1	1	0	1
2018	1.008	0.996	1.012	0.25	1.003
2019	1.022	0.997	1.026	0.5	1.013
2020	1.032	0.996	1.036	0.75	1.027
2021	1.041	0.992	1.049	1	1.049
2022	1.049	0.988	1.062	1	1.062
2023	1.064	0.989	1.075	1	1.075
2024	1.074	0.987	1.089	1	1.089
2025	1.083	0.982	1.103	1	1.103
2026	1.089	0.975	1.117	1	1.117

Calculate non-coincident forecasts

The non-coincident reconciled connection point forecast is calculated by taking the unreconciled version and applying the index ratio, as outlined in Table 10.

Table 10 Example of non-coincident connection point forecast

Year	Non-coincident (unreconciled) connection point forecast (MW)	Index Ratio	Non-coincident (reconciled) connection point forecast (MW)
2017	100	1	100
2018	102	1.003	102.3
2019	104	1.013	105.3
2020	106	1.027	108.9
2021	108	1.049	113.3
2022	110	1.062	116.8
2023	112	1.075	120.4
2024	114	1.089	124.1
2025	116	1.103	127.9
2026	118	1.117	131.8

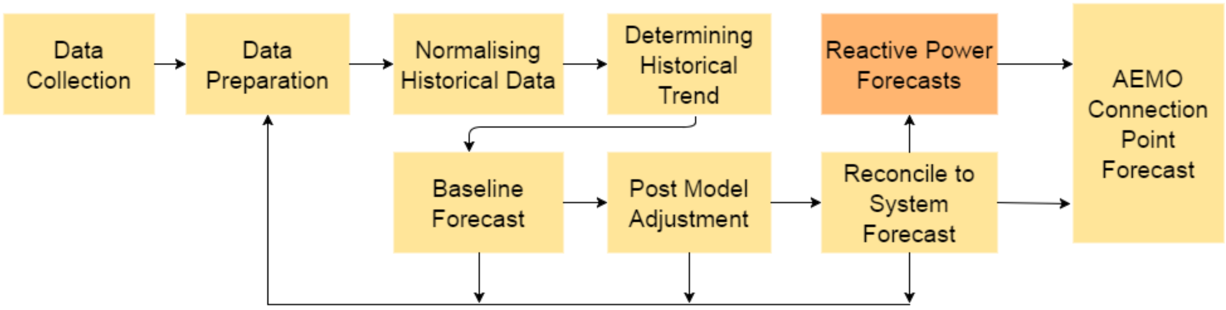
2.7.3 The implied diversity factor

After reconciling the coincident and non-coincident forecasts separately, implied diversity factors exist. In instances where the reconciliation process increases the coincident forecast to the extent that it is higher than the reconciled non-coincident forecast, the implied diversity factor exceeds 1. This has the highest possibility of occurring when the original historical diversity factor was already close to 1.

To address this, a method of capping the implied diversity factors is applied. In this method, if an implied diversity factor is found to be greater than 1 its value is capped at 1 and the non-coincident reconciled forecast is recalculated to be equal to its coincident counterpart.

For example, if the unreconciled non-coincident forecast is 100 MW and the diversity factor is 0.98, then the coincident forecast is calculated to be 98 MW. If a scaling factor of 1.05 is applied to the coincident forecast, then the coincident forecast is reconciled upwards and becomes 103 MW. If this has happened in the first forecast year, then the index ratio for the non-coincident forecast is 1 and therefore the implied diversity factor is 1.03. In accordance with the methodology the diversity factor is capped at 1, so the non-coincident forecast is recalculated to be 103 MW.

2.8 Reactive power (MVAr) estimates



Reactive power estimates are generated based on the active power forecasts and an estimate of the power factor for each connection point, which is held constant throughout the outlook period. They represent the reactive power demand at the time of maximum active power demand.

The power factor is estimated using active and reactive power measured at the distribution side of the connection point transformer(s).

The following steps are undertaken to produce non-coincident and coincident reactive power estimates for each connection point:

- Estimate power factor for each season.
- Apply power factor to active power forecasts.

Estimate power factor used

Power factors are calculated using active and reactive power values from the top 1% of half-hour demand periods in each season and year, ranked by active power. The average value is then adopted as the typical power factor for each year and season.

Giving consideration to the trend of calculated average power factors, a reasonable estimate of future power factors is determined by (in order of preference):

- Averaging the power factor over the previous two years *if power factors are within a narrow band of tolerance, 0.03 of each other* and there are two years of data available for that connection point.
- Averaging the power factor over the previous three years *if power factors are within a broader band of tolerance, 0.07 of each other* and there are only three years of data available for that connection point.
- Averaging the power factor over all the previous years of available data and using this long-term average as the estimated future power factor *if the most recent power factor estimate is within a band of tolerance, 0.1 from the long term average.*
- Taking the average power factor in the top 1% of MW periods in the most recent year if there is only a single year of data for the connection point.
- Should none of the methods listed above apply to the set of average season/year power factor data, the estimated future power factor is set to average value from top 1% of MW demand periods in the previous season/year.

For each of the criteria listed above, a lagging/leading assessment is also undertaken, whereby a '*leading*' label is determined if the reactive power is negative for the majority of these periods, otherwise a '*lagging*' label is applied.

Apply power factor to active power forecasts

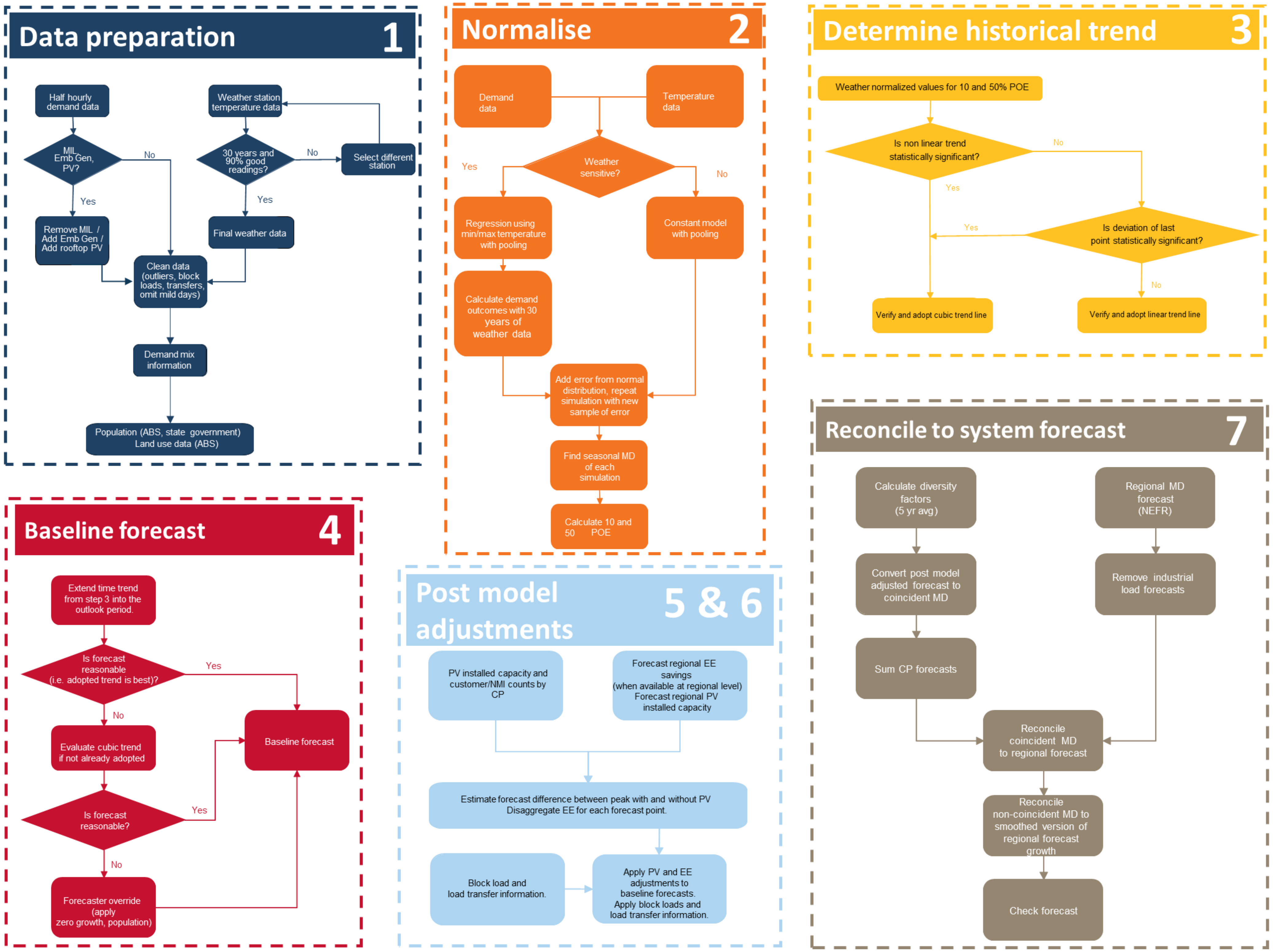
The power factor is then applied to the active power forecasts, coincident and non-coincident at each POE level for each season and year, to produce reactive power forecasts as shown in Table 11.

$$Reactive\ Power = \frac{active\_power \times \sin(cos^{-1}(power\_factor))}{power\_factor}$$

Table 11 Example of power factor applied to active power connection point forecast

Year	Connection point active power forecast (MW)	Power Factor	Connection point reactive power forecast (MVAr)
2018	110.1	0.98	22.4
2019	114.3	0.98	23.2
2020	117.6	0.98	23.9
2021	120.9	0.98	24.6

APPENDIX A. DETAILED METHODOLOGY FLOWCHART



MEASURES AND ABBREVIATIONS

Term	Definition
AEMO	Australian Energy Market Operator
AER	Australian Energy Regulator
BSP	Bulk Supply Point
DNSP	Distribution Network Service Provider
MD	Maximum demand
MW	Megawatt
NMI	Network Meter Identifier
NEFR	National Electricity Forecast Report
NEM	National Electricity Market
NER	National Electricity Rules
NSP	Network Service Provider
POE	Probability of Exceedance
PV	Photovoltaic
TNI	Transmission Node Identity
TNSP	Transmission Network Service Provider

GLOSSARY

Definitions

This report uses many terms that have meanings defined in the National Electricity Rules (NER). The NER meanings are adopted unless otherwise specified. Other key terms used are listed below.

Term	Definition
Active energy	A measure of the energy that can be converted into useful work, generally expressed in kilowatt hours (kWh).
Active power	The rate at which active energy is transferred.
Apparent power	The square root of the sum of the squares of the active power and the reactive power.
Average annual (rate of change)	The compound average growth rate, which is the year-over-year growth rate over a specified number of years.
Block loads	Large loads that are connected or disconnected from the network.
Bulk supply point	A substation at which electricity is typically transformed from the higher transmission network voltage to a lower one.
Connection point	A point at which the transmission and distribution network meet.
Coincident forecasts	Maximum demand forecasts of a connection point at the time of system peak.
Distribution network	The downstream part of the energy network that distributes energy directly to customers. This is generally at lower voltages than the transmission network.
Distribution system	A distribution network, together with the connection assets associated with the distribution network (such as a transformer), which is connected to another transmission or distribution system. Connection assets on their own do not constitute a distribution system.
Electrical energy	The average electrical power over a time period, multiplied by the length of the time period.
Electrical power	The instantaneous rate at which electrical energy is consumed, generated or transmitted.
Electricity demand	The electrical power requirement met by generating units.
Energy efficiency	Potential annual energy or maximum demand that is mitigated by the introduction of energy efficiency measures.
Generating unit	The actual generator of electricity and all the related equipment essential to its functioning as a single entity.
Generation	The production of electrical power by converting another form of energy in a generating unit.
Installed capacity	The generating capacity in megawatts of the following (for example): • A single generating unit. • A number of generating units of a particular type or in a particular area. • All of the generating units in a region. Rooftop PV installed capacity is the total amount of cumulative rooftop PV capacity installed at any given time.
Large industrial load	There are a small number of large industrial loads – typically transmission-connected customers – that account for a large proportion of annual energy in each National Electricity Market (NEM) region. They generally maintain consistent levels of annual energy and maximum demand in the short term, and are weather insensitive. Significant changes in large industrial load occur when plants open, expand, close, or partially close.
Load	A connection point or defined set of connection points at which electrical power is delivered to a person or to another network or the amount of electrical power delivered at a defined instant at a connection point, or aggregated over a defined set of connection points.
Load transfer	A deliberate shift of electricity demand from one point to another.
Maximum demand (MD)	The highest amount of electrical power delivered, or forecast to be delivered, over a defined period (day, week, month, season or year) either at a connection point, or simultaneously at a defined set of connection points.
National Electricity Market (NEM)	The wholesale exchange of electricity operated by AEMO under the National Electricity Rules.

Term	Definition
Network service provider (transmission – TNSP; distribution – DNSP)	A person who engages in the activity of owning, controlling or operating a transmission or distribution system and who is registered by AEMO as a Network Service Provider.
Network Meter Identifier (NMI)	A unique identifier for connection points and associated metering points used for customer registration and transfer, change control and data transfer.
Non-coincident forecasts	The maximum demand forecasts of a connection point, irrespective of when the system peak occurs.
Probability of exceedance (POE) maximum demand (MD)	The probability, as a percentage, that a maximum demand (MD) level will be met or exceeded (for example, due to weather conditions) in a particular period of time. For example, for a 10% POE MD for any given season, there is a 10% probability that the corresponding 10% POE projected MD level will be met or exceeded. This means that 10% POE projected MD levels for a given season are expected to be met or exceeded, on average, one year in 10.
Power factor	The ratio of the active power to the apparent power at a metering point.
Reactive energy	A measure, in varhour (varh), of the alternating exchange of stored energy in inductors and capacitors, which is the time-integral of the product of voltage and the out-of-phase component of current flow across a connection point.
Reactive power	The rate at which reactive energy is transferred. Reactive power is a necessary component of alternating current electricity which is separate from active power and is predominantly consumed in the creation of magnetic fields in motors and transformers and produced by plant such as: • Alternating current generators • Capacitors, including the capacitive effect of parallel transmission wires • Synchronous condensers.
Region	An area determined by the Australian Energy Market Commission (AEMC) in accordance with Chapter 2A of the National Electricity Rules.
Residential and commercial load	The annual energy or maximum demand relating to all consumers except large industrial load. Mass market load is the load on the network, after savings from energy efficiency and rooftop PV output have been taken into account. Includes light industrial load.
Rooftop photovoltaic (PV) systems	A system comprising one or more photovoltaic panels, installed on a residential or commercial building rooftop to convert sunlight into electricity.
Summer	Unless otherwise specified, refers to the period 1 November – 31 March (for all regions except Tasmania), and 1 December – 28 February (for Tasmania only).
Transmission network	A network within any National Electricity Market (NEM) participating jurisdiction operating at nominal voltages of 220 kV and above plus: (a) any part of a network operating at nominal voltages between 66 kV and 220 kV that operates in parallel to and provides support to the higher voltage transmission network (b) any part of a network operating at nominal voltages between 66 kV and 220 kV that is not referred to in paragraph (a) but is deemed by the Australian Energy Regulator (AER) to be part of the transmission network.
Transmission Node Identity (TNI)	Identifier of connection points across the NEM.
Transmission system	A transmission network, together with the connection assets associated with the transmission network (such as transformers), which is connected to another transmission or distribution system.
Winter	Unless otherwise specified, refers to the period 1 June – 31 August (for all regions).