Electricity Demand Forecasting Methodology Information Paper

February 2019

Important notice

PURPOSE

AEMO has prepared this document to provide information about methodologies used to forecast annual consumption and maximum and minimum demand in the National Electricity Market (NEM) for use in planning publications such as the Electricity Statement of Opportunities (ESOO), and the Integrated System Plan (ISP)

The methodologies described here may also be considered in other jurisdictions, such as forecasting the Wholesale Electricity Market (WEM) in Western Australia.

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VERSION CONTROL

Version	Release date	Changes
1	26/09/2018	Initial release
2	28/02/2019	Updated release addressing comments raised in AEMO's Demand Forecasting Methodology Consultation.

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1. Introduction

The National Electricity Forecasts used for publications such as the Electricity Statement of Opportunities (ESOO) and Integrated System Plan (ISP) provide independent forecasts of electricity consumption, maximum and minimum demand over a 20-year forecast period for the National Electricity Market (NEM), and for each NEM region. This report outlines the forecasting methodologies currently in use

1.1 Key definitions

AEMO forecasts are reported as[1]:

- Operational: Electricity demand is measured by metering supply to the network rather than what is consumed. Operational refers to the electricity used by residential, commercial and large industrial consumers, as supplied by scheduled, semi-scheduled, and significant non-scheduled generating units with aggregate capacity ≥ 30 MW. Operational demand generally excludes electricity demand met by non-scheduled wind/solar generation of aggregate capacity < 30 MW, non-scheduled non-wind/non-solar generation and exempt generation.

  The exceptions which are included in the operational demand definition are:

  - Yarwun (registered as non-scheduled generation but treated as scheduled generation).
  - Mortons Lane wind farm, Yaloak South wind farm, Hughenden solar farm, Longreach solar farm (non-scheduled generation < 30 MW but due to power system security reasons AEMO is required to model in network constraints).
  - Non-scheduled diesel generation in South Australia.
  - Batteries that are owned, operated or controlled with a nameplate rating of 5 MW or above, as these need to be registered as both a scheduled generator and a market customer.[2]

- Consumption: Consumption refers to electricity used over a period of time, conventionally reported as gigawatt hours (GWh). It is reported on a "sent-out" basis unless otherwise stated (see below for definition).
- Demand: Demand is defined as the amount of power consumed at any time. Maximum and minimum demand is measured in megawatts (MW) and averaged over a 30-minute period. It is reported on a "sent-out" basis unless otherwise stated (see below for definition).
- "As generated" or "sent out" basis: "Sent out" refers to electricity supplied to the grid by scheduled, semi-scheduled, and significant non-scheduled generators (excluding their auxiliary loads, or electricity used by a generator). "As generated" refers to the same consumption, but including auxiliary loads, or electricity used by a generator.

[1] More definition information is available at http://www.aemo.com.au/-/media/Files/Electricity/NEM/Security_and_Reliability/Dispatch/Policy_and_Process/Demand-terms-in-EMMS-Data-Model.pdf (Accessed 21 February 2019)

[2] Registering a Battery System in the NEM – Fact Sheet is available at https://aemo.com.au/-/media/Files/Electricity/NEM/Participant_Information/New-Participants/battery_fact_sheet_final.pdf (Accessed 18 January 2019)

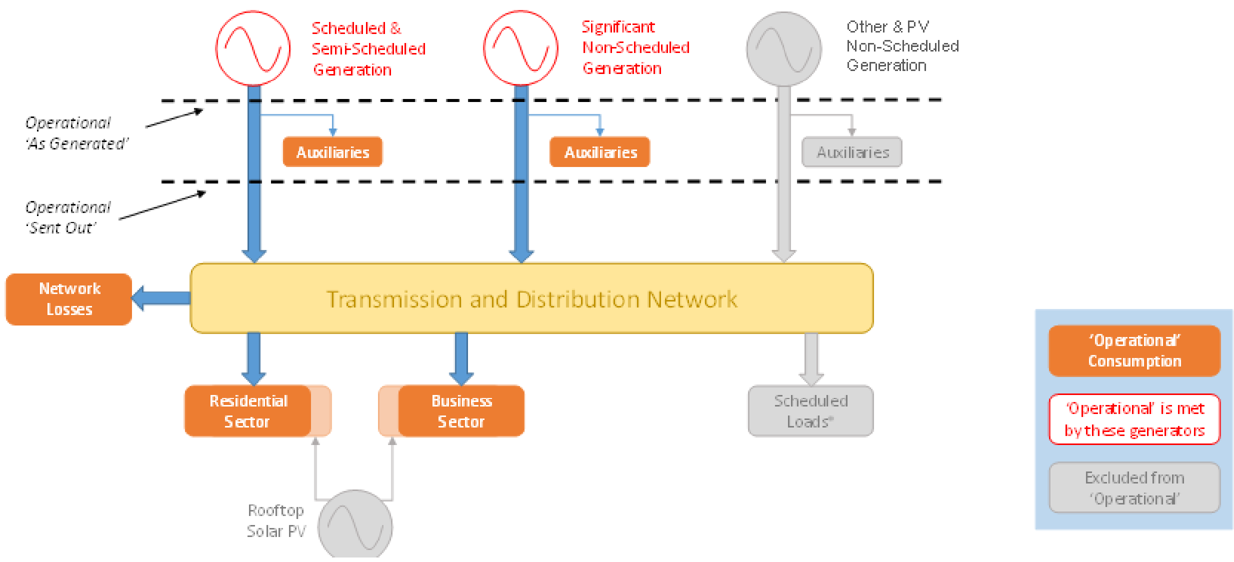
- Auxiliary loads: Auxiliary load, also called ‘parasitic load’ or ‘self-load’ refers to energy generated for use within power stations, but excludes pumped hydro. The electricity consumed by battery storage facilities within a generating system is not considered to be auxiliary load. Electricity consumed to charge by battery storage facilities is a primary input and treated as a market load.

Other key definitions used are:

- Probability of Exceedance (POE): POE is the likelihood a maximum or minimum demand forecast will be met or exceeded. A 10% POE maximum demand forecast, for example, is expected to be exceeded, on average, one year in 10, while a 90% POE maximum demand forecast is expected to be exceeded nine years in 10.
- Rooftop PV: Rooftop PV is defined as a system comprising one or more photovoltaic (PV) panels, installed on a residential or commercial building rooftop to convert sunlight into electricity. The capacity of these systems is less than 100 kilowatts (kW).
- PV Non-Scheduled Generators (PVNSG): PVNSG is defined as PV systems larger than 100 kW but smaller than 30 MW non-scheduled generators.
- Other Non-Scheduled Generators (ONSG): ONSG represent non-scheduled generators that are smaller than 30 MW and are not PV.
- Energy Storage Systems (ESS): ESS are defined as small distributed battery storage for residential and commercial consumers.

Figure 1 provides a schematic of the breakdown and linkages between demand definitions. Operational demand “sent out” is computed as the sum of residential, commercial and large industrial consumer electricity consumption plus distribution and transmission losses minus rooftop solar photovoltaic (PV) and other non-scheduled generation (ONSG).

Figure 1 Operational demand/consumption definition



1.2 Recent methodology changes

AEMO continues to derive more detailed ‘bottom-up’ models that capture an improved mix of economic and technical methods to better capture the continuing transformation of the energy supply and demand system.

This transformation, since 2010, has been driven by changes in technology that:

- Are positioned between the consumer and the grid, such as rooftop PV, energy-efficient appliances, and technologies that enable greater control of appliance operation and energy usage.
- Have become increasingly affordable to typical residential and business consumers.
- Are increasingly being adopted, in part as a possible solution to rising energy costs.

Business consumption has also been impacted by changes in the Australian economy with the continued transition away from energy-intensive industries.

While much of the change has been occurring within the distribution networks, it has major implications for the transmission grid's operation and development, and therefore for AEMO's forecasting and planning reports.

Bulk transmission data has traditionally been used as the primary source of data for forecasting. However, this data:

- Is highly aggregated (so may not provide fine detail in some instances).
- May not provide identifiable and/or reliable indicators of a changing future.
- Does not reveal dynamics that originate within distribution networks.

This lack of granularity has made it challenging, in a changing energy environment, to quickly detect and understand key trends. In response, AEMO continues to integrate new data streams obtained beyond the transmission grid, such as:

- Consumer energy meter data.
- Battery discharge profiles.
- Complementary data from other agencies and sources, such as National Accounts data from the Australian Bureau of Statistics (ABS), to support greater understanding of structural change in the economy.
- Granular high-frequency weather data from the Bureau of Meteorology (BoM).

By integrating detailed data beyond the transmission grid, AEMO is shifting the forecast method towards an increasingly segmented 'bottom-up' approach that embraces predictive analytics and behavioural forecasting.

1.3 Consumer segmentation

Consumption and demand forecasts are based on aggregated customer segments:

- Residential: residential customers only.
- Business: includes industrial and commercial users. This categorisation recognises the different drivers affecting forecasts. This sector is further categorised as follows:
  - Coal seam gas (CSG) – associated with the extraction and processing of CSG for export as liquefied natural gas (LNG) or supplied to the domestic market.
  - Aluminium smelting, including the Bell Bay, Boyne Island, Portland, and Tomago aluminium smelters.
  - Coal mining – customers mainly engaged in open-cut or underground mining of bituminous thermal and metallurgical coal.
  - Manufacturing – traditional manufacturing business sectors, with energy-intensive operations. This excludes aluminium smelting as covered separately.
  - Other business – business customers not covered by the categories above, which are broadly correlated with population growth. This group is dominated by entities providing services such as education, health care, telecommunications, financial services, transport, and construction.

2. Business annual consumption

The business sector captures all non-residential consumers of electricity in the NEM. These have been segmented into two broad categories:

1. Energy-intensive *Manufacturing*, and
2. Relatively non-energy-intensive *Other Business*.

For modelling purposes, these sectors were further segmented into sub-categories:

i. Coal seam gas
ii. Aluminium
iii. Coal Mining
iv. Electric Vehicles
v. Manufacturing
vi. Other Business.

The key reason for this segmented sector modelling is to apply an integrated, sectoral-based approach to business forecasts to capture structural changes in the Australian economy. In doing so, business sectors exhibiting different levels of growth are identified, thereby mitigating the risk of bias which could otherwise arise due to the dominating effect of certain sectors.

2.1 Data sources

Business sector modelling relies on a combination of sources for input data where possible. Table 1 outlines the schedule of sources for each data series.

Table 1 Historical and forecast input data sources for business sector modelling

Data series	Source 1	Source 2	Source 3
Electricity consumption data	AEMO Database	Transmission and distribution industrial surveys	
Historical consumption data by industry sector	Dept. of Energy and Environment		
Economic data*	ABS	Economic Consultancy	
Retail electricity price	Retail Standing Offers	AEMC Price Trend Report 2017	Network Regulatory Information Notices
Wholesale electricity price	Internal		
Energy efficiency	Strategy. Policy. Research.	Energy User Survey	
Rooftop PV/Battery/Electric vehicle generation	CSIRO		

* Economic data includes the Input Producer Price Index, Gross State Product and Household Disposable Income.

2.2 Methodology

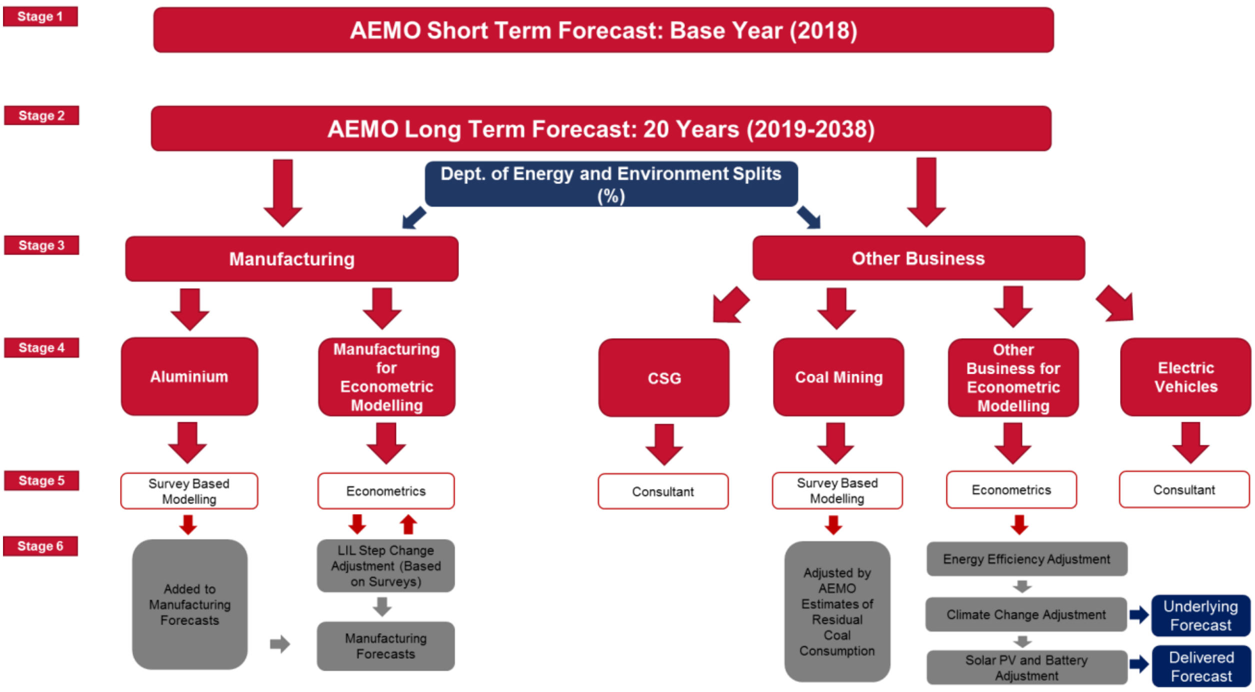
The overall approach to forecasting business consumption is to measure the energy-intensive (Manufacturing) sector separately from the non-energy intensive (Other Business) sector, based on the observation they have each historically been subject to different underlying drivers. AEMO periodically reviews whether further segmentation of the business sector is feasible; the availability of consumption data and the size of sector are limiting factors to whether AEMO can monitor the segments separately.

Either surveys or standard econometric methods were used to forecast consumption in these sectors:

- Other Business sector: econometric modelling.
- Manufacturing sector large industrial loads (LIL): survey-based forecasts.
- Manufacturing sector remaining: econometric modelling.

Figure 2 illustrates the process flow of splitting actual consumption (using the most recent data history) to initiate the start point for forecast development.

Figure 2 Overview of business sector consumption forecasting process



2.2.1 Short-term forecast

The business sector short-term forecast was developed using a linear regression model with ordinary least squares to estimate coefficients. The independent variables are described in Table 2 with subscript *i* representing days.

The business forecasts for underlying annual consumption were aggregated by end-use components (base load[3], heating, and cooling components).

The short-term forecast, also referred to as the *Base Year* forecast, predicts the weather normalised starting year forecast in the absence of behavioural changes to economic drivers. This gives a

[3] Base load is the non-temperature sensitive demand, covering categories such as water heating, lighting, white goods, and home entertainment.

refined starting point (to reflect current consumption patterns) that considers intra-year variation to seasonality, holidays and weather. Long-term forecasts launch off base year forecasts.

$$\mathrm{Bus\_Cons_i} = \beta_0 + \beta_1 \mathrm{HDD_i} + \beta_2 \mathrm{CDD_i} + \beta_3 \mathrm{non-workday_i} + \varepsilon_i$$

Table 2 Short-term base model variable description

Variable	Abbreviation	Units	Description
Business consumption	Bus_Cons	GWh	Total business consumption including rooftop PV but excluding network losses. Adjustments were made to account for business closures. For businesses that have closed before the time of modelling, their consumption was removed from historical data.
Heating Degree Days	HDD	°C	The number of degrees that a day's average temperature is below a critical temperature. It is used to account for deviation in weather from normal weather standards*.
Cooling Degree Days	CDD	°C	The number of degrees that a day's average temperature is above a critical temperature. It is used to account for deviation in weather from normal weather standards*.
Dummy for non-work day	non-workday	{0,1}	A dummy variable that captures the ramp-down in industrial processes and electricity consumption, for a non-work day (public holidays, Saturdays, and Sundays)

*Weather standard is used as a proxy for weather conditions. The formulation for weather standard indicates that business loads react to extreme weather conditions by increasing the power of their climate control devices *only* when the temperature deviates from the 'comfort zone,' inducing a threshold effect.

More detail on critical temperatures applied in the calculation of HDD and CDD is provided in Appendix A2.

2.2.2 Data segmentation to attain starting point for long-term forecasting

As outlined in Section 2.1, AEMO used a combination of internally sourced meter data and publicly available external sources to segment base year forecasts (from Section 2.2.1) into subsectors. This formed the starting point for the long-term modelling.

Stage 1: Segmenting into Manufacturing and Other Business sector consumption

The latest *Australia Energy Statistics* dataset[4], published by the Department of Energy and Environment, was used to obtain the weighting assigned to Manufacturing and Other Business.

The weightings were applied to the short-term forecast for the first year of projections, which was developed based on analysis of AEMO meter data (see Section 2.2.1).

The weightings for the latest year of actual consumption are shown in Table 3.

Table 3 Manufacturing to Other Business weightings for 2018

Region	Manufacturing (%)	Other Business (%)
New South Wales	40.0	60.0
Queensland	35.3	64.7
South Australia	26.9	73.1
Tasmania	70.6	29.4
Victoria	36.6	63.4

[4] Refer to Table F of *Australian Energy Statistics* data, available at https://www.energy.gov.au/publications/australian-energy-update-2017 (Accessed 21 February 2019).

Stage 2: Segmenting into subsectors

Manufacturing

Manufacturing was divided into two categories:

1. Aluminium – AEMO surveyed all aluminium smelter loads in the NEM regions. The aggregate of these survey responses for the first year formed the base year forecast.
2. Manufacturing – the remaining Manufacturing sector consumption was derived by subtracting Aluminium from the total Manufacturing sector calculated in Stage 1. This was the starting point for longer-term econometric modelling.

Other Business

The starting points for longer-term forecasts were established for four categories of Other Business:

1. CSG – electricity consumption for CSG was forecast by Lewis Grey Advisory. The first year of forecast was used as the reference base year projection[5].
2. Coal Mining – electricity consumption for Coal Mining does not generally vary significantly with weather, so AEMO used the latest available financial year of historical consumption, adjusted for any announced coal mine step changes, as the base starting point.
3. Electric Vehicles – the starting point for these forecasts was obtained for small, medium, and large electric vehicles, as well as large commercial electric vehicles (trucks and buses), from AEMO's consultants[6] (see Appendix A4).
4. Other Business – the consumption starting point was derived by subtracting the other sectors from the total Other Business sector calculated during Stage 1.

2.2.3 Manufacturing sector long-term forecasting

The following subsections detail the methodology for producing forecasts for each of the Manufacturing subsectors.

Aluminium

The aluminium forecast was based on a survey and interview process (see Section 2.2.5). To maintain confidentiality[7], AEMO aggregated these forecasts with the econometric results prior to publishing the manufacturing forecast.

Manufacturing (remainder)

The remainder of the manufacturing sector was modelled using linear regressions with some adjustments for likely step changes in large industrial loads not captured by the econometric trend.

[5] See http://www.aemo.com.au/Gas/National-planning-and-forecasting/Gas-Statement-of-Opportunities.

[6] CSIRO consultancy report "Projections for small-scale embedded technologies", available at https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/NEM-Electricity-Statement-of-Opportunities (Accessed 21 February 2019)

[7] As required by the National Electricity Law (NEL).

Long-term regression model

The long-term manufacturing sector forecast was estimated using a log-linear regression model[8] with ordinary least squares to estimate coefficients[9], which were then benchmarked against those observed in academic literature. Specific variables are described in Table 4, with subscript *i* representing years.

$$\ln(\widehat{\text{Man\_Cons}})_i = \hat{\beta}_0 + \hat{\beta}_1 \ln(\text{Elec\_P}_i) + \hat{\beta}_2 \ln(\text{GSP})_i + \delta_i D_i + \varepsilon_i$$

Table 4 Manufacturing model variable description

Variable names	Abbreviation	Units	Description
Manufacturing consumption	Man_Cons	GWh	Manufacturing consumption.
Electricity price	Elec_P	$MWh	Large Industrial retail electricity price for business users*.
Gross State Product	GSP	$ million	Real GSP is a measurement of the economic output of a state. It is the sum of all value added by industries within the state.
Dummy variables	D	{1,0}	Dummy variables are added in to stabilise the historical data for temporary shocks that may otherwise bias the coefficients, e.g. the Global Financial Crisis (GFC).

* Coefficients for price elasticity of industrial consumers were benchmarked against a broad literature review[10] by AEMO.

Large industrial load (LIL) adjustments

LIL step changes are a product of the survey-based process. For more details see Section 2.2.5.

On the basis of interviews and surveys, AEMO adjusted the forecasts for step changes such as expansions and closures which would not be captured by the econometric models. This was performed as a post-model adjustment by identifying those LILs with a year-on-year variation in excess of ±10%. Those LILs with an excess variation relative to the econometric model result were adjusted on an iterative basis. Year 1 of the model result was estimated and was adjusted by the LIL step change before the model result for Year 2 was estimated. The iterative process continues for the 20-year period. The estimation and scaling process re-bases LIL demand to updated values while retaining demand behaviour.

2.2.4 Other Business sector long-term forecasting

The following subsections detail the methodology for producing forecasts for each of the Other subsectors.

Coal seam gas

Electricity forecasts for the CSG sector reflect the grid-supplied electricity consumed predominantly in the extraction and processing of CSG to service sales to domestic consumers or exports of LNG.

[8] By using GSP variables within the regression models, infrastructure investment such as rail or government regional projects are considered implicitly.

[9] The coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$ represent elasticity response to the demand drivers which give the percentage change in consumption in response to a 1% change in electricity price and GSP respectively (all else being equal).

[10] See Appendix A8.

Surveys of CSG production forecasts were obtained directly from the east coast LNG consortia for projected demand over the next five years. Electricity consumption was adjusted to align with these responses. For longer-term indications, independent advice was obtained from external consultants.

Coal Mining

Coal mining and port service companies were surveyed, and selected operations were interviewed, to obtain a baseline for the coal industry. The consumption forecast was based on these survey result[11].

Electric Vehicles

Projections for electricity consumption by electric vehicles were produced by consultants[12]. For more detail refer to Appendix A4.

Other Business (remainder)

The remainder of the Other Business sector was modelled using log-linear regressions with some adjustments for likely step changes in LIL not captured by the econometric trend.

Long-term regression model

The long-term Other Business sector forecast was developed using a log-linear regression model with ordinary least squares to estimate coefficients13, which were then benchmarked against those available

$$\ln(\widehat{Oth\_Cons})_i = \hat{\beta}_0 + \hat{\beta}_1 \ln(POP_i) + \hat{\beta}_2 \ln(HDI_i) + \hat{\beta}_3 \ln(Elec\_P_i) + \delta i D_I + \varepsilon_i$$

in academic literature. Specific variables are described in Table 5 with subscript i representing years.

Table 5 Other Business model variable description

Variable names	Abbreviation	Units	Description
Other Business consumption	Oth_Cons	GWh	Other business consumption.
Population	POP	Persons	Population of a state (net of deaths, births, and migration).
Household Disposable Income	HDI	$ million	Real level of money households have available for spending and saving, after income taxes are deducted.
Electricity price	Elec_P	$MWh	Commercial retail electricity price for business users*.
Dummy variables	D	{1,0}	Dummy variables are added in to stabilise the historical data for temporary shocks that may otherwise bias the coefficients, e.g. the Global Financial Crisis (GFC).

* Coefficients for price elasticity of industrial consumers were benchmarked against a broad literature review by AEMO.

[11] This approach accounts for additional growth in existing assets as well as for new projects.

[12] CSIRO consultancy report "Projections for small-scale embedded technologies", available at https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/NEM-Electricity-Statement-of-Opportunities (Accessed 21 February 2019)

[13] These coefficients represent elasticity responses.

Energy efficiency adjustment

Forecast business sector energy efficiency improvements were provided by *Strategy. Policy. Research. Pty Ltd* consultants, and applied to the Other Business sector, since the majority of the improvements are targeting businesses within that category[14].

Based on calibration against estimated energy efficiency savings and observed metered consumption, AEMO only applied 60% of the forecast savings, accounting for the following:

- Some energy efficiency improvements will be present in the forecast from the econometric model.
- Some energy efficiency of state-based schemes addresses large-scale manufacturing (and is accounted therefore through AEMO's surveys).
- The rebound effect, where lower electricity bills from more energy efficient operation may increase consumption as customers cost of use decrease.

Current snapshots of electricity consumption reflect current energy efficiency trends realised through the meter data. It is the additional energy efficiency savings relative to the latest year of consumption that are needed to be applied. As the energy efficiency forecasts are all baselined to the year 2000, an adjustment needs to be applied to the application of the first forecast year to incrementally apply the energy efficiency impacts otherwise a large step change would occur.

For more details on trends and drivers on energy efficiency see the energy efficiency report produced by *Strategy. Policy. Research. Pty Ltd*[15].

Climate change adjustment

This was the final step in producing the underlying consumption econometric forecast for the Other Business sector. While the forecasts were produced assuming normalised weather standards, these standards evolve over the forecast period due to climate change (see Appendix A2).

A climate change index was used to adjust heating and cooling load[16] forecast for industrial sector consumption. All heating and cooling loads were assumed to be from the Other Business sector. Manufacturing consumption is mainly through operational use of machinery, which is insensitive to temperature variation and captured in base load consumption. For this reason, the climate change adjustment was done to the Other Business section.

This first required splitting Other Business consumption into Heat, Base, and Cool elements for the start year; growing the Heat and Cool load by the econometric growth rate, adjusted for the climate change index. The base load was grown by the econometric growth rate only.

The details of the climate change adjustment process are outlined below.

Step 1: Split Other Business Sector into Heating, Cooling and Base load in first year

A short-term linear regression model (see Section 2.2.1) was used to estimate daily actual consumption data for the latest year available and regress against the Heating Degree Day (HDD) or Effective Degree Day

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[14] The forecast included estimated savings from appliances and buildings, but excluded industrial processes, as these are covered directly by AEMO through its survey process of these industries.

[15] *Strategy. Policy. Research. Pty Ltd. Energy Efficiency Impacts on Electricity and Gas Demand to 2037-38.* June 2018. Available at: https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/NEM-Electricity-Statement-of-Opportunities (Accessed 21 February 2019)

[16] Heating load is defined as consumption that is temperature dependent (e.g. electricity used for heating). Load that is independent of temperature (e.g. electricity used in cooking) is called Baseload or Non-heating load.

(EDD)[17] and Cooling Degree Day (CDD). This allowed AEMO to segment the base year forecast by heating load, cooling load and base load[18]. Model parameters were derived using ordinary least squares (OLS) estimates.

$$Actual\ Consumption_{t1} = \hat{\gamma}_0 + \hat{\gamma}_1 HDD_{t1}\ or\ EDD_{t1} + \hat{\gamma}_2 CDD_{t1} + \sum_{j=0}^{n} \hat{\gamma}_j\, D_{j,t_1}$$

The total consumption for projected base year (t_1) was split into heating load, cooling load and base load as follows[19]:

$$\text{Heating Load}_{t1} = (\beta_1 * \text{HDD or EDD}_{t1})$$

$$\text{Cooling Load}_{t1} = (\beta_1 * \text{CDD or EDD}_{t1})$$

$$\text{Base Load}_{t1} = \text{Total Other Business Load}_{t1} - \text{Heating Load}_{t1}$$

Step 2A: Heating load forecast

Heating load for the forecast period was computed by combining the climate change index with the regression model specified above.

$$\text{Oth\_Heat\_Cons}_t = \text{Oth\_Heat\_Cons}_{t-1} * \frac{\text{HDD}_t}{\text{HDD}_{t_{-1}}} * \frac{\text{Econometric}_t}{\text{Econometric}_{t_{-1}}}$$

Step 2B: Cooling load forecast

Cooling load for the forecast period was computed by combining the climate change index with the regression model specified above.

$$\text{Oth\_Cool\_Cons}_t = \text{Oth\_Cool\_Cons}_{t-1} * \frac{\text{CDD}_t}{\text{CDD}_{t_{-1}}} * \frac{\text{Econometric}_t}{\text{Econometric}_{t_{-1}}}$$

Step 2C: Base load forecast

Base load for the forecast period was computed using the regression model specified above without a climate change adjustment.

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[17] Effective degree day is used in Victoria only.

[18] Cooling load is consumption that increases with warmer temperatures such as air conditioners; Heating load is consumption that increases with cooler temperatures such as heating appliances; Base load refers to load that does not vary with varying temperature such as lighting and cooking appliances.

[19] This is done at the annual level after projected the base year using a daily model and aggregating to annual consumption (GWh).

$$\text{Oth\_Base\_Cons}_t = \text{Oth\_Base\_Cons}_{t-1} * \frac{\text{Econometric}_t}{\text{Econometric}_{t-1}}$$

$$\text{Oth\_Tot\_Cons}_t = \text{Oth\_Heat\_Cons}_t + \text{Oth\_Cool\_Cons}_t + \text{Oth\_Base\_Cons}_t$$

Rooftop PV and battery storage losses adjustment

This adjustment was made to translate from an underlying consumption forecast to a delivered consumption forecast. Underlying consumption refers to behind the meter consumption for a business and does not distinguish between consumption met by energy delivered via the electricity grid or generated from rooftop PV. Delivered consumption is the metered consumption from the electricity grid and is derived by netting off rooftop PV generation from underlying consumption.

An addition of battery losses was made to account for a round-trip efficiency of around 85 % associated with the utilisation of battery storage.

For more details on trends and drivers see Appendix A3, and the CSIRO report[20].

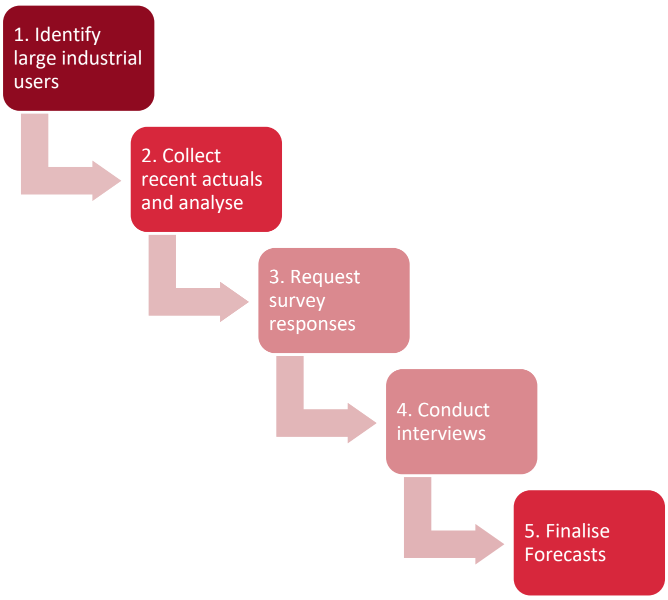
2.2.5 Survey-based forecasting process

AEMO maintains a list of large industrial users identified primarily by interrogating AEMO's meter data. A cut off threshold criteria is used to identify those loads with greater than 10 MW for greater than 10% of the latest financial year. This threshold aims to capture the most energy intensive consumers.

AEMO conducted a survey and interview process with a selection of these large industrial users, and, on this basis, derived the aggregated survey-based forecasts for each region.

The survey process had five steps, illustrated in Figure 3.

Figure 3 Steps for large industrial load survey process



[20] CSIRO consultancy report "Projections for small-scale embedded technologies", available at https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/NEM-Electricity-Statement-of-Opportunities (Accessed 21 February 2019)

Large industrial users

Large industrial users were identified through two methods:

- *Distribution and transmission surveys*: request information on aggregate and new loads.
- *Media search*: augmenting the existing portfolio of users with new users if AEMO is made aware of such users through public sources including media, conferences and industry forums.

Update observed data

Updated actual consumption data for each site of the large industrial loads was analysed to:

- Understand consumption trends at the site level.
- Prioritise industrial users to improve the effectiveness of the interview process.

Request survey responses and conduct interviews

Step 1: Initial survey

AEMO surveys identified LILs[21] requesting historical and forecast electricity consumption information by site. The survey requested annual electricity consumption and maximum demand forecasts for three scenarios:

1. Neutral Scenario – electricity consumption when economy follows the most likely economic pathway.
2. Fast Change Scenario – electricity consumption when economy follows a stronger economic pathway.
3. Slow Change Scenario – electricity consumption when economy follows a weaker economic pathway.

Step 2: Detailed interviews

After the survey, large industrial users were contacted to expand on their responses. This included discussions about:

- Key electricity consumption drivers, such as exchange rates, commodity pricing, availability of feedstock, current and potential plant capacity, mine life, and cogeneration.
- Current exposure of business to spot pricing and management of price exposures, such as contracting with retailers, Power Purchase Agreements and hedging.
- Future management of prices and impact of prices on consumption, based on AEMO provided guidelines.
- Potential drivers of major change in electricity consumption (e.g. expansion, closure, cogeneration, fuel substitution).
- Assumptions governing the Fast, Neutral, and Slow scenarios.

Not all large industrial loads were interviewed. Interviews with large industrial loads were prioritised based on the following criteria:

- Volume of load (highest to lowest) – movement in the largest volume consumers can have broader market ramifications (such as an impact on realised market prices).
- Year-on-year percentage variation – assess volatility in load, noting that those with higher usage variability influences forecast accuracy.
- Year-on-year absolute variation – relative weighting of industrial load is needed to assess materiality of individual variations.

[21] Defined by AEMO as those who had a maximum demand of 10 MW or more for at least 10% of the time in a year.

- Forecast vs actual consumption and load for historic survey responses – forecast accuracy is an evolving process of improvement and comparisons between previous year actual consumption and load against the forecast will help improve model development.

2.2.6 Total business forecasts

The aggregation of all sector forecasts was used to obtain total underlying business forecasts. These aggregations are shown in Figure 4 and 5.

Figure 4 Aggregation process for final underlying forecast

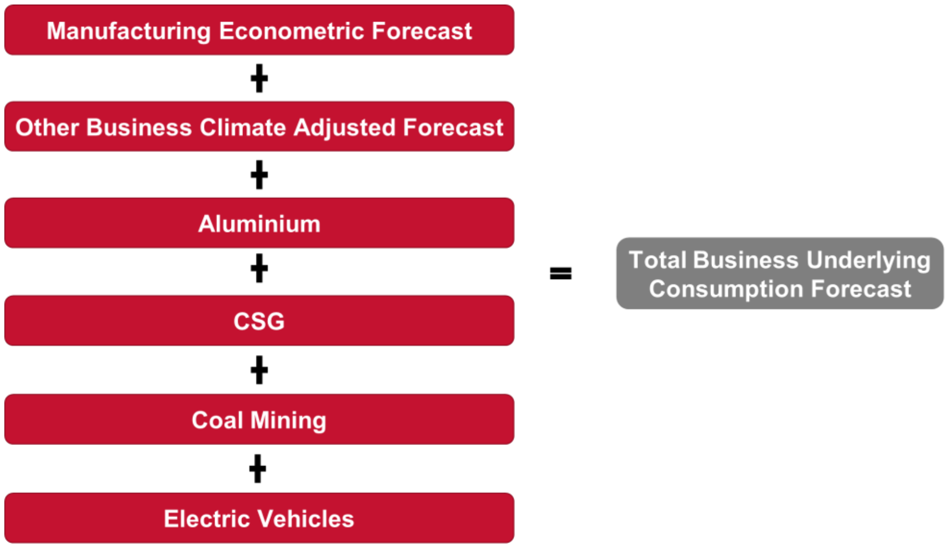


Figure 5 Aggregation process for final delivered forecast

3. Residential annual consumption

This chapter outlines the methodology used in preparing residential annual consumption forecasts for each NEM region.

3.1 Data sources

Residential consumption forecasts require large datasets to adequately represent the complex consumption behaviours of residential users. Data sources are presented in Table 6 and Table 7.

Table 6 Historical input data sources for residential sector modelling

Data series	Reference
Total daily residential connections for each region*	AEMO metering database
Total daily underlying consumption for all residential customers for each region**	AEMO metering database
Daily actual weather measured in HDD and CDD***	Bureau of Meteorology temperature observations

* Daily residential connections were estimated by interpolating annual values.
** See Appendix A7 for more information
*** See Appendix A2 for more information

Table 7 Forecast input data sources for residential sector modelling

Data series	Reference
Forecast annual HDD and CDD in standard weather conditions	Appendix A2
Forecast annual residential connections	Appendix A5
Forecast climate change impact on annual HDD and CDD	Appendix A2
Forecast residential retail electricity prices	Appendix A1
Forecast annual energy efficiency savings for residential base load, heating and cooling consumption	*Strategy. Policy. Research. Pty Ltd**
Forecast gas to electric appliance switching	2018 GSOO**
Forecast annual rooftop PV generation	Appendix A3
Forecast electric appliance uptake	Appendix A5
Forecast electric vehicles	CSIRO***

* *Strategy. Policy. Research. Pty Ltd. Energy Efficiency Impacts on Electricity and Gas Demand to 2037-38*. June 2018, available at: https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/NEM-Electricity-Statement-of-Opportunities (Accessed 21 February 2019)
** AEMO *2018 Gas Statement of Opportunities Methodology Information Paper*. Available at: http://www.aemo.com.au/Gas/National-planning-and-forecasting/National-Gas-Forecasting-Report (Accessed 21 February 2019)
*** CSIRO consultancy report. *Projections for small-scale embedded technologies,* available at https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/NEM-Electricity-Statement-of-Opportunities (Accessed 21 February 2019)

3.2 Methodology

3.2.1 Process overview

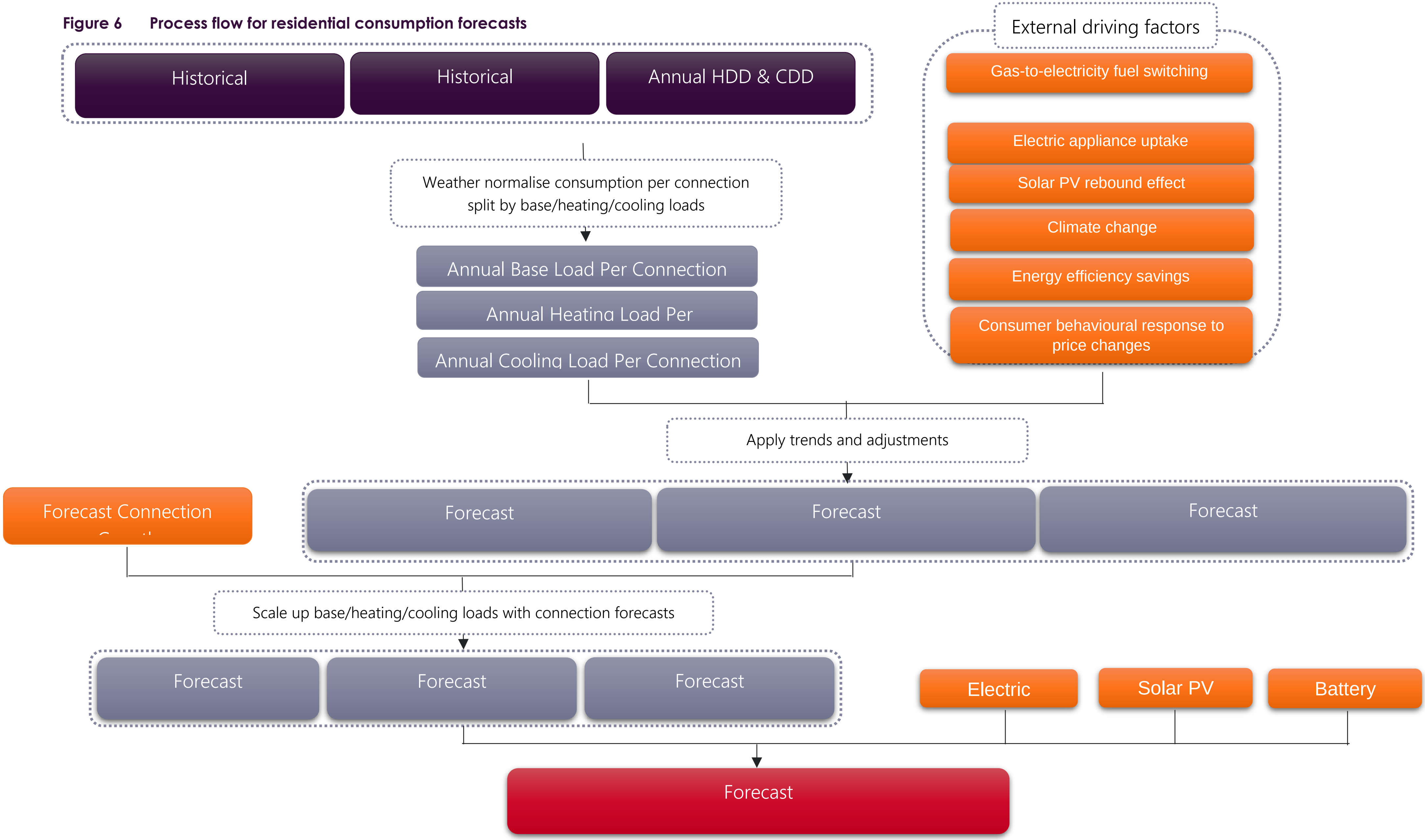
AEMO applied a "growth" model to generate 20-year annual residential electricity consumption forecasts. At the core of the forecast were the following stages:

- The average annual base load, heating load, and cooling load at a per-connection level were estimated. This was based on projected annual heating degree days (HDD) and cooling degree days (CDD) under 'standard' weather conditions.
- The forecast then considered the impact of the modelled consumption drivers including electric appliance uptake, energy efficiency savings, changes in retail prices, climate change impacts, gas-to-electricity switching, and the rooftop PV rebound effect.
- The forecasts were then scaled up with the connections growth forecast to project future base, heating, and cooling consumption by region over the forecast period[22].
- The forecast of underlying residential consumption was estimated as the sum of base, heating, and cooling load as well as the consumption from electric vehicles. The contribution from rooftop PV was then subtracted to compute the forecast of delivered residential consumption, as well as adding back the losses incurred in operating battery systems.

Figure 6 illustrates the steps undertaken to derive the underlying residential consumption forecast. Analysis of the historical residential consumption trend is based on daily consumption per connection, on a regional basis. The analysis conducted for each of these steps is discussed below.

[22] The connection forecast methodology has been refined with a split of residential and non-residential connections. Only the residential connections are used. For further information, see Appendix A5.

Figure 6 Process flow for residential consumption forecasts



3.2.2 Model process

Step 1: Weather normalisation of residential consumption

Historical residential consumption was analysed to estimate average annual temperature-insensitive consumption (base load) and average annual temperature-sensitive consumption in winter and summer (heating load and cooling load) at a per-connection level. The estimates were independent of the impact from year-to-year weather variability and the installed rooftop PV generation. The process is described in more detail in the following steps.

Step 1.1: Analyse historical residential consumption

Daily average consumption per connection was determined by:

- Estimating the underlying consumption by removing the impact of rooftop PV generation (adding the expected electricity generation from rooftop PV including avoided transmission and distribution network losses from residential consumers to their consumption profile to capture all the electricity that the sector has used, not just from the grid).
- Calculating the daily average underlying consumption in each region.
- Estimating the daily underlying consumption per residential connection by dividing by the total connections.

Daily consumption per connection was regressed against temperature measures (namely, CDD and HDD) over a two-year window (training data) leading up to the reference year, using OLS estimates. The two-year window is chosen to reflect current usage patterns, e.g. the dwelling size and housing type mix but long enough to capture seasonality in residential consumption.

A similar regression approach was applied to all regions, except Tasmania (due to cooler weather conditions in this region). The models are expressed as follows:

Regression model applied to all regions except Tasmania:

$$Res\_Con_{i,t} = \beta_{Base,i} + \beta_{HDD,i}HDD_{i,t} + \beta_{CDD,i}CDD_{i,t} + \beta_{Non-workday,i}Non-workday_{i,t} + \varepsilon_{i,t}$$

Regression model applied to Tasmania:

$$Res\_Con_{i,t} = \beta_{Base,i} + \beta_{HDD,i}HDD_{i,t} + \beta_{HDD^2,i}HDD_{i,t}^2 + \beta_{Non-workday,i}Non-workday_{i,t} + \varepsilon_{i,t}$$

The above parameters were then used to estimate the sensitivities of residential loads per connection to warm and cool weather.

For all regions (excluding Tasmania) this is expressed as:

$$CoolingLoadPerCDD_i = \beta_{CDD,i}$$

$$HeatingLoadPerHDD_i = \beta_{HDD,i}$$

For Tasmania this is expressed as:

$$CoolingLoadPerCDD_i = 0$$

$$HeatingLoadPerCDD_i = \frac{\sum_{t=1}^{n}\left(\beta_{HDD,i} \times HDD_t\right) + (\beta_{HDD^2,i} \times HDD_t^2)}{\sum_{t=1}^{n} HDD_t}$$

Where n is the total number of days in the two-year training data set.

Step 1.2: Estimate average annual base load, heating load and cooling load per connection, excluding impacts from weather conditions and installed rooftop PV generation

$$Baseload\_Con_i = \beta_{Base,i} \times 365$$

$$HeatingLoad\_Con_i = HeatingLoadPerCDD_i \times AnnualHDD_i$$

$$CoolingLoad\_Con_i = CoolingLoadPerCDD_i \times AnnualCDD_i$$

The variables of the model are defined in Table 8.

Table 8 Weather normalisation model variable description

Variable	Description
$Res\_Con_{i,t}$	Daily average underlying consumption per residential connection for region i on day t
$HDD_{i,t}$	Average heating degree days for region i on day t
$CDD_{i,t}$	Average cooling degree days for region i on day t
$HDD_{i,t}^2$	Square of average heating degree days for region i on day t which is to capture the quadratic relationship between daily average consumption and HDD
$Non-workday_{i,t}$	Dummy variable to flag a day-off for region i on day t. This includes public holidays and weekends.
$CoolingLoadPerCDD_i$	Estimated cooling load per CDD for region i.
$HeatingLoadPerHDD_i$	Estimated heating load per HDD for region i
$AnnualHDD_i$	Projected annual HDD in standard weather conditions for region i
$AnnualCDD_i$	Projected annual CDD in standard weather conditions for region i
$Baseload\_Con_i$	Estimated average annual base load per connection for region i
$Heatingload\_Con_i$	Estimated average annual heating load per connection for region i
$Coolingload\_Con_i$	Estimated average annual cooling load per connection for region i

Step 2: Apply forecast trends and adjustments

The average annual base load, heating load and cooling load per connection estimated in Step 1 will not change over the forecast horizon, being unaffected by the external driving factors. The adjustment that accounts for external impacts, was performed in this second step.

For the purpose of forecasting changes to the annual consumption:

- Forecast residential retail prices are expressed as year-on-year percentage change.
- Forecast impact of annual energy efficiency savings, appliance uptake, and climate change are expressed as indexed change to the reference year.

Step 2.1: Estimating the impact of electrical appliance uptake

The change in electrical appliance uptake is expressed using indices for each forecast year (set to 1 for the reference year), for each region and split by base load, heating load and cooling load. The indices reflect growth in appliance ownership, and also changes in the sizes of appliances over time (larger refrigerators and televisions) and hours of use per year. See Appendix A5 for more detailed discussion of appliance uptake.

Excluded, however, were impacts from energy efficiency, which are captured in Step 2.6 below.

Certain appliances affect base load (such as fridges and televisions) while others are weather-sensitive (such as reverse-cycle air-conditioners). The annual base load, heating load, and cooling load per connection is scaled with the relevant indices to reflect the increase or decrease in consumption over time, relative to the base year.

Step 2.2: Estimating the impact of gas-to-electricity fuel switching

Gas-to-electric appliance switching relates to gas hot water heating being switched to electric-boosted solar hot water heaters or heat pumps, and gas space heating being switched to electric heating using reverse-cycle air-conditioners[23].

The following adjustments were made to convert the reduction in gas load to a forecast increase in electricity consumption:

- An assumed 50% of the reduction in gas hot water heating was attributed to electric boosted solar water heaters.
- A heating Coefficient of Performance (COP) of 5 was assumed for reverse-cycle air-conditioners, which use 80% less energy than the gas space heater they replace.
- Heat loss through ducted systems for gas central heating was assumed to be 25%.

Step 2.3: Estimating the impact of solar PV rebound effect

It was assumed that households with installed rooftop PV are likely to increase consumption due to lower electricity bills. The PV rebound effect was set equal to 20% of average forecast PV generation allocated proportionally to base load, heating, and cooling load per connection.

Step 2.4: Estimating impact of climate change

The Bureau of Meteorology and CSIRO assisted AEMO in understanding the impact of climate change on projected temperatures. AEMO then adjusted the consumption forecast to account for the impact of increasing temperatures (see Appendix A2 for more information). Climate change is anticipated to cause milder winters and warmer summers which, as a result, reduce heating load while increasing cooling load in the forecast. Due to the opposing effects of climate change on weather-sensitive loads, the annual net impact of climate change can take a positive or negative value depending on which effect, on average, is larger.

Step 2.5: Estimating impact of consumer behavioural response to retail price changes

Changes in electricity prices have an impact on how consumers use electricity. Household response to price change that was not captured by energy efficiency and rooftop PV was modelled through consumer behavioural response. The asymmetric response of consumers to price changes is reflected in the price elasticity estimation, with price impacts being estimated in the case of increases, but not for price reductions. A price rise was estimated to have minimal impact on residential base load, which is largely from the operation of appliances such as refrigerators, washing machines, microwaves, and lights. Hence, the price elasticity for base load was set to be 0. For weather-sensitive loads, price elasticity was projected to be -0.1, applied to both heating and cooling load per connection.

[23] AEMO *2018 Gas Statement of Opportunities Methodology Information Paper*. Available at: http://www.aemo.com.au/Gas/National-planning-and-forecasting/National-Gas-Forecasting-Report. (Accessed 21 February 2019)

Step 2.6: Estimating impact of energy efficiency savings

Ongoing improvements in energy efficiency affect appliance consumption and the energy required to achieve desired temperature settings within houses. Historical and forecast energy efficiency savings were forecast for a number of programs by a consultancy[24]:

- Current federal and state energy efficiency programs for appliances and buildings.
- Future programs, expecting additional initiatives to be implemented over time to assist meeting the target set in the National Energy Productivity Plan for a 40% improvement in energy productivity by 2030.

The applied energy efficiency savings represent the expected achievable energy efficiency savings, accounting for a consumption rebound effect. The energy efficiency rebound effect was estimated by AEMO to be 40%, based on the calibration and OLS regression against residential consumption meter data. This means the effective savings from energy efficiency are 60% of the S.P.R forecast estimate. The impact of energy efficiency savings on residential annual consumption was apportioned to base, heating, and cooling loads per connection within the estimation model.

Step 2.7: Estimating the forecasts of annual base load, cooling load and heating load per connection accounting for external impacts

The forecasts of base load, heating load and cooling load per connection are then adjusted, considering the impacts of external drivers estimated from Step 2.1 to 2.6. The external impacts are added to or subtracted from the forecasts depending on how they affect each of the loads.

$$
\begin{aligned}
TOTBaseload\_Con_{i,j} &\\
= Baseload\_Con_i &+ API\_BL\_Con_{i,j} + FSI\_BL\_Con_{i,j} + PVRB\_BL\_Con_{i,j} - EEI\_BL\_Con_{i,j}
\end{aligned}
$$

$$
\begin{aligned}
TOTHeatingload\_Con_{i,j} &\\
= Heatingload\_Con_i &+ API\_HL\_Con_{i,j} + FSI\_HL\_Con_{i,j} + PVRB\_HL\_Con_{i,j} - EEI_{HL_{Con\,i,j}} \\
&- CCI\_HL\_Con_{i,j} + PI\_HL\_Con_{i,j}
\end{aligned}
$$

$$
\begin{aligned}
TOTCoolingload\_Con_{i,j} &\\
= Coolingload\_Con_i &+ API\_CL\_Con_{i,j} + PVRB\_CL\_Con_{i,j} - EEI_{CL_{Con_{i,j}}} + CCI\_CL\_Con_{i,j} \\
&+ PI\_CL\_Con_{i,j}
\end{aligned}
$$

Variables and their descriptions are detailed in Table 9.

Table 9 Variables and descriptions for residential consumption model

Variable	Description
$TOTBaseload\_Con_{i,j}$	Forecast total base load per connection for region *i* in year *j*
$TOTHeatingload\_Con_{i,j}$	Forecast total heating load per connection for region *i* in year *j*
$TOTCoolingload\_Con_{i,j}$	Forecast total cooling load per connection for region *i* in year *j*
$API\_BL\_Con_{i,j}$	Impact of electrical appliances uptake on annual base load per connection for region *i* in year *j*
$API\_HL\_Con_{i,j}$	Impact of electrical appliances uptake on annual heating load per connection for region *i* in year *j*
$API\_CL\_Con_{i,j}$	Impact of electrical appliances uptake on annual cooling load per connection for region *i* in year *j*

[24] *Strategy. Policy. Research. Pty Ltd. Energy Efficiency Impacts on Electricity and Gas Demand to 2037-38*. June 2018. Available at: https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/NEM-Electricity-Statement-of-Opportunities. (Accessed 21 February 2019)

Variable	Description
$FSI\_BL\_Con_{i,j}$	Impact of fuel switching on annual base load per connection for region *i* in year *j*
$FSI\_HL\_Con_{i,j}$	Impact of fuel switching on annual heating load per connection for region *i* in year *j*
$PVRB\_BL\_Con_{i,j}$	Impact of rooftop PV rebound effect on annual base load per connection for region *i* in year *j*
$PVRB\_HL\_Con_{i,j}$	Impact of rooftop PV rebound effect on annual heating load per connection for region *i* in year *j*
$PVRB\_CL\_Con_{i,j}$	Impact of rooftop PV rebound effect on annual cooling load per connection for region *i* in year *j*
$CCI\_HL\_Con_{i,j}$	Impact of climate change on average heating load per connection for region *i* in year *j*
$CCI\_CL\_Con_{i,j}$	Impact of climate change on average cooling load per connection for region *i* in year *j*
$PI\_HL\_Con_{i,j}$	Impact of consumer behavioural response to price changes on annual heating load per connection for region *i* in year *j*. This takes negative value, reflecting reduction in consumption due to price rises.
$PI\_CL\_Con_{i,j}$	Impact of consumer behavioural response to price changes on annual cooling load per connection for region *i* in year *j*. This takes negative value, reflecting reduction in consumption due to price rises.
$EEI\_BL\_Con_{i,j}$	Impact of energy efficiency savings on annual base load per connection for region *i* in year *j*
$EEI\_HL\_Con_{i,j}$	Impact of energy efficiency savings on annual heating load per connection for region *i* in year *j*
$EEI\_CL\_Con_{i,j}$	Impact of energy efficiency savings on annual cooling load per connection for region *i* in year *j*

Step 3: Scale by connections forecasts

Forecasts of annual base load, cooling load, and heating load at per connection level, after adjustment for future appliance and technology trends, were then scaled up by connections forecast over the projection period.

Forecasts of annual base load, heating load and cooling load were modelled as follows:

$$TOTBaseload_{i,j} = TOTBaseload\_Con_{i,j} \times TotalNMI_{i,j}$$

$$TOTHeatingload_{i,j} = TOTHeatingload\_Con_{i,j} \times TotalNMI_{i,j}$$

$$TOTCoolingload_{i,j} = TOTCoolingload\_Con_{i,j} \times TotalNMI_{i,j}$$

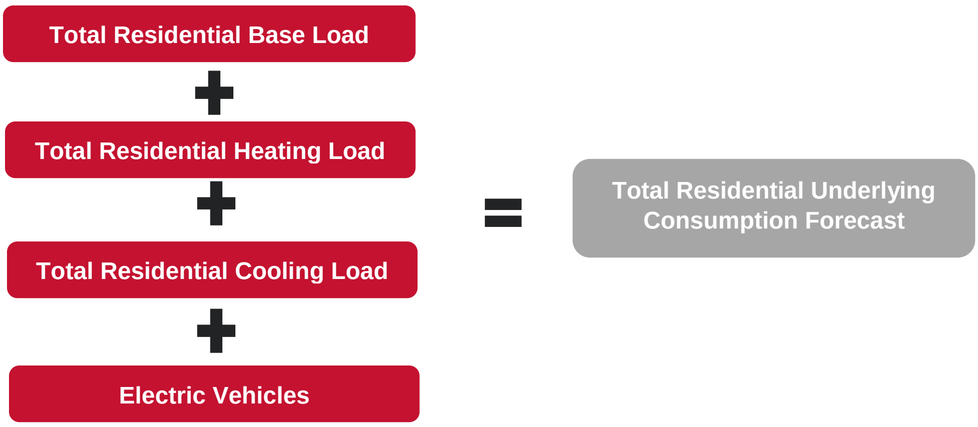
Table 10 Residential base load, heating load and cooling load model variables and descriptions

Variable	Description
$TotalNMI_{i,j}$	Total connections for region i in year j
$TOTBaseload_{i,j}$	Forecast total base load for region i in year j
$TOTHeatingload_{i,j}$	Forecast total heating load for region i in year j
$TOTCoolingload_{i,j}$	Forecast total cooling load for region i in year j

Step 4: Estimate underlying and delivered annual consumption forecast

The forecast underlying annual consumption is expressed as the sum of base, heating and cooling loads and residential electric vehicles:

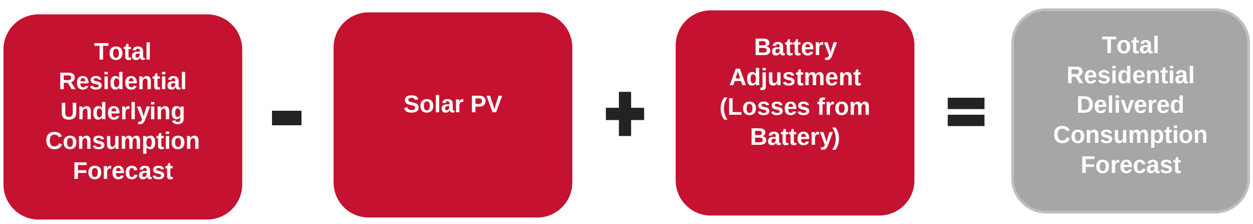
Figure 7 Aggregation process for final residential underlying forecast



External advice was obtained from CSIRO for estimates of historical and forecast electric vehicle uptake[25].

Forecast delivered annual consumption refers to underlying consumption, adjusted for consumption offsets due to solar PV and customer battery storage system losses (assumed round trip efficiency of 85%), forecast by CSIRO (see Appendix A3 for more information):

Figure 8 Aggregation process for final residential delivered forecast



[25] See Appendix A4 for more information

4. Operational consumption

AEMO forecasts operational consumption, representing consumption from residential and business consumers, as supplied by scheduled, semi-scheduled and significant non-scheduled generating units[26]. The remainder of non-scheduled generators are referred to as small non-scheduled generation (NSG). When calculating operational consumption, energy supplied by small NSG was subtracted from delivered residential and business sector consumption. Estimations of the transmission and distribution losses are added to the delivered consumption to arrive at the operational consumption forecast.

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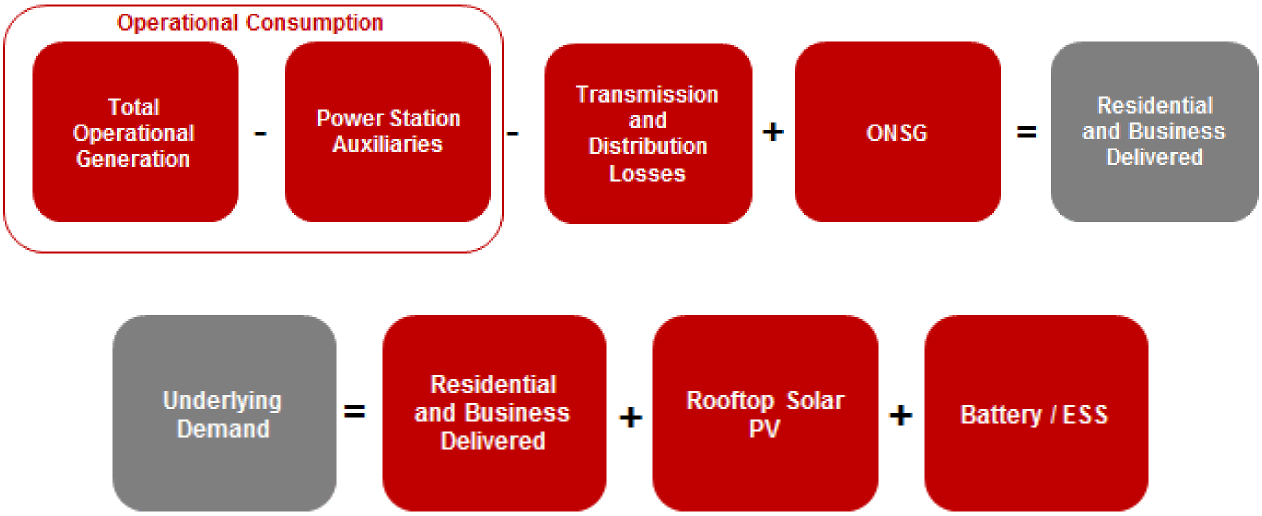
Figure 9 Demand relationships



4.1 Small non-scheduled generation

This section discusses the methodology of the PV non-scheduled generation (PVNSG) and Other non-scheduled generation (ONSG).

[26] Operational definition may be found here http://www.aemo.com.au/-/media/Files/Electricity/NEM/Security_and_Reliability/Dispatch/Policy_and_Process/Demand-terms-in-EMMS-Data-Model.pdf (Accessed 21 February 2019)

4.1.1 Data sources

AEMO forecast small NSG based on the following data sources:

- AEMO's generation information pages[27].
- Publicly available information.
- Data provided by network businesses.
- Projection of PV uptake[28].

4.1.2 Methodology

The small NSG forecast was split into two components:

- PVNSG: PV installations above 100 kW but below 30 MW. Until 2016, this was combined with ONSG. In 2017 this was forecast separately for the first time, though based on growth rates for commercial rooftop PV. In 2018, this sector was forecast with a different approach; Larger projects require special purpose financing and their uptake has been forecast by the CSIRO by modelling whether the return on investment for different size systems meets a required rate of return threshold for a given year and region.
- ONSG: All other technologies, such as small-scale wind power, hydro power, gas or biomass-based cogeneration, generation from landfill gas or wastewater treatment plants, and smaller peaking plants or emergency backup generators.

PVNSG

The PVNSG annual generation forecast was developed using:

- Forecast PV capacity in the 100 kW to 30 MW range.
- A simulated normalised generation trace.

Annual PVNSG generation was obtained by multiplying the normalised generation trace by the capacity forecast to produce a MW generation trace at half-hourly resolution, which was then aggregated to determine annual energy in MWh.

The normalised generation trace was produced by:

- Simulating historical normalised generation of single axis tracking PV systems for a selection of geographic locations across the NEM, using NREL's System Advisor Model[29] software. Satellite solar irradiance observations and ground station temperature measurements are used to estimate PV generation for every half hour back to 2009.
- Determining regional normalised generation traces by averaging traces for all Renewable Energy Zones in each region.
- Finding a median normalised generation value for each half hour of the year, based on the historical traces. This median trace is used as a proxy for future PV generation in each forecast year.

ONSG

For the other technologies, AEMO reviewed the list of generators making up the current ONSG fleet, and made adjustments to add newly commissioned or committed generators and remove retired generators or

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[27] https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/Generation-information. (Accessed 21 February 2019)

[28] CSIRO consultancy report "Projections for small-scale embedded technologies" available at: https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/NEM-Electricity-Statement-of-Opportunities. (Accessed 21 February 2019)

[29] NREL System Advisor Model is available at https://sam.nrel.gov/. (Accessed 21 February 2019)

units that may already be captured though net metering of the load it is embedded under. This resulted in a forecast capacity, for each NEM region, for each technology.

The forecast capacity was converted into annual energy generation projections, based on historical capacity factors for these technologies in each region. The capacity factors used for the projections were calculated using up to five years of historical data. AEMO assumed that the installed capacity of existing projects would remain unchanged over the 20-year outlook period, unless a site has been decommissioned or announced to retire.

All new projects were assumed to begin operation at the start of the financial year in which they are due for completion and remain at this level over the 20-year outlook period.

Capacity factors for existing projects were estimated using a weighted average of the historical capacity factors for each project, based on the past five years of data.

For future ONSG projects, where historical output is not available, AEMO estimated capacity factors using the following methods:

- Where similar projects already exist, in terms of NEM region and generator class (fuel source), AEMO used the total historical output from all similar, existing projects, divided by their combined rated capacity.
- Where no similar projects exist typically a new generator class in a particular NEM region, AEMO either used the regional average for all existing generators or applied the capacity factor of similar generators from another region.

AEMO then combined the resulting capacity factor profile with the expected capacities of all future generator projects and used this to forecast the expected generation per project over the outlook period.

Similarly, the forecast impact on maximum and minimum demand is calculated based on the technologies' historical generation at time of maximum or minimum demand[30].

4.2 Network losses and auxiliary loads

4.2.1 Network losses

Transmission losses forecast methodology

Transmission losses represent energy lost due to electrical resistance and the heating of conductors as electricity flows through the transmission network.

The Australian Energy Regulator (AER) and the network operators provide AEMO with historical transmission loss factors. AEMO use the transmission loss factors to calculate historical losses across the transmission network for each region.

AEMO forecast annual transmission losses by using the historical normalised transmission losses averaged over the last five years. Annual transmission losses were normalised by electricity consumption by large industrial customers as well as residential and commercial customers.

Distribution losses

To calculate operational demand from estimated delivered demand, distribution losses are needed in addition to transmission losses. The distribution losses were estimated as a volume weighted

[30] For maximum demand, the top 10 highest demand half-hours each year were used to calculate the average generation at time of maximum demand. For minimum demand, the bottom 10 demand periods were used.

average per region, generally based on recent losses reported to the Australian Energy Regulator (AER) by distribution companies as part of the Distribution Loss Factor approvals process.

4.2.2 Auxiliary loads methodology

Auxiliary loads account for energy used within power stations (the difference between "as generated" energy and "sent-out" energy).

Auxiliary loads (historical)

Analysis for auxiliary loads requires historical data obtained from the wholesale market system – Market Management System (MMS). Auxiliary loads are not directly measured and so are modelled with the assumption that they are equal to the difference between total generation as measured at generator terminals and the electricity that is sent out into the grid. The amount of energy that is sent out to the grid is estimated by multiplying the metered generation for an individual generating unit by using an estimated *auxiliary percentage*[31] for the generation station such that:

$$\text{Auxilary Load} = \text{Metered Generation x Auxilary Percentage}$$

For example, a new combined cycle gas turbine has an assumed auxiliary factor of 3%, such that if the metered generation in a day was 30 MWh will have a calculated auxiliary load of 0.9 MWh. The sent out energy for this power station is therefore determined to be 29.1 MWh.

This method is applied for approximately 250 generating units in the NEM to arrive at the calculated historical auxiliary load and operational demand as sent out on a half hourly basis.

Auxiliary loads (forecast)

The annual auxiliary loads in each region was forecast using the auxiliary loads from a future generation forecast that have a mix of technologies. Forecasts of the future generation mix are based on the 2018 Integrated System Plan (ISP) auxiliary Load forecasts in the corresponding Fast, Neutral and Slow scenarios. As the ISP forecasts were based on the 2017 ESOO consumption forecasts they needed to be rebased to reflect the ISP consumption forecasts but preserve a similar percentage of auxiliary loads. To arrive at this adjustment, the forecast auxiliary factor for each financial year and for each NEM region in the 2018 ESOO was defined as:

$$\text{Auxiliary Load Factor (2018 ESOO)} = \frac{\text{Total Auxililary Load (ISP)}}{\text{Operational Consumption Forecast as sent out (ISP)}}$$

The annual auxiliary load forecast was then determined by first calculating the operational consumption forecast (as generated) by dividing the 2018 ESOO operational consumption forecast (as sent-out) by the 2018 ESOO Auxiliary Load Factor. The auxiliary load forecast is then the difference between the operational consumption forecast (as generated) and the operational forecast (as sent out).

[31] Fuel and Technology Cost Review (ACIL Allen), Available at: https://www.aemo.com.au/-/media/Files/XLS/Fuel_and_Technology_Cost_Review_Data_ACIL_Allen.xlsx (Accessed 21 February 2019)

5. Maximum and minimum demand

Regional minimum and maximum demands sent-out are developed by season using a probabilistic methodology. Demand is heavily dependent on weather conditions and random variability in response to weather.

Due to this variability, forecast maximum demand (MD) is expressed as probability of exceedance (POE) values from a distribution, rather than a point forecast. For any given season or year:

- A 10% POE MD value is expected to be exceeded, on average, one year in ten.
- A 50% POE MD value is expected to be exceeded, on average, one year in two.
- A 90% POE MD value is expected to be exceeded, on average, nine years in ten.

For the purpose of forecasting demand, AEMO defined summer as the period from November to March (inclusive) except for Tasmania where summer was defined as the period from December to February (inclusive). Winter was defined as being from June to August for all jurisdictions.

AEMO forecasts unconstrained maximum and minimum demand. That is, demand that is unconstrained by subregional; network constraints, generation constraints or outages, wholesale market dynamics and demand side participation.

5.1 Data preparation

Data preparation for both the minimum and maximum demand models was similar to the requirements for annual consumption, however each requires the use of half-hourly data. The requirement for higher-frequency data drives the need to consider the load profile of small-scale technologies and large industrial loads.

At a half-hour frequency by region the following data inputs were used:

- Historical and forecast rooftop PV capacity, generation and normalised generation.
- Historical and forecast PVNSG installed capacity, generation and normalised generation.
- Forecast electric vehicles numbers and charge profile.
- Forecast ESS installed capacity and charge/discharge profile
  - a proportion of ESS is considered virtual power plant (VPP) or distributed energy resource (DER) with the proportion varying by scenario. This proportion is included in operational demand.
- National Meter Identifier (NMI) data for the top 100 large industrial loads (loads over 10 MW, 10% of the time).
- Historical and forecast Large industrial loads.
- Projected climate change adjusted dry temperature.
- Historical underlying demand.

AEMO sourced half-hourly weather data from the BoM for the weather stations listed in Appendix A.2. The weather data was climate change-adjusted for temperatures expected in the forecast horizon based on information available on www.climatechangeinaustralia.gov.au.

The model aimed to generate forecasts of underlying demand less large industrial load. Large industrial load was subtracted from underlying demand before constructing the model. Large industrial load may be seasonal but is not considered to be weather-sensitive, although it can have the potential to cause structural shifts in demand.

Forecasts were defined to represent the power required to be sent out from generating sources (operational demand as sent out (OPSO)).

5.2 Exploratory data analysis

Exploratory data analysis (EDA) was used to detect outliers and identify important demand drivers during model development.

5.2.1 Outlier detection and removal

Outlier detection procedures were used to detect and remove outliers caused by data errors and outages. A basic linear model was specified to examine all observations to ensure values do not lie more than three standard deviations from the predicted value at each half-hour.

The resulting list of outliers and the known list of network outages was used to remove these data points to constrain the dataset. Any data errors detected through this process were tracked to determine cause followed by appropriate data corrections. No augmentation of data was performed for missing data.

5.2.2 EDA to identify important short-term demand drivers

EDA was used to identify key variables that drive demand over the course of the year, by examining summary statistics of each variable, correlations between explanatory variables to identify multicollinearity, and correlations between explanatory variables and demand.

Broadly, the EDA process examined:

- Weather data – temperature variables including:
  - Instantaneous cooling degree (CDs) and heating degree (HDs) as half-hourly up to three hour rolling average of temperature.
  - Heatwaves and 'coolwaves' as daily up to three day rolling average of temperature.
    - Heatwaves were collinearly related with temperature variables derived from humidity. To avoid multicollinearity, the heatwave variables were retained, and the temperature variables derived from humidity were dropped.
  - Dry bulb temperature – both instantaneous and heatwave/coolwave.
  - Apparent temperature[32] – both instantaneous and heatwave/coolwave.
  - EHF – excess heating factor is a measure of heatwave intensity. When maximum daily temperatures are above the 95th percentile[33] for three consecutive days, then these days are deemed to be in heatwave conditions with the variable increasing with the intensity.
  - Heat index[34] – both instantaneous and heatwave.

[32] Measures the temperature perceived by humans. Ii is a function of dry bulb air temperature, relative humidity and wind speed.

[33] The 95th percentile on the daily maximum temperature for that weather station in the region

[34] Measures the perception of temperature above 27 degrees. It is a function of dry bulb air temperature and humidity.

– Higher order terms of the above variables, for example CD^2 and HD^2, to capture changing dynamics between temperature and demand.

- Calendar/seasonal variables, including weekday/weekend and public holiday Boolean (true/false) variables.

Alternative critical temperature cut-offs were explored to formulate the CD and HD variables. The critical temperature cut-offs that best captured inflection points between temperature and demand were selected for the model.

The Calendar/seasonal variables and other indicator variables in practise work to stratifies the data in different seasons, weekends and weekdays. CD and HD variables take a value of zero when greater than or less than the critical temperature respectively. This split the model into cooling demand and heating demand.

5.3 Model development and selection

Models for each region were specified using the variables identified as statistically significant during the EDA process. Models were trained on the previous 3-4 years of historical data (region-dependent) at a half-hourly frequency.

The models aimed to describe the relationship between underlying demand and key explanatory variables including calendar effects such as public holidays, day of the week and month in the year and weather effects (such as CD, HD, CD^2 and HD^2).

An array of linear models using available variables was ranked by explanatory power. The model with the optimal combination of variables was chosen for each region.

An algorithm was used to discard models that had:

- Variance Inflation Factor > 4[35].
- Illogical coefficients.
- Non-statistically significant coefficients.

The algorithm then ranked and selected the best model, based on:

- Goodness-of-fit – R-Squared, Akaike information criterion, and Bayesian information criterion.
- Out-of-sample goodness-of-fit – for each model, AEMO performed 10-fold cross validation[36] to calculate the out-of-sample forecast accuracy.
- Histogram of the residuals, quantile-quantile (Q-Q) plot, and residual plots to ensure no discernible patterns that could indicate missing explanatory factors.

Table 11 details the variables selected as important in the EDA process after rejecting the other variables for reason of weak correlation with demand or multicollinearity with other explanatory variables. In the case of multicollinearity, the EDA process opted for simplicity by selecting more easily understood variables such as dry temperature. These variables were then used in the final minimum/maximum demand model.

Table 11 List of Variables included for minimum/maximum demand model

Variable	Description
Public holiday	Dummy flag for public holiday

[35] The variance inflation factor is a measure of multicollinearity between the explanatory variables in the model. Multicollinearity occurs when multiple explanatory variables are linearly related and is undesirable because it could have the effect of increasing the variance of the model.

[36] A 10-fold cross validation was performed by breaking the data set randomly into 10 smaller sample sets (folds). The model was trained on 9 of the folds and validated against the remaining fold. The model was trained and validated 10 times until each fold was used in the training sample and the validation sample. The forecast accuracy for each fold was calculated and compared between models.

Variable	Description
Weekend dummy	Dummy flag for weekend
Month factor	A factor variable with values for each months of the year
Dry temperature CD	Half-hourly dry temperature with a CD cut off
Dry temperature HD	Half-hourly dry temperature with a HD cut off
Dry temperature CD^2	Half-hourly dry temperature with a CD cut off squared
Dry temperature HD^2	Half-hourly dry temperature with a HD cut off squared
Dry temperature 3-day rolling average CD	Three-day rolling average of dry temperate with a CD cut off
Dry temperature 3-day rolling average HD	Three-day rolling average of dry temperate with a CD cut off
Dry temperature 2-day rolling average CD	Two-day rolling average of dry temperate with a CD cut off
Dry temperature 2-day rolling average HD	Two-day rolling average of dry temperate with a CD cut off
Dry temperature 1-day rolling average CD	One-day rolling average of dry temperate with a CD cut off
Dry temperature 1-day rolling average HD	One-day rolling average of dry temperate with a CD cut off

5.4 Simulate base year (weather and calendar normalisation)

The linear models selected from the above process were used to simulate demand for each region. Historical weather events were simulated to develop a weather distribution to weather-normalise demand and random shocks in response to demand drivers:

$$Underlying_{hh} = f(x_{hh}) + \varepsilon_{hh}$$

where

- $f(x_{hh})$ is the relationship between demand and the demand drivers such as weather and calendar effects.
- ε_{hh} represents random normally distributed[37] changes in demand not explained by the model demand drivers.

The weather was simulated for the base year by block bootstrapping historical weather observations (x_{hh}) to create a year consisting of 17,520 half-hourly weather observations. A synthetic weather-year was constructed by randomly selecting 26 fortnightly weather patterns ("weather blocks"), ensuring that a weather block was assigned to the corresponding time of the year. A total of 20 years of historical weather data was bootstrapped[38]. A total of 1,000 weather simulations were created to derive 1,000 weather years of data (at half-hourly observations)[39].

The weather blocks were spliced together from midnight to midnight 14 days after. No attempt was made to smooth the joins between the fortnights. Only a given half-hour is considered in the context of minimum and maximum demand not the full time-series or the shape of the data.

Linear regression models were used to estimate demand for the given conditions of a synthetic year, which accounts for the correlation between demand and the conditions implied by the models. Simultaneously, a random shock was simulated to account for the component of demand variability unexplained by weather conditions and other demand drivers captured in the linear model (ε_{hh}). This shock recognised random

[37] A fundamental assumption of Ordinary Least Squares (OLS) is that the error term follows a normal distribution. This assumption was tested using graphical analysis and the Jarque–Bera test.

[38] Bootstrapping with replacement preserves empirical correlations between time-of-year, temperature, and solar irradiance time series.

[39] Previous tests indicate that 500 Monte Carlo simulations is a sufficient number of simulations to converge to a stable result that varies around half a percent in the early years, while 1000 simulations reduce the variability to about 0.3% in the early years. Variability does increase in the later years of the forecast horizon.

variability that is not captured through the weather correlation estimate but was needed to appropriately simulate stochastic variability observed in a weather-sensitive process. The synthetic half-hourly demand traces were estimated for 1,000 simulated years.

The simulation process recognised that there are several drivers of demand including weather, day of week, and hour of day, as well as random shocks in demand. The process also preserved the probabilistic relationship between demand and its key drivers.

5.5 Forecast probability of exceedance

The forecast process grows half-hourly demand by economic conditions such as price and GSP, demographic conditions such as connections growth, and technological conditions such as electric vehicle uptake to derive an annual growth index.

The forecast year-on-year change was applied to each of the 17,520 half-hours for each simulation and to each forecast year. The process breaks demand for each half-hour into heat-base-cooling load. The process then grows half-hourly heat-base-cooling load by annual or seasonal growth indices such as energy efficiency of air-conditioners decreasing cooling load, or population growth and price impacting half-hourly heat, base and cooling load. As a result, the load factor between maximum demand and annual energy changes over time.

The process then calculates demand not met by solar by subtracting rooftop PV and PVNSG generation.

This process yields minimum/maximum demand values at each half-hour over a simulated year. This represents the minimum/maximum half-hourly prediction of the 17,520 half-hourly predictions in a given year, for each year in the forecast horizon. After simulating 1,000 times there were 1,000 values for each forecast year, for each season for each scenario. From the 1,000 simulated minima/maxima, AEMO then extracted the 50% and 10% POEs as well as the characteristics at times of the minimum/maximum (such as weather conditions and calendar positioning at the time of minimum/maximum).

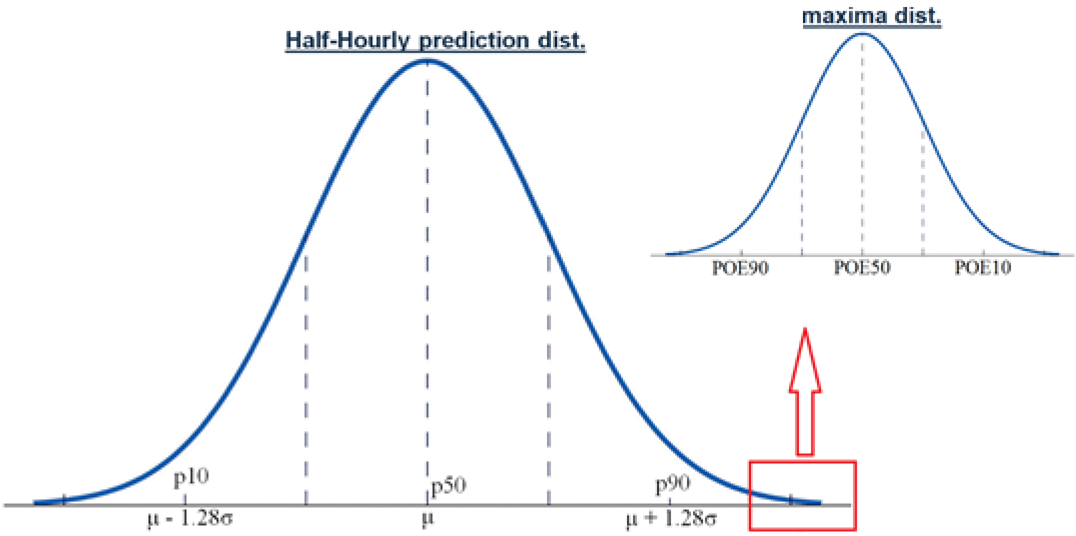
In Figure 10:

- The first distribution represents the variability of 17,520 half-hour demand for each simulation. This is obtained for all years needed to produce a forecast year. Data for one half-hour representing the largest predicted MD (indicated by the red box and arrow) was then extracted from the 17,520 half-hours and added to the distribution of annual maxima (represented by the smaller bell curve). This extraction was repeated 1,000 times, once for each simulation.
- The second smaller bell curve represents the distribution of maxima which may or may not be normally distributed.[40]

AEMO extracts minimum/maximum values by region from this minima/maxima distribution by selecting the 10th, 50th and 90th percentile as 90%, 50% POE and 10% POE values, respectively.

[40] It is not necessary for the minima or maxima to follow a normal distribution. Regardless of whether the distribution is skewed, leptokurtic, mesokurtic or platykurtic, the percentiles can be found by ranking the minimum/maximum demand values and extracting the desired percentile.

Figure 10 Theoretical distribution of annual half-hourly data to derive maxima distribution



Auxiliary and transmission and distribution losses

AEMO forecast auxiliary and transmission and distribution losses during maximum and minimum demand by estimating the average percentage of losses by time-of-day and day-of-year. AEMO then applied the average percentage for the relevant time of minimum and maximum demand to the losses forecast. For instance, if the maximum operational demand value in the simulation occurs at 18:00, then the average auxiliary percentage at 18:00 is applied to calculate auxiliary at that time.

Large industrial loads

Based on analysis, AEMO assumed that large industrial loads in all regions except for Tasmania are not correlated with the regional maximum demand. Further, large industrial loads have a load factor of greater than 0.9 in most cases. For all regions except Tasmania AEMO includes average large industrial load demand in the maximum regional demand. In the case of Tasmania, however, large industrial loads drive the regional minima and maxima. AEMO apply the large industrial load minimum and maximum to Tasmania's regional minimum and maximum rather the average.

6. Half-hourly demand traces

Demand traces (referred to as demand time-series in general terms) were prepared by deriving a trace from a historical reference year and growing (scaling) it to meet specified future characteristics using a constrained optimization function to minimize the differences between the grown trace and the targets.

The traces were prepared on a financial year basis, to various targets, categorised as:

- Maximum summer demand (at a specified probability of exceedance level).
- Maximum winter demand (at a specified probability of exceedance level).
- Minimum demand (at a specified probability of exceedance level).
- Annual energy (consumption).

Traces were differentiated by:

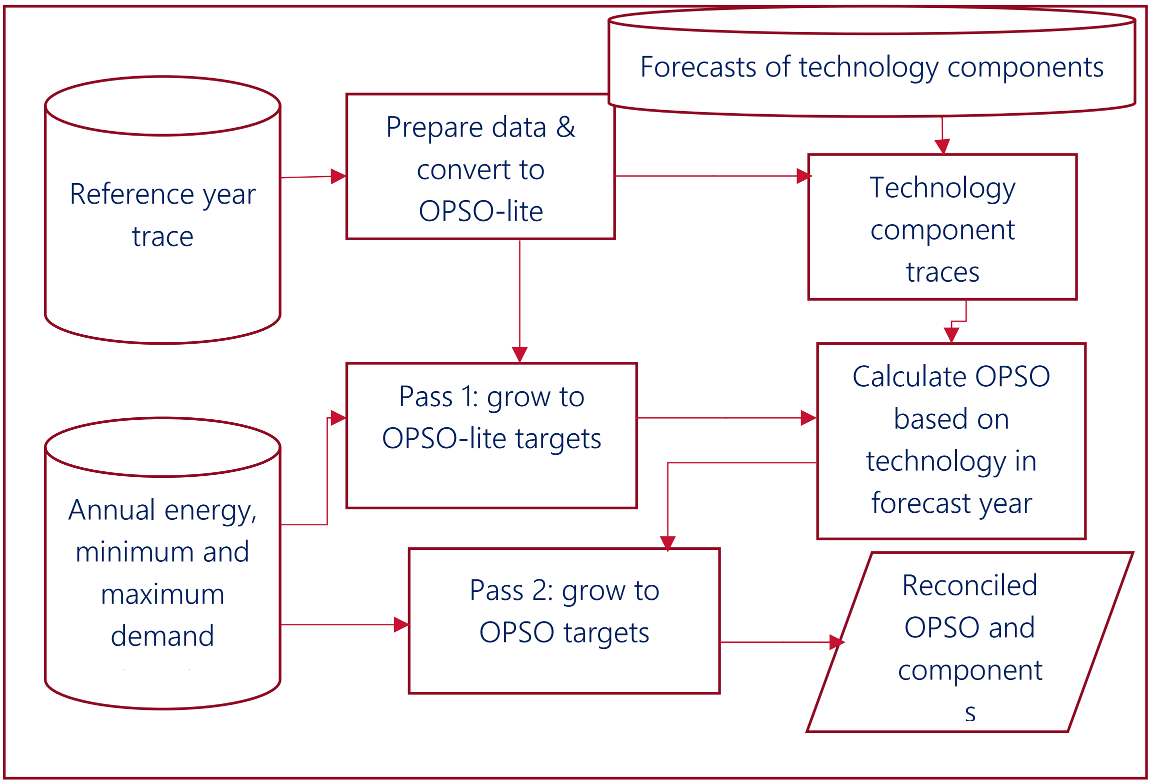
- NEM region.
- Historical reference year.
- Target year.
- Scenario.
- POE level.

The trace development process was conducted in two passes:

- Pass 1. Growing the reference year trace on an operational demand as sent-out *lite (OPSO-lite)* basis (demand trace has technology components removed, refer to Section 6.2 for full description).
- Pass 2. Reinstating technology components and reconciling the time series to meet the OPSO characteristics.

The trace development process is summarised as a flow diagram in Figure 11. A worked example of the growth scaling algorithm (discussed in section 6.1) is also provided in Appendix A8.

Figure 11 Trace development process flow diagram



6.1 Growth (scaling) algorithm

Demand from the particular reference year was scaled to match the targets of the forecast year using a constrained optimisation algorithm. Each pass of the two-pass approach followed this growth algorithm. The algorithm found scaling factors for each half-hour which minimised the difference between the adjusted demand and the demand and consumption targets such that seasonality, weekly and intra-day demand patterns are preserved. The demand trace was adjusted for each period so that the target was met for each pass.

The approach:

1. Categorised each day in the reference year into day-type groups (high-demand days in summer, high-demand days in winter, low-demand periods, and other). A threshold number of days or periods in each group was nominated as an input parameter. The threshold number was configurable by region and was based on the characteristics of the region and analyst judgement to optimise the demand targets.
2. Applied a day-swapping algorithm, such that weekends or public holidays in the reference year align with weekdays or public holidays in the forecast year.
3. Scaled the half-hourly demands across all high-demand days for each season so that only the highest demand point exactly matches that maximum demand target for that season.
4. Scaled the minimum demand of the low demand days in the reference year to the annual minimum demand target.
5. Determined the scaling factor for each day-type group such that the sum of demand across the year equals the annual energy target.
6. Calculated future annual energy for each day-type group by multiplying the energy in each day-type group with demand scaling factors.

7. The "other" day type had no scaling factor for the purpose of meeting a demand target. As such, the approach allocated the remainder of future energy to the 'other' day-type category for purpose of meeting the annual energy target.
8. Checked the grown traces against the targets. If all targets were met, the process was complete. If any of the targets were not fully met, the algorithm re-grew the demand traces for the reference year recursively by repeating steps 1 to 4 until the targets were met. At each repeat the threshold number of days or periods is increased to enlarge the coverage of periods at which the changes in energy are guided by the target maxima and minimum.

In the case of negative operational demand, the process managed the handling of periods near or below zero by adding a fixed amount to all periods before growing. This was then removed after growing.

6.2 Pass 1 – grow to OPSO-lite targets

As highlighted in Figure 11, the first pass grew the OPSO-lite reference year traces to the forecast year OPSO-lite targets. OPSO-lite is operational demand that has been cleaned to remove atypical demand events and has had the impact of the following technologies removed:

- Rooftop PV (PVROOF).
- Non-scheduled PV (PVNSG).
- Energy storage systems (ESS).
- Electric vehicles (EV).
- In the case of Queensland, CSG.

After growing the traces, the technology components were reinstated. This produced an unreconciled OPSO. The technology components were also prepared to reflect changing installed capacities, vehicle numbers, installation numbers or, in the case of CSG, demand, such that these components were consistent with the forecasts for the forecast year.

6.3 Reconciling to the OPSO targets

The second pass sought to ensure that the grown maximum operational demand met the OPSO targets.

Generally, because the trace is based on historical information, the unreconciled OPSO maximum demand doesn't always meet the OPSO target once rooftop PV and PVNSG were taken into account, as well as DSP. This is because the OPSO targets were based on simulating weather 1,000 times, while the reference year is a single weather year. Further, the reference year may be an unexceptional demand year grown to a 10% POE demand year and this stretching can cause the OPSO targets to be missed.

The second pass re-ran the growth algorithm in Section 5.2 to ensure the OPSO characteristics were met. The technology components were not modified, therefore this process, in effect, ensured that OPSO targets were met but could only be done if proximity to OPSO-lite targets was relaxed.

6.4 Reporting

AEMO prepared the traces with all the components such that they were modular, and the user could apply the components to calculate the desired demand definition. The choice of trace definition depended on the purpose of the modelling performed. For example, the market modelling strategy could elect to model PV separately or model ESS as a virtual power plant, in turn necessitating control over how those resources were discharged.

A1. Electricity retail pricing

AEMO assesses behavioural and structural changes of consumers in response to real or perceived high retail prices. AEMO calculated the retail price forecasts sourcing a combination of AEMO internal modelling and publicly available information. Separate prices have been prepared for three market segments:

1. Residential prices
2. Commercial prices
3. Industrial prices

The electricity retail price projections were formed from bottom-up projections based on separate forecasts of the various components of retail prices. The key components of retail prices included:

- Network costs.
- Wholesale costs.
- Environmental costs.
- Retail costs and margins.

In the 2018 ESOO, AEMO developed wholesale price forecasts for the three scenarios, separating the network, environmental, and retail components for different customer classes, based on the method used in the Retail Electricity Price History and Projected Trends Jacobs Report[41].

Residential pricing was modelled and estimated against published pricing data and recent price trends discussed in the 2017 Residential Electricity Price Trends AEMC Report[42]. The process of residential pricing modelling is summarised in Table 12.

[41] Jacobs, Retail Electricity Price History and Projections, available at https://www.aemo.com.au/-/media/Files/Electricity/NEM/Planning_and_Forecasting/Demand-Forecasts/EFI/Jacobs-Retail-electricity-price-history-and-projections_Final-Public-Report-June-2017.pdf (Accessed 21 February 2019)

[42] AEMC, 2017 Residential Electricity Price Trends, available at https://www.aemc.gov.au/markets-reviews-advice/2017-residential-electricity-price-trends. (Accessed 21 February 2019)

Table 12 Residential pricing model component summary

Component	Process summary
Wholesale costs*	• Employ wholesale cost methodology from Retail Electricity Price History and Projected Trends Jacobs Report and apply to AEMO's wholesale spot price.
Network costs	• Use 2017 Residential Electricity Price Trends AEMC Report. • Employ network costs methodology from Retail Electricity Price History and Projected Trends Jacobs Report and apply to extrapolate the trajectories. • Benchmark against published network tariffs.
Environmental costs	• Use 2017 Residential Electricity Price Trends AEMC Report. • Refine parameters using Retail Electricity Price History and Projected Trends Jacobs Report • Extrapolate the trajectories based on publicly available information of environmental schemes. These include federal and state-based renewable energy, energy efficiency and feed-in-tariff schemes.
Retail costs and margin	• Use 2017 Residential Electricity Price Trends AEMC Report.

* The wholesale costs component of retail price consists of wholesale price, hedging cost, ancillary services, market fees and energy losses from networks.

Commercial and industrial pricing models were developed using the residential pricing model as a baseline. Each component is then adjusted based on methodology from the Retail Electricity Price History and Projected Trends report. Price elasticity coefficients are applied in each of the residential, commercial and industrial models, details of which are discussed in the respective chapters for these segments.

A2. Weather and climate

A2.1 Heating Degree Days (HDD) and Cooling Degree Days (CDD)

HDD and CDD are measures of heating and cooling demand, respectively. They are estimated by differencing air temperature from a critical temperature.[43]

Table 13 Critical regional temperatures for HDD and CDD

Region	Critical Temperature in degrees C	
	HDD critical temperature	**CDD critical temperature**
New South Wales	17.0	19.5
Queensland	17.0	20.0
South Australia	16.5	19.0
Tasmania	16.0	20.0
Victoria	16.5	18.0

Note: The HDD and CDD critical temperatures for each region are not Bureau of Meteorology standard values but are selected for each region based on the temperature at which a demand response is detected that demonstrates the greatest predictive power of the models.

The formula for HDD[44] is:

$$HDD = Max(0, \overline{T} - \mathrm{CT})$$

The formula for CDD[45] is:

$$CDD = Max(0, \mathrm{CT} - \overline{T})$$

Where $\overline{T}$ is average 30 minute temperature between 9:00 PM of the previous day's consumption to 9:00 PM of the consumption day-of-interest, to account for the demand response with temperature that could be due (in-part) to the previous day's heat/cool conditions. CT is the critical temperature threshold in relation to the relevant region.

HDD and CDD are used in modelling and forecasting of consumption and are calculated at the regional level.

The weather station temperature data is sourced from the BoM [46] and the stations used are given below.

[43] Critical temperature is a threshold temperature for electricity heating.

[44] All the HDDs in a year are aggregated to obtain the *annual* HDD.

[45] All the CDDs in a year are aggregated to obtain the *annual* CDD.

[46] Bureau of Meteorology Climate Data, http://www.bom.gov.au/climate/data/.

Table 14 Weather stations used for HDD and CDD

Region	Station name	Data range
New South Wales	BANKSTOWN AIRPORT AWS	1989/01 ~ Now
Queensland	ARCHERFIELD AIRPORT	1994/07 ~ Now
South Australia	ADELAIDE (KENT TOWN) [47]	1993/10 ~ Now
Tasmania	HOBART (ELLERSLIE ROAD)	1882/01 ~ Now
Victoria	MELBOURNE (OLYMPIC PARK)	2013/05 ~ Now
Victoria	MELBOURNE REGIONAL OFFICE	1997/10 ~ 2015/01

A2.2 Determining HDD and CDD Standards

The data used to derive a median weather trend are from 2000 to the reference year. AEMO has used the derived median weather standard for future HDD/CDD projections using a probabilistic methodology for a given region. This was calculated based on the following formulas:

$$\mathrm{AnnualHDD} = \mathrm{POE50}(\sum HDD_{365})$$

$$\mathrm{AnnualCDD} = \mathrm{POE50}(\sum CDD_{365})$$

where HDD_{365} is heating degree days over a 365-day period, based on a daily-rolling period starting from 1 January 2000 until the latest available data point in the reference year, and POE50 is where 50% Probability of Exceedance is expected for the given total heating/cooling degree days within that 365-day period.

Dry-bulb temperature (DBT) is the temperature measured by a thermometer freely exposed to air but shielded from radiation and moisture. DBT is equivalent to air temperature. In contrast, wet-bulb temperature (WBT) is the temperature read by a wet-bulb thermometer (a thermometer shrouded in a water-soaked cloth) over which air is passed. At 100% relative humidity, the wet-bulb temperature is equal to the air temperature (dry-bulb temperature) and is lower at lower humidity.

A2.3 Climate change

AEMO incorporated climate change into its minimum and maximum demand forecast as well as its annual consumption forecast. For the annual consumption forecast, average annual temperatures are increasing by a constant rate. However, half-hourly temperatures have higher variability and increasing extremes due to the higher frequency of the data.

AEMO collaborated with the BoM and CSIRO to develop a climate change methodology for the purpose of half-hourly demand forecasting. This process recognised that climate change is impacting temperature differently across the temperature distribution. Generally, higher temperatures are increasing by more than average temperatures which are increasing more than low temperatures. This results in higher extreme temperatures relevant to maximum demand.

The methodology adopted a quantile-to-quantile marching algorithm to statistically downscale publicly available daily minimum, mean and maximum temperature projects out to 20 to 50 years.

The methodology can be broken into six steps:

- Step 1. Collect climate projection data from www.climatechangeinaustralia.gov.au for weather stations relevant to the region.

[47] Kent Town station is anticipated to close permanently. Adelaide Airport weather station will be used for South Australia once Kent Town is unavailable.

- Step 2. Collect historical actual half-hourly weather station observations from the BoM and calculate the daily minimum, mean and maximum temperature.
- Step 3. Calculate the empirical temperature cumulative density function (CDF) in the projection period for the daily minimum, mean and maximum temperatures.
- Step 4. Calculate the empirical temperature CDF of the historical weather data for the daily minimum, median and maximum temperatures.
- Step 5. Match the temperature quantiles of the projected temperature distribution with the quantiles of the historical temperature distribution. Assign a scaling factor for each quantile for daily minimum, mean/median and maximum temperature.
- Step 6. Interpolate the daily minimum, mean/median and maximum scaling factor for each quantile down to the half-hourly level.

Step 1 – Collect daily temperature projection data

- Collect daily minimum and maximum temperature projection data from: https://www.climatechangeinaustralia.gov.au/en/climate-projections/explore-data/data-download/station-data-download/
- Collect data for each climate model:
  - ACCESS1-0, CanESM2, CESM1-CAM5, CNRM-CM5, GFDL-ESM2M, HadGEM2, MIROC5, NorESM1
- The mean temperature for each day is calculated (i.e., simple average equated as (daily minimum + daily maximum)/2).

Step 2 – Collect historical actual half-hourly temperature observations and calculate daily minimum, median and maximum

- Collect half-hourly temperature data for weather stations in each region relevant to the energy demand centres of those regions.
- Find the daily minimum, median and maximum temperatures.
- To ensure that the daily mid-point matches to an actual half-hourly value the median is used in place of the daily mean. As temperature is (normally) normally distributed the median should be roughly equal to the mean to within a fraction of a percent.

Step 3 – Calculate the empirical temperature CDF of projected daily temperatures data

- Set up an 11-year rolling window to account for variability in weather between different years including the 8 different weather models in the same window (in effect 8 * 11 years in the window).
- Rank the daily minimum, mean and maximum temperatures from lowest to highest for the 11-year window including the 8 weather models.
- Attribute a percentile to each temperature value in the forecast horizon.

Step 4 – Calculate the empirical temperature CDF of historical daily observations

- Set up an 11-year rolling window to account for variability in weather between different years.
- Rank the daily minimum, median and maximum temperatures from lowest to highest for the 11-year window.
- Attribute a percentile to each temperature value in history.

Step 5 – Map historical temperature quantiles to projected temperature quantiles and assign a scaling factor

- Map quantiles of the forecast model daily CDF onto quantiles of the historical CDF.

- Calculate a scaling factor for each quantile for daily minimum, mean/median and maximum temperatures.

Step 6 – Interpolate daily scaling factors to half-hourly and scale

- Rank the 48 half-hourly temperature observations for each day from the daily minimum to the daily mid-point and to the daily maximum.
- Interpolate the scaling factor for each half-hour.
- Scale up each historical half-hour for each historical weather year to match each projected weather years.

The final result is a table with dimensions $T_A \times T_H \times 17520$, where:

- T_h is the number of historical actual weather years;
- T_H is the number of projected weather years in the forecast horizon; and
- 17520 half-hourly data points in each weather year.

A3. Rooftop PV and energy storage

A3.1 Rooftop PV forecast

A3.1.1 Installed capacity forecast

AEMO's 2018 forecast of installed capacity for rooftop PV (installations with a capacity < 100 kW) was based on advice from external consultancy CSIRO, whose report provides details of the approach[48].

The main drivers behind the forecast rooftop PV uptake were:

- Financial incentives, such as Small Technology Certificates (STCs) and feed-in tariffs (FiTs).
- Installation costs, including both system/component costs and non-hardware "soft costs", including marketing and customer acquisition, system design, installation labour, permitting and inspection costs, and installer margins.
- The payback period considering forecast retail electricity prices and feed-in tariffs.
- Population growth across most states in Australia, allowing for more rooftop PV systems to be adopted before saturation is reached.

CSIRO forecast effective capacity, which is the capacity adjusted for degradation of panels over time. AEMO rebased the CSIRO forecast so the forecast starts from the most recent Clean Energy Regulator (CER) data.

A3.1.2 Rooftop PV generation

AEMO has developed, with the University of Melbourne, a rooftop PV generation model which, for each region, estimates the historical 30-minute generation of installed systems. The historical generation is based on weather data since 1 January 2000.

This model produces a measure of total generation, as well as the average generation of a notional 1 kW unit of capacity, with the average generation being the 50th percentile of the observed annual generation since 2000.

For each region, two profiles were calculated, one for north-facing PV panels and one for west-facing PV panels.

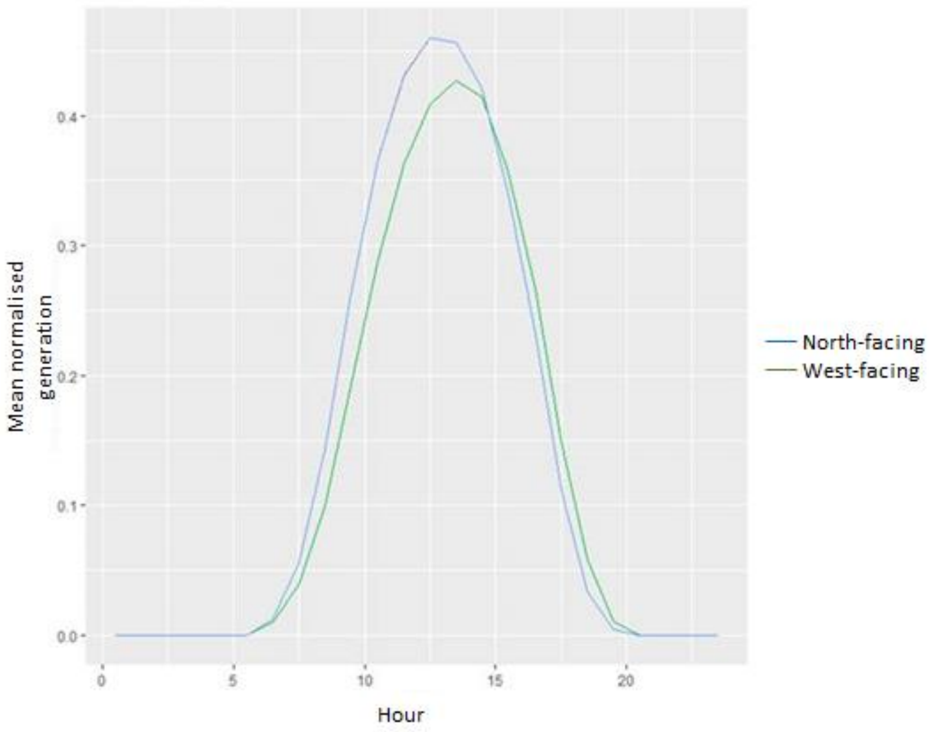
The generation profiles were used to calculate total rooftop PV generation in future years, by multiplying with the forecast effective rooftop PV capacity. The north-facing and west-facing profiles were blended, starting from purely the north-facing profiles. Further to this, AEMO has assumed that over time there will be a shift towards a more westerly shift in rooftop panel orientation, reaching 10% of the forecast effective capacity after 20 years. This reflects AEMO's assumptions that:

- As more and more solar generation is connected to the NEM, grid-supplied electricity will increase in cost, relative to the value of exporting rooftop PV generation to the grid around the time of the evening peak.

[48] CSIRO consultancy report "Projections for small-scale embedded technologies", available at http://www.aemo.com.au/Electricity/Planning/Forecasting.

- Consumer incentives will continue to evolve over the forecast period to reflect the lower value of generation mid-day and increasing value towards the evening peak.
- West-facing panels, which better align rooftop PV generation with the period of peak consumption and assumed higher energy cost, will remain economic for installation and use and add approximately 10% to generation output during the late afternoon compared to north-facing panels. As illustrated in Figure 9, west-facing panels generate around 15% less power at midday and 15% more power towards sunset relative to north-facing panels. The proportion of west-facing panels is estimated to reach 10% by 2027-28 so the change in PV output from west-facing panels will amount to around 1.5% at the time of maximum. This is immaterial relative to total operational demand.

Figure 12 North-facing vs west-facing PV generation



Source: Melbourne University

A3.2 Energy Storage Systems forecast

A3.2.1 Installed capacity forecast

The CSIRO provided AEMO's forecast of Energy Storage Systems (ESS). The ESS forecast is behind-the-meter residential and business batteries integrated with PV systems less than 100 kW. These forecasts do not include grid-connected batteries.

The main drivers for the ESS installed capacity forecast were:

- State and Federal incentive schemes.
- The payback period for integrated PV and ESS systems considering forecast retail prices.
- Population growth.
- The uptake of rooftop PV systems (as ESS is forecast as an integrated PV and ESS system)

A3.2.2 ESS charge discharge profile used in minimum and maximum demand

CSIRO also provided AEMO the daily charge and discharge profile for behind-the-meter ESS used in the minimum and maximum demand modelling. The profiles were based on historical solar irradiance (as ESS charges of the rooftop PV) and with the strategy to minimise household/commercial business bills without any concern for whether the aggregate outcome is also optimised for the electricity system. In the strategy, the consumer considers the price of electricity at the time, the feed-in-tariff to export to the grid, the retail price as well as the opportunity cost for the energy being available later in the day.

A3.2.3 ESS in annual consumption

For the purpose of annual consumption, ESS simply stores energy to use later – it does not generate energy like rooftop PV. So, ESS consumes energy due to its round-trip efficiency of around 90%. That is, for the amount of installed capacity in the system in kWh, ESS suffers 10% losses, effectively acting like consumption in a similar way as network losses. This load is accounted for in business and residential consumption forecasts.

A4. Electric vehicles

A4.1.1 Electric vehicles forecast

The CSIRO provided AEMO's forecast of electric vehicles (EVs), including residential, light commercial, and heavy commercial such as buses and trucks. The CSIRO report is available on AEMO's forecasting website[49].

The main drivers for the EV forecast were:

- Relative price between EV and alternatives.
- Payback period – EVs have higher upfront costs in the initial period of the forecast but lower "fuel" cost as kW per km.
- Level of increased ride sharing – reducing the number of vehicles.
- Battery and technology improvements.

A4.1.2 Electric vehicles charge profiles used in minimum and maximum demand

CSIRO also provided AEMO the daily charge and discharge profile for EVs used in the minimum and maximum demand modelling. The profiles were based on a study of around 1,000 vehicles in the UK and adjusted for Australian driving patterns and retail pricing structures.

CSIRO provided three different charge profiles:

- Convenience charging, where the average driver plugs their vehicle into charge as soon as they get home in the case of residential. This charge profile represents about a 40% diversity factor recognising that residential vehicles get home at different times of day.
- Smart day charge, where the assumption is made that vehicles are incentivised and able to charge in the middle of the day during the solar trough and avoiding charging during peak electricity demand times.
- Smart night charge – where the assumption is made that vehicles are incentivised and able to charge overnight outside of peak hours.

The charge profiles were used in the minimum and maximum demand simulation process.

A4.1.3 Electric vehicles annual consumption

For the purpose of annual consumption, EVs travel a certain number of kilometres in a year, with a certain level of efficiency per charge. The time of charge is not important when considering annual consumption.

[49] https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/NEM-Electricity-Statement-of-Opportunities (Accessed 21 February 2019)

A5. Connections and uptake of electric appliances

A5.1 Connections

As the retail market operator for most Australian electricity retail markets (except NT and TAS), AEMO has access to historical connections data for these markets, historical connections data for the other markets are acquired from a confidential survey. AEMO forecast the number of new connections to the electricity network, starting from the most recent data history, as this is a key driver for residential electricity demand. The number of new connections is driven by demographic and social factors like population projections and changes to household density.

The electricity connection forecasts were made up of two components, residential and non-residential electricity connection forecasts. AEMO only used the residential electricity connections to forecast residential sector consumption. The non-residential component was captured by the commercial sector which is driven by economic indicators. Therefore, AEMO underwent a process of splitting the residential connections projections from the non-residential connections[50].

Residential electricity connections are determined by:

- Forecasting the total number of households for each state:
  - To forecast the number of households for each state, AEMO projected the number of dwellings based on the Housing Industry Association (HIA) dwelling completion forecasts and the Australian Bureau of Statistics (ABS) population and density forecasts.
  - The starting point was the current number of residential connections as reported by network businesses, used as proxy for households. The HIA growth forecasts were applied to the historical number of households from the previous year, with HIA's forecasts implemented for the short-term forecast (the first three years) before transitioning into the ABS population and density forecasts over the medium to long-term.
- Forecasting the number of residential electricity connections. The total number of electricity connections was assumed to be a single connection for each household over the outlook period. This assumption appears to be consistent with the historical number of electricity connections of each network operator for each state.

HIA forecasts have been slightly modified by AEMO so that the long-term growth rate converges smoothly into the growth rate of the long-term ABS population projections.[51] HIA provided forecasts for the period

[50] Residential connections forecasts are available on AEMO's Forecasting Data Portal. Please see http://forecasting.aemo.com.au.

[51] Australian Bureau of Statistics, 2013, Population Projections, Australia 2012 (base), cat. no. 3222.0.

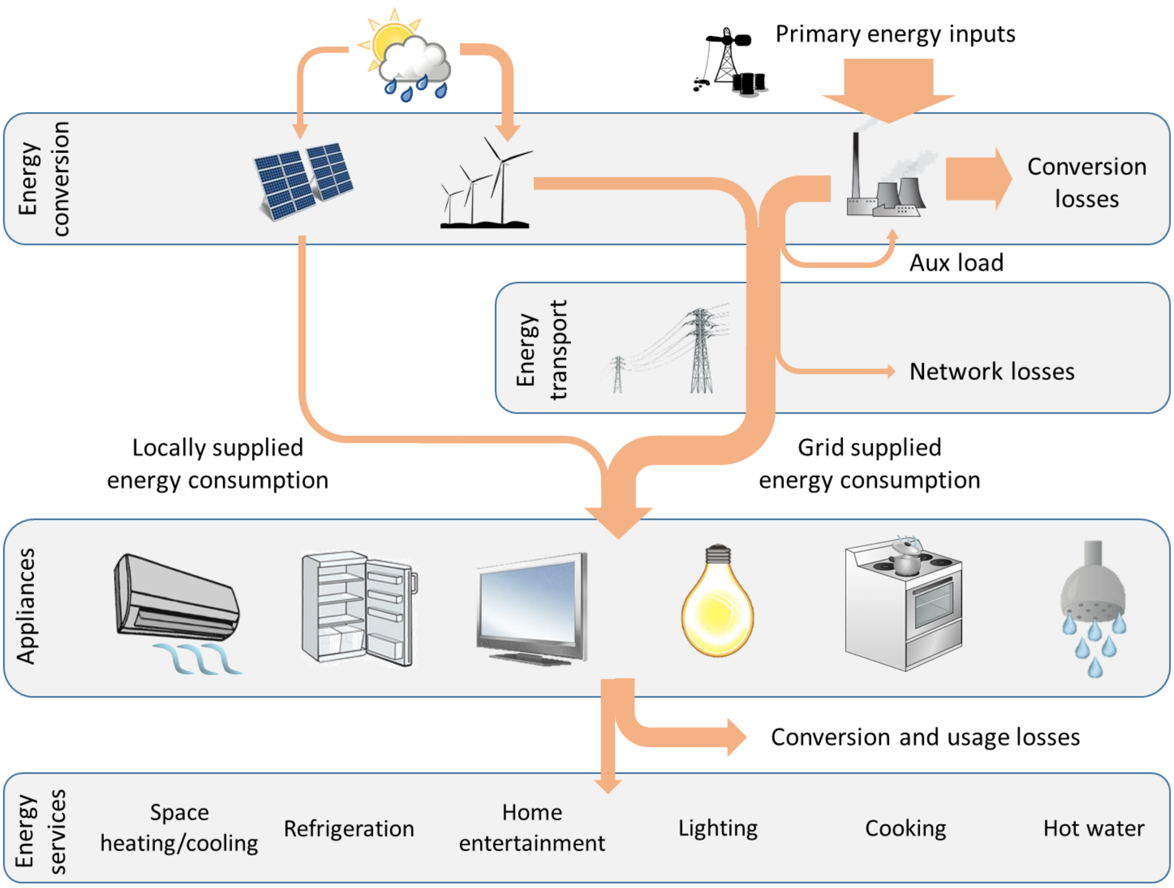
2018-19 to 2025-26. Beyond 2026, the number of connections was forecast using the same year-on-year growth rate as the ABS population projections.

A5.2 Uptake and use of electric appliances

AEMO uses appliance data from the Australian Government Department of the Environment and Energy[52] to forecast growth in electricity consumption by the residential sector.

The data allowed AEMO to estimate changes to the level of energy services supplied by electricity per households across the NEM. Energy services here is a measure based on the number of appliances per category across the NEM, their usage hours, and their capacity and size. Figure 13 illustrates the difference between energy services and energy consumption.

Figure 13 Energy services vs energy consumption



A5.2.1 Appliance growth calculation

The following lists how AEMO calculates energy services by appliance group per connection. "Appliance penetration" is the number of appliances in total divided by the number of connections.

- Heating/cooling: Appliance penetration × output capacity of appliance × hours used per year.

[52] AEMO would like to thank the E3 Committee for access to the appliance model underpinning the 2015 *Residential Baseline Study for Australia 2000 – 2030*, available at: www.energyrating.com.au.

- White goods: Appliance penetration × capacity (volume of freezer/refrigerators/washing machine) × number of times used per year (dishwashers, washing machines and dryers only).
- Home entertainment: Number of appliances × hours used per year × size (TVs only).
- Lighting: Number of light fittings.
- Cooking: Appliance penetration.
- Hot water: Appliance penetration.

The calculated demand for energy services by appliance group is converted into a growth index with the reference year of the consumption forecast being the base year (index = 100). These indices are combined into a composite index for all appliances based on their relative estimated energy consumption in the base year. As the index captures the benefits to users from the appliance use, it is also referred to as the benefits index.

The table below shows the appliances covered by the calculations.

Table 15 List of appliance categories used in calculating the appliance growth index

Demand type	Category	Group
Heating/cooling load	Combined space heating/cooling	AC ducted
Heating/cooling load	Combined space heating/cooling	AC non-ducted (split and window/wall units)
Heating/cooling load	Space cooling	Evaporative (mostly central)
Heating/cooling load	Space cooling	Fans
Heating/cooling load	Space heating	Electric resistive
Heating/cooling load	Space heating	Mains gas non-ducted
Heating/cooling load	Space heating	Mains gas ducted
Heating/cooling load	Space heating	LPG gas non-ducted
Heating/cooling load	Space heating	Wood Heaters
Base load	White goods	Refrigerators
Base load	White goods	Freezers
Base load	White goods	Dishwashers
Base load	White goods	Clothes washers
Base load	White goods	Clothes dryers
Base load	IT & Home Entertainment	Television – composite average
Base load	IT & Home Entertainment	Set-top box – free-to-air
Base load	IT & Home Entertainment	Set-top box – subscription
Base load	IT & Home Entertainment	Video players and media recorders
Base load	IT & Home Entertainment	Home entertainment – other (mostly audio)
Base load	IT & Home Entertainment	Game consoles
Base load	IT & Home Entertainment	Computers – desktop
Base load	IT & Home Entertainment	Computers – laptop
Base load	IT & Home Entertainment	Monitors (used with desktop computers)
Base load	IT & Home Entertainment	Wireless/Wired networked device
Base load	IT & Home Entertainment	Miscellaneous IT equipment

Demand type	Category	Group
Base load	Lighting	MV incandescent
Base load	Lighting	MV halogen
Base load	Lighting	ELV halogen
Base load	Lighting	CFL
Base load	Lighting	Linear fluorescent
Base load	Lighting	LED
Base load	Cooking Products	Upright – Electric
Base load	Cooking Products	Cooktop – Electric
Base load	Cooking Products	Oven – Electric
Base load	Cooking Products	Upright – Gas
Base load	Cooking Products	Cooktop – Gas
Base load	Cooking Products	Oven – Gas
Base load	Cooking Products	Upright – LPG
Base load	Cooking Products	Cooktop – LPG
Base load	Cooking Products	Oven – LPG
Base load	Cooking Products	Microwave
Base load	Hot water heaters	Electric water heater, storage – small
Base load	Hot water heaters	Electric water heater, storage – medium/large
Base load	Hot water heaters	Electric water heater, instant
Base load	Hot water heaters	Gas water heater, storage (mains)
Base load	Hot water heaters	Gas water heater, storage (LPG)
Base load	Hot water heaters	Gas water heater, instant (mains)
Base load	Hot water heaters	Gas water heater, instant (LPG)
Base load	Hot water heaters	Solar electric
Base load	Hot water heaters	Solar gas
Base load	Hot water heaters	Heat pump
Base load	Hot water heaters	Wood, wetbacks
Base load	Other Equipment	Pool Equipment - Electric
Base load	Other Equipment	Pool Equipment - Gas
Base load	Other Equipment	Pumps
Base load	Other Equipment	Battery chargers
Base load	Other Equipment	Miscellaneous
Base load	Other Equipment	Class 2 Common Areas

A5.2.2 Difference between scenarios

In addition to forecast changes in appliance uptake and use for known appliance categories, AEMO adds to the composite index a small increase in growth from “new” appliance types/categories (not shown specifically in Table 15), representing yet unknown technologies that are expected to enter the market over the forecast period and affect electricity demand. The three scenarios have different assumptions of how much these new and yet unknown appliances would add to the composite appliance growth index.

A6. Data sources

Table 16 ANZSIC code mapping for industrial sector disaggregation

ANZSIC division ID	ANZSIC division name	AEMO sector category
A	Agriculture, Forestry and Fishing	Other
B	Mining (including CSG)	Other
C	Manufacturing	Manufacturing
D	Electricity, Gas, Water and Waste Services	Other
E	Construction	Other
F	Wholesale Trade	Other
G	Retail Trade	Other
H	Accommodation and Food Services	Other
I	Transport, Postal and Warehousing	Other
J	Information Media and Telecommunications	Other
K	Financial and Insurance Services	Other
L	Rental, Hiring and Real Estate Services	Other
M	Professional, Scientific and Technical Services	Other
N	Administrative and Support Services	Other
O	Public Administration and Safety	Other
P	Education and Training	Other
Q	Health Care and Social Assistance	Other
R	Arts and Recreation Services	Other
S	Other Services	Other

Table 17 Historical and forecast input data sources

Data series	Data sources	Reference	Notes
Historical Consumption data by region	AEMO Database	http://forecasting.aemo.com.au/	Actuals derived from aggregate of these sources are reported and available on our forecasting data portal
Historical Consumption data by industry sector	AEMO Database	http://forecasting.aemo.com.au/	Actuals derived from aggregate of these sources are reported and available on our forecasting data portal
Large Industrial Historical Consumption data by region	Transmission & Distribution, Industrial Surveys	http://forecasting.aemo.com.au/	Actuals derived from aggregate of these sources are reported and available on our forecasting data portal

Data series	Data sources	Reference	Notes
Residential and Commercial Historical Consumption data by region	AEMO Database (for Victoria) Distribution businesses (other regions)	http://forecasting.aemo.com.au/	Actuals derived from aggregate of these sources are reported and available on our forecasting data portal
Weather & Climate Change Data	BOM	http://www.bom.gov.au/	
Weather & Climate Change Data	CSIRO	https://www.csiro.au/	
Weather & Climate Change Data	Climate Change Australia	https://www.climatechangeinaustralia.gov.au/	
Household Forecasts	Housing Industry Association	https://www.hia.com.au	AEMO uses the new dwelling completion forecasts from HIA.
Historical Number of NMIs	AEMO Database	http://forecasting.aemo.com.au/	Actuals derived from aggregate of these sources are reported and available on our forecasting data portal
ABS Population Forecasts	ABS	http://www.abs.gov.au/AUSSTATS/abs@.nsf/allprimarymainfeatures/5A9C0859C5F50C30CA25718C0015182F?opendocument	AEMO uses population growth projections series A (Fast change scenario); series B (Neutral scenario); series C (Slow change scenario)
Demographic and Economic Data	ABS	http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/5206.0Mar%202014?OpenDocument	Population, Gross State Product, Household Disposable Income, Input Producer Price Index,
Economic Data	Economic Consultancy	http://forecasting.aemo.com.au/	Economic projections were developed by an economic consultant, according to AEMO's scenario requirements
Wholesale Electricity Price	AEMO Database	https://aemo.com.au/Electricity/National-Electricity-Market-NEM/Data-dashboard#aggregated-data	
Transmission losses	AEMO database (Victoria); Transmission businesses (other regions)	https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Security-and-reliability/Loss-factor-and-regional-boundaries	
Distribution losses	AEMO database (Victoria); Distribution businesses (other regions)	https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Security-and-reliability/Loss-factor-and-regional-boundaries	
Operational demand	AEMO database (Victoria), Transmission businesses where permission has been granted	http://forecasting.aemo.com.au/	Actuals derived from aggregate of these sources are reported and available on our forecasting data portal

A7. Data segmentation

AEMO used a combination of Residential to Business annual percentage splits (provided to AEMO by the Australian Energy Regulator) and its own meter data classification to calculate the half-hourly Residential and Business split for the latest year of actual consumption. This forms the starting point for the forecasting process. This segmentation process delivered:

- Delivered consumption.
- Underlying consumption.

For the definition of the consumption types see Section 1.1.

A7.1 AER residential to business splits

The Australian Energy Regulator (AER) annually surveys Distribution Network Survey Providers and from this provides AEMO with Residential to Business sector annual splits of distribution connected delivered consumption for the latest financial year of data available. AEMO used this to derive annual consumption targets to calibrate to when performing half-hourly splits between residential and business sector consumption. The configuration and execution of the separate business and residential forecast models, - with their different demand drivers – will determine the total for the business and residential components for each subsequent period in the forecast.

A7.2 AEMO meter data and half-hourly profile

Since the introduction of smart metering technology in 2003, there has been varied adoption of smart meters across states. While all meters in Victoria have been transitioned to smart meters, in other states there are still many households and smaller businesses on basic meters.

The key distinction is that smart meter reads give actual recording of delivered consumption at the half-hourly level while basic meters are read quarterly and require some estimation to interpolate into half-hourly delivered consumption. Typically, most basic meter customers are residential customers while most businesses have transitioned to smart meters (also known as interval meters).

With this assumption in mind, AEMO preserved the profile of business half-hourly data over a financial year (as it was deemed more accurate), but determined the profile of the residential half-hourly data by taking the difference between the total grid consumption half-hourly profile (derived from the metred half hourly operational demand data) and the business half-hourly profile.

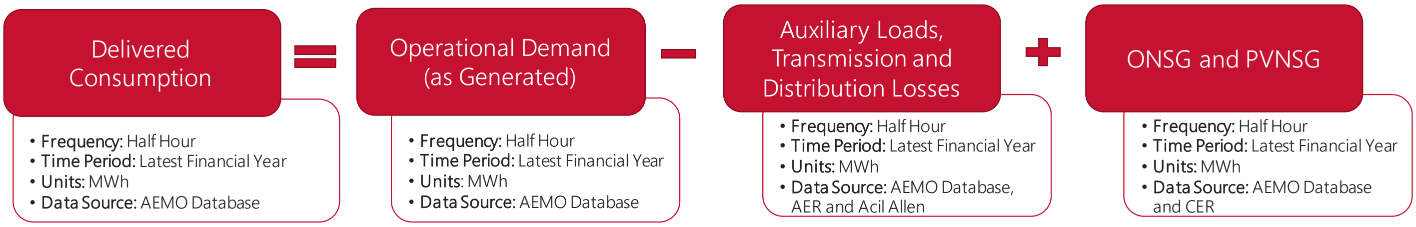
Business Half-hourly data

In 2015 AEMO conducted a meter data analytics study to refine the classification of its business meters. While it is not possible to capture all business sector meters, the bulk of the business delivered consumption was captured by querying AEMO's database and then scaling up to meet the target annual business delivered consumption, derived by applying AER's business percentage to AEMO's total delivered annual consumption.

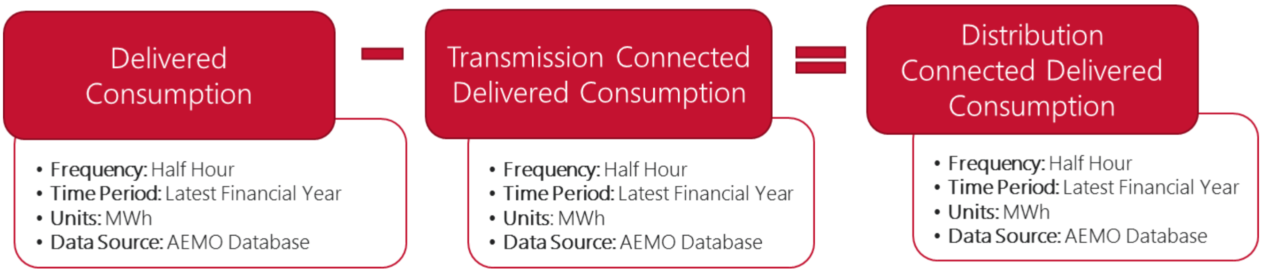
A7.3 Methodology

Stage 1: Developing residential to business delivered consumption split

Calculate delivered consumption to energy users from the metered operational demand (as generated) data, netting off auxiliary load and distribution and transmission losses and adding in the small non-scheduled generation (PVNSG and ONSG):

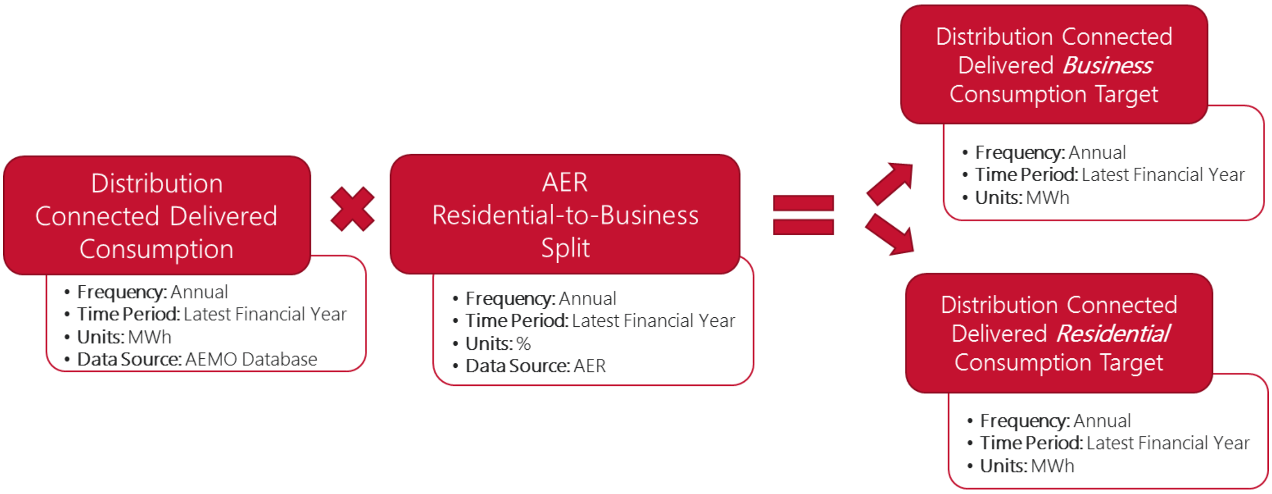


Translate AEMO half-hourly meter data into distribution connected delivered consumption:



Transmission connected consumption was assumed to be business load, and was separated from the total demand to keep AEMO's meter data on the same basis as the AER's percentage splits.

Aggregate AEMO half-hour data to financial year data and apply AER split to obtain annual target:



Calculate business scaling factor and scale half-hourly business delivered data to annual target:

Distribution Connected Delivered Business Consumption Target ÷ **Unscaled Distribution Connected Business Delivered Consumption** = **Business Scaling Factor**

Distribution Connected Delivered Business Consumption Target:
- **Frequency:** Annual
- **Time Period:** Latest Financial Year
- **Units:** MWh
- **Data Source:** Derived in previous step

Unscaled Distribution Connected Business Delivered Consumption:
- **Frequency:** Annual
- **Time Period:** Latest Financial Year
- **Units:** MWh
- **Data Source:** AEMO Database

Business Scaling Factor:
- **Frequency:** Annual
- **Time Period:** Latest Financial Year
- **Units:** Number

The unscaled distribution-connected business delivered consumption is the aggregate consumption of the known business sector meters (for more detail see *Business Half-hourly data* above). This consumption was summed to the annual level and the total delivered business consumption annual target (derived in the previous step) was divided by this unscaled business consumption to get a scaling factor. This scaling factor was applied to the half-hour frequency unscaled business delivered consumption to get the total half-hour distribution connected delivered business consumption. In this way, AEMO preserves the business sector half hourly profile and calibrates to an annual target to capture any missing business sector meters.

Business Sector Scaling Factor × **Unscaled Distribution Connected Business Delivered Consumption** = **Distribution Connected Business Delivered Consumption**

Business Sector Scaling Factor:
- **Frequency:** Annual
- **Time Period:** Latest Financial Year
- **Units:** Number

Unscaled Distribution Connected Business Delivered Consumption:
- **Frequency:** Half Hour
- **Time Period:** Latest Financial Year
- **Units:** MWh
- **Data Source:** AEMO Database

Distribution Connected Business Delivered Consumption:
- **Frequency:** Half Hour
- **Time Period:** Latest Financial Year
- **Units:** MWh

Calculate business half-hourly delivered consumption:

Distribution Connected Business Delivered Consumption + **Transmission Connected Delivered Consumption** = **Business Delivered Consumption**

Distribution Connected Business Delivered Consumption:
- **Frequency:** Half Hour
- **Time Period:** Latest Financial Year
- **Data Source:** AEMO Database

Transmission Connected Delivered Consumption:
- **Frequency:** Half Hour
- **Time Period:** Latest Financial Year
- **Data Source:** AEMO Database
- **Details:** These are industrial loads

Business Delivered Consumption:
- **Frequency:** Half Hour
- **Time Period:** Latest Financial Year
- **Data Source:** AEMO Database

Note that all transmission-connected loads are heavy industrial users and fall in the business category.

Calculate residential half-hourly delivered consumption:

Distribution Connected Delivered Consumption − **Distribution Connected Delivered Business Consumption** = **Residential Delivered Consumption**

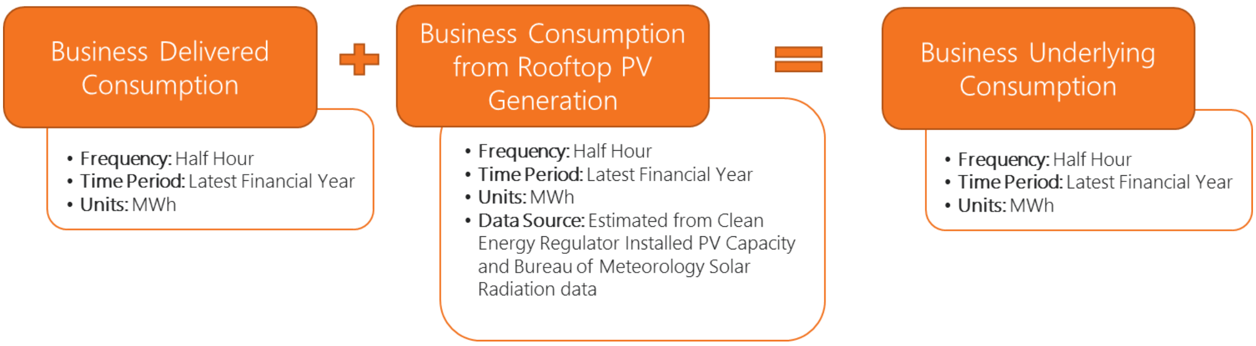
Distribution Connected Delivered Consumption:
- **Frequency:** Half Hour
- **Time Period:** Latest Financial Year
- **Units:** MWh
- **Data Source:** AEMO Database

Distribution Connected Delivered Business Consumption:
- **Frequency:** Half Hour
- **Time Period:** Latest Financial Year
- **Units:** MWh
- **Data Source:** AEMO Database

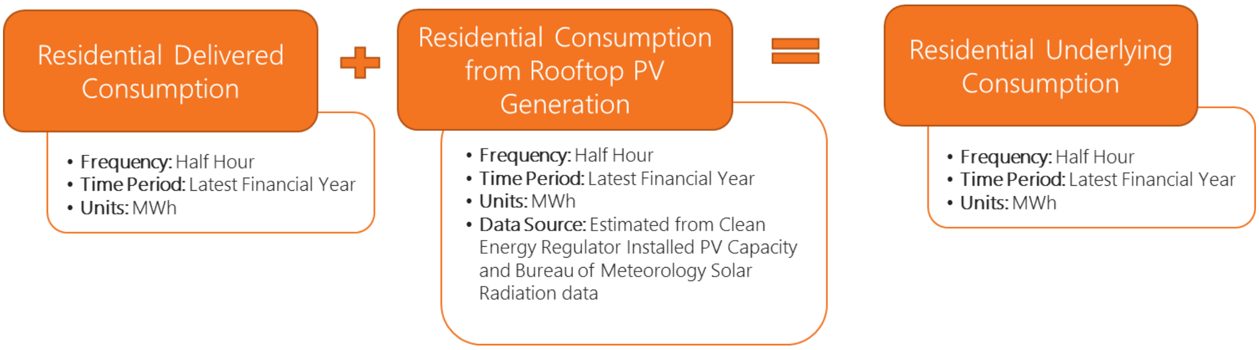
Residential Delivered Consumption:
- **Frequency:** Half Hour
- **Time Period:** Latest Financial Year
- **Units:** MWh
- **Data Source:** AEMO Database

Stage 2: Developing Residential to Business Underlying Consumption Split

Calculate business underlying consumption:



Calculate residential underlying consumption:

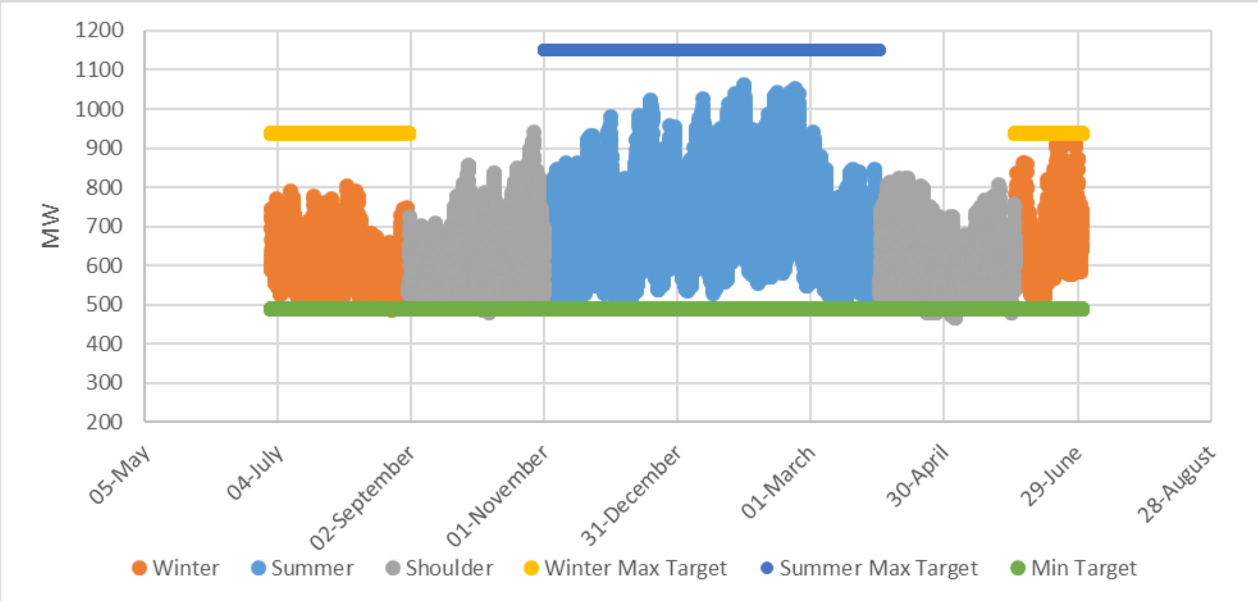


A8. Demand Trace Scaling Algorithm

This appendix provides a worked example of how half-hourly demand traces are scaled for the outlook period. The method is described in Section 6.

The example begins with a financial-year time series of demand to be scaled to predefined targets. It has been prepared by taking demand from a reference year and converting the values to OPSO-lite (removing influence of PV, other non-scheduled generation, CSG, ESS and EVs). The example trace is presented in Figure 14.

Figure 14 Prepared trace



The targets are summarised in Table 18. All targets represent an increase to the reference trace.

Table 18 Prepared trace and targets

	Prepared trace	Target	Unit
Summer Max	1063.231	1148.29	MW
Winter Max	911.79	938.33	MW
Minimum	466.695	488.695	MW
Energy	5733.727	6364.407	GWh

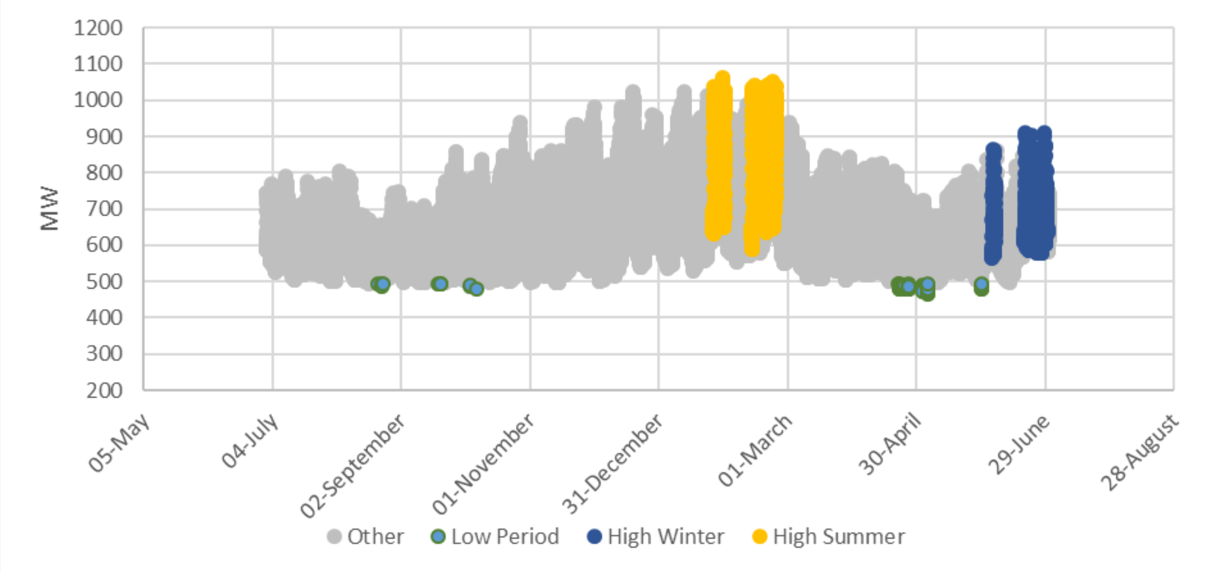
The series is categorised into *n* highest-demand days in summer (using daily maximum as the reference), *n* highest demand days in winter, *p* lowest demand periods. In this example,

n = 10 days

p = 70 periods

The day-type categorisation is displayed in Figure 15.

Figure 15 Day-type categories



Day swapping is then performed to exchange weekend and holiday dates between the reference year and the forecast year. In this example, day swapping is assumed to have taken place.

Scaling then commences. The demand, categorised into day-types, is scaled according to the ratios in Table 19. The ratios are calculated as *target / prepared trace* using the information from Table 18.

Table 19 Scaling ratios

Day-type category	Prepared trace	Unit	Target/Base ratio
Summer high days	169.81	GWh	1.080000
Winter high days	166.53	GWh	1.029108
Low periods	35.37	GWh	1.047140

The scaling ratios for the key day-type categories are based on maximum or minimum demand targets therefore the maximum demand and minimum demand targets are met by applying this process. Nevertheless, energy still needs to be addressed further. Application of the scaling factors results in the energy and demand presented in Table 20 and the remaining energy difference is calculated as the *target minus the current grown total*.

Table 20 Resulting Energy and demand

	Resulting GWh	Units
Summer high days	183.40	GWh
Winter high days	171.38	GWh
Low periods	37.04	GWh
Remaining energy difference	610.58	GWh

The remaining energy difference from Table 20 equates to an 11.38% increase on the 'other' category's energy. This is applied to the demand in the other category and the targets are checked. The check is summarised Table 21 and the grown trace is plotted in Figure 16.

Figure 16 Grown trace and targets

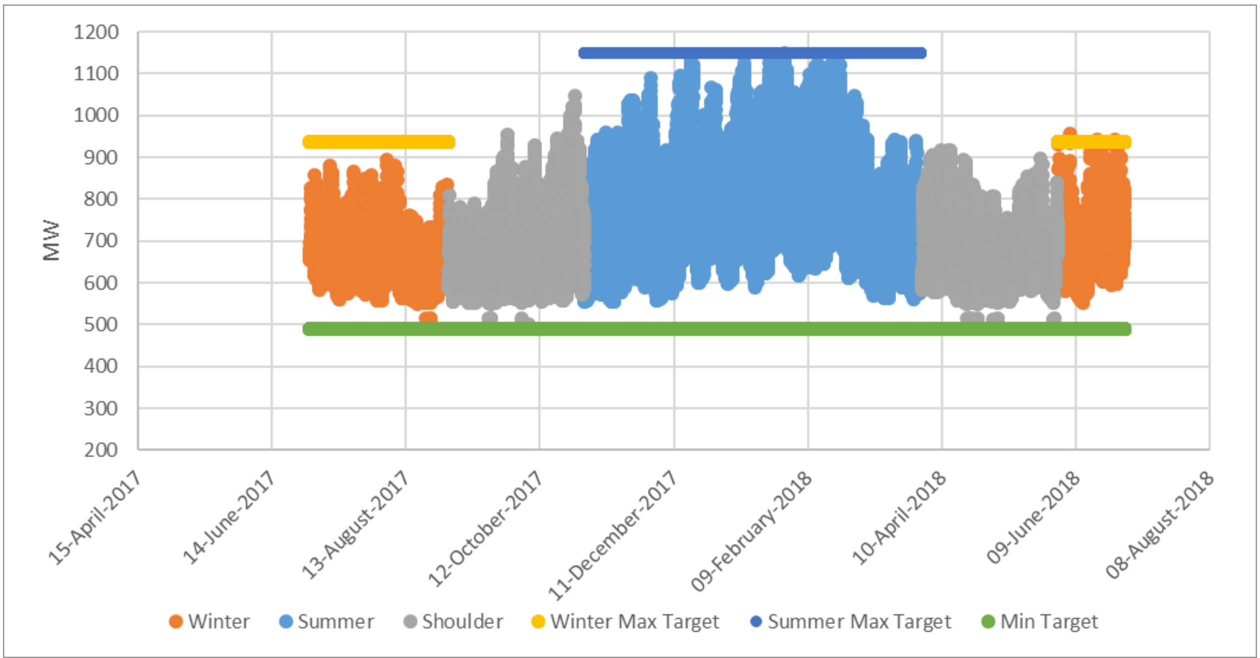


Table 21 Check of grown trace against targets

	Base trace	Target	Grown	Units
Summer Max	1063.231	1148.29	1148.29	MW
Winter Max	911.79	938.33	**957.54**	MW
Minimum	466.695	488.695	488.695	MW
Energy	5733.727	6364.407	6364.407	GWh

The check summarised in Table 21 uncovers an inconsistency between the grown winter maximum and the target (bold highlight). This was caused by the allocation of energy in the 'other' category which increased some winter values above the initial peak.

In accordance with the methodology, the process is repeated until the targets are met.

Following completion of this first-pass growing process, and in accordance with the methodology, the technology components are added back to the trace to derive the unreconciled OPSO trace. Each component-trace is prepared to reflect the forecast capacities or numbers in the target year and the nominal or normalised power trace (from the reference year). In this way, the influence of PV, other non-scheduled generation, CSG, ESS and EVs is appropriately applied to each half hour to derive the unreconciled OPSO trace.

The growing process is then repeated on the unreconciled OPSO trace as per the 'second pass' of the methodology. Demand and energy targets are changed accordingly to reflect demand being on the OPSO basis.

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Abbreviations

Abbreviation	Full name
ABS	Australian Bureau of Statistics
AER	Australian Energy Regulator
BoM	Bureau of Meteorology
CD	Cooling degree
CDD	Cooling degree day
CDF	Cumulative density function
CER	Clean Energy Regulator
COP	Coefficient of performance
CSG	Coal seam gas
DER	Distributed energy resource
DSP	Demand side participation
DBT	Dry bulb temperature
EDA	Exploratory data analysis
EDD	Effective degree day
ESS	Energy storage systems
EV	Electric vehicle
FiTs	Feed-in tariffs
GFC	Global Financial Crisis
GWh	Gigawatt hours
HD	Heating degree

Abbreviation	Full name
HIA	Housing Industry Association
HDD	Heating degree day
ISP	Integrated System Plan
KW	Kilowatts
LIL	Large industrial loads
LNG	Liquefied natural gas
MD	Maximum demand
MMS	Market Management System
MW	Megawatts
NEM	National Electricity Market
NMI	National meter identifier
NSG	Non-scheduled generation
OLS	Ordinary least squares
ONSG	Other non-scheduled generators
OPSO	Operational demand as sent out
POE	Probability of exceedance
PVNSG	PV non-scheduled generators
PVROOF	Rooftop PV
STCs	Small-scale technology certificates
VPP	Virtual power plant
WBT	Wet bulb temperature