Electricity Demand Forecasting Methodology Information Paper

August 2020

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 demand in the Wholesale Electricity Market (WEM) in Western Australia.

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VERSION CONTROL

Version	Release date	Changes
1	27/8/2020	Initial release of the 2020 demand forecasting methodologies

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1. Introduction

AEMO produces independent customer electricity demand forecasts for use in publications such as the Electricity Statement of Opportunities (ESOO) and the Integrated System Plan (ISP). These forecasts provide projections of customer connections, customer technology adoption, electricity consumption, maximum and minimum demand over a forecast period up to 30 years for each region of the National Electricity Market (NEM) and up to 10 years for the Wholesale Electricity Market (WEM). This report outlines the forecasting methodologies in use.

1.1 Forecasting principles

AEMO is committed to producing quality forecasts that support informed decision-making. For decision-makers to act on forecasts, they must be credible and dependable. Forecasting principles help guide the multitude of decisions that need to be made towards this goal. Principles guide choices about how the forecasts are done, particularly where there are trade-offs in outcome. For example, simplicity versus comprehensiveness, speed versus insight.

To achieve this, AEMO's forecast team work to three main objectives:

1. **Transparency – to ensure inputs and forecast methodologies are well understood.**
   - AEMO consults broadly to develop scenario inputs and model methodologies. This document further aims to improve adequate stakeholder understanding of the methodologies deployed.
2. **Accountability – to measure forecasting performance, refine and improve where issues are detected.**
   - AEMO monitors the accuracy of past forecasts by comparing actual data against forecasted data. Forecasting accuracy reports[1] explore both the levels of accuracy and any causes of inaccuracy and have generated numerous process improvements.
3. **Accuracy – to adopt best practise methodologies and monitor lead indicators of change.**
   - AEMO employs good practises, such as developing clear work instructions, clearly identifying information sources and using best practise model development techniques.

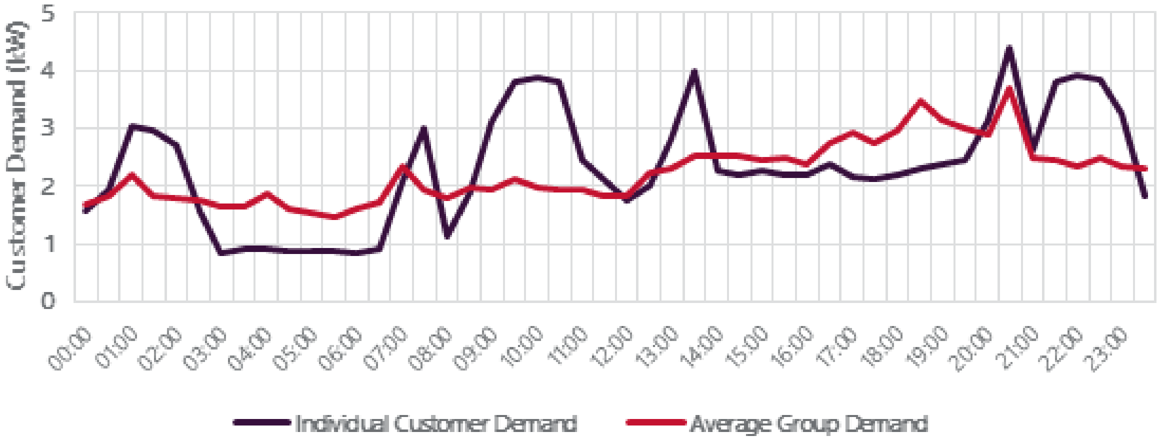
1.2 Modelling consumer behaviour

Individual consumers do not behave consistently every day and can sometimes behave unpredictably. Even on days with identical weather, the choices of individuals are not identical, and reflect the lifestyle of the household, or operation of the business. It is only when customer electrical demand is aggregated to a regional level that the group behaviour becomes more predictable. This is because the group demand largely cancels out the idiosyncratic behaviour of the individual.

[1] Forecasting accuracy reports can be found at https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/Forecasting-Accuracy-Reporting

Figure 1 shows the load profile of an individual customer, compared to the average of a group of similar customers. While the load profile of the individual is spikey and erratic, the group profile has smoothed out some of idiosyncrasies of the customer.

Figure 1 Example individual and group demand shown on one day

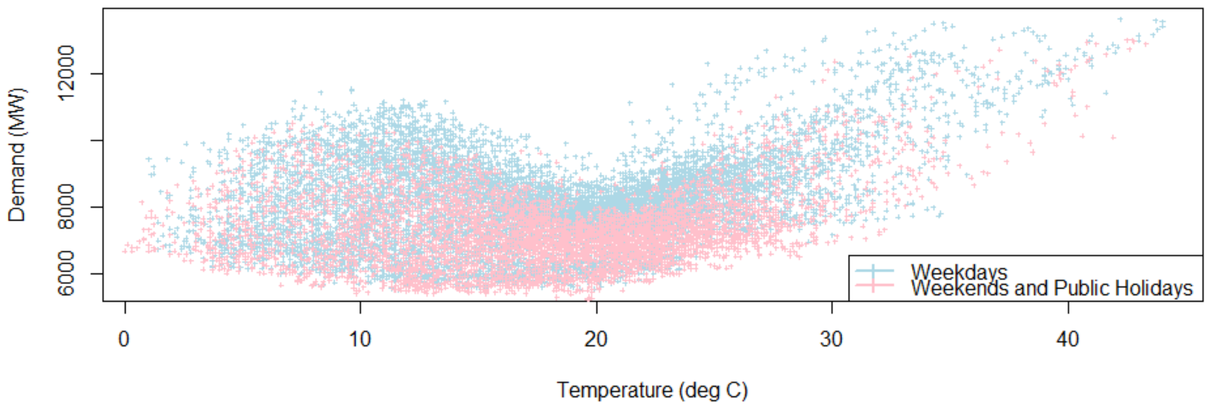


Although demand becomes more predictable when aggregated, it remains a function of individual customer decisions. Periods of high demand only become so because individual customers choose to do the same things at the same time. Peak demand is therefore driven by the degree of coincident appliance use across customers, across regions. There are many factors that drive customers to make similar appliance choices at the same time including:

- Work and school schedules, traffic and social norms around meal times.
- Weekdays, public holidays, and weekends.
- Weather, and the use of heating and cooling appliances.
- Many other societal factors, such as whether the beach is pleasant, or the occurrence of retail promotions.

Figure 2 shows a scatter plot of temperature and electrical load. A strong relationship between temperature and group electrical load can be seen, however the relationship cannot explain all variations. Even when all observable characteristics are considered, the variance attributable to coincident customer choices remains.

Figure 2 Scatterplot of New South Wales demand and temperature, example based on 2017 calendar year



It is standard industry practise to model the drivers of demand in two parts:

- Structural drivers, which are modelled as scenarios, including considerations such as:
  - Population.
  - Economic growth.
  - Electricity price.
  - Technology adoption.
  - Atmospheric greenhouse gas concentration.
- Random drivers, which are modelled as a probability distribution, including considerations such as:
  - Weather-driven coincident customer behaviour.
  - Weather-driven embedded generation output.
  - Non-weather-driven coincident customer behaviour.

The methods deployed by AEMO are consistent with standard industry practice, in that:

- numerous scenarios are developed to test uncertainty in structural drivers.
- maximum and minimum demand forecasts use probability distributions to describe uncertainty in random drivers.

Consumption and demand forecasts are based on aggregated customer segments:

- **Residential**: residential customers only.
- **Business**: includes industrial and commercial users. This sector is categorised into large industries and small/medium sized businesses (subcategorised further in accordance with Section 2) as follows:
  - **Large industrial loads (LIL)**, including transmission-connected facilities, and
  - **Small/medium businesses**, covering any distribution connected loads not included in the LIL category.

1.3 Key definitions

AEMO forecasts are reported as[2]:

- **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 megawatts (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.

[2] More definition information is at https://www.aemo.com.au/-/media/files/electricity/nem/security_and_reliability/dispatch/policy_and_process/2020/demand-terms-in-emms-data-model.pdf.

  - 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.[3]
  - Intermittent Loads in Western Australia[4].
- **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 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.
- **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:

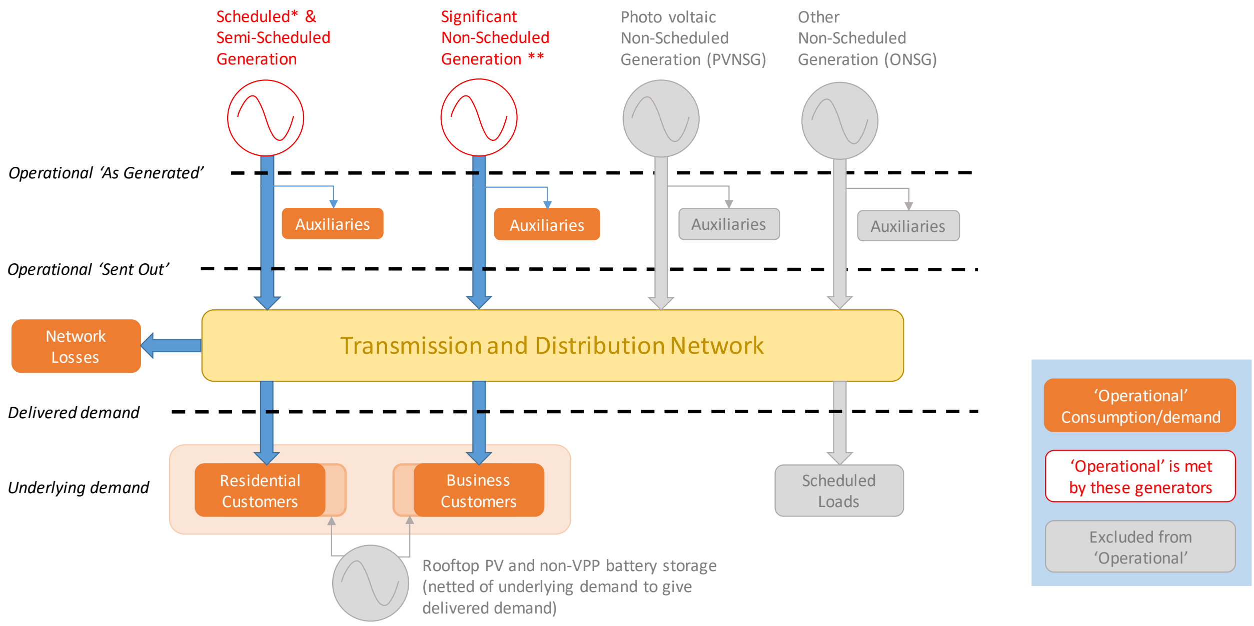
- **Probability of Exceedance (POE)**: POE is the likelihood a maximum or minimum demand forecast will be met or exceeded. A 10% POE maximum demand forecast, for example, is expected to be exceeded, on average, one year in 10, while a 90% POE maximum demand forecast is expected to be exceeded nine years 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.
- **Electric Vehicle (EV)**: EVs are residential and business battery powered vehicles, ranging from small residential vehicles such as motor bikes or cars to large commercial trucks

Figure 3 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 customer electricity consumption plus distribution and transmission losses minus rooftop PV, PVNSG and ONSG.

[3] Registering a Battery System in the NEM – Fact Sheet is at https://aemo.com.au/-/media/Files/Electricity/NEM/Participant_Information/New-Participants/battery_fact_sheet_final.pdf.

[4] Intermittent Loads are electricity loads that have behind the fence generation that are also connected to the grid. On occasion, these loads draw electricity from the grid.

Figure 3 Operational demand/consumption definition



* Including VPP from aggregated behind-the-meter battery storage.

** For definition, see: https://www.aemo.com.au/-/media/files/electricity/nem/security_and_reliability/dispatch/policy_and_process/2020/demand-terms-in-emms-data-model.pdf.

1.4 Changes since the previous version of this methodology

This is the 2020 version of AEMO's Electricity Demand Forecasting Methodology Information Paper. It was last refreshed with the 2019 ESOO, in August 2019.

Since that publication, AEMO has updated its forecasts in accordance with data updates, as outlined in the companion Inputs, assumptions and scenarios report (IASR)[5]. In addition to data updates, AEMO has updated the methodologies applied to forecast electricity consumption, maximum and minimum demand as follows:

Continuous improvements to existing methodologies:

- **Business annual electricity consumption forecast:** As outlined in the Forecast Accuracy Report, AEMO improved its business consumption forecast model by forecasting the small-medium enterprise (SME) sector with reference to a near-term trend in consumption, before extending to a longer term forecast approach. The addition of the near-term trend method was outlined as a key improvement to ensure that the short term dynamics and a transition to the scenario conditions affecting energy consumption were reflected in the forecast, before economic and technical fundamentals produce the longer term trajectory.
- **Large industrial loads associated with water infrastructure facilities**: This sector has been improved in the 2020 forecast by identifying and including additional existing desalination facilities that were not explicitly included within the 2019 forecast.
- **Distributed PV uptake forecasts:** As outlined in the 2019 Forecast Accuracy Report[6], distributed PV installations have exceeded previous estimates as customer investment in DER has outpaced recent expectations. AEMO and its DER consultants – CSIRO and Green Energy Markets in 2020 – explicitly sought to improve the PV forecasts. For CSIRO, this included greater consideration of the near-term trend as an explicit short term model (conceptually similar to the SME forecast trend model described above). GEM's forecasts also consider installer surveyed market intelligence. In working with the DER consultants,

[5] AEMO, 2020 Inputs, Assumptions and Scenarios Report, at https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/Inputs-Assumptions-and-Methodologies.

[6] At https://aemo.com.au/en/energy-systems/electricity/national-electricity-market-nem/nem-forecasting-and-planning/forecasting-and-reliability/forecasting-accuracy-reporting

AEMO also received the latest information available at the time from the Clean Energy Regulator (CER) to assist in model calibration.

- **Updated appliance index and dwelling forecast:** AEMO has developed an improved, updated residential and appliance stock model to ensure appropriate consideration of building age, size and building material quality informs the forecasts of energy efficiency and connections forecasts.
- **Maximum/minimum demand annual growth:** Forecast maximum/minimum demand has been changed is grown year-on-year by a composite growth index based on drivers like population, economic growth and price, rather than indices specific to baseload, heating and cooling used previously. This was found to get better alignment with the historical change in relationship between annual maximum demand and consumption figures.
- **ONSG and maximum/minimum demand:** Generation from peaking-type ONSG units is now modelled as DSP[7] rather than being an offset to maximum/minimum demand.
- **Coordinated EV charging:** Additional step added to half-hourly trace growing algorithm, that each day spreads coordinated EV charging across the lowest demand periods.
- **Inclusion of specific Covid-19 effects in most forecasting components:** The methodology has been adjusted to accommodate the impact of the COVID-19 pandemic, which is introducing social, economic and operational challenges to many sectors, including energy. Specifically:
  - The methodology for adjusting the consumption forecast for structural shocks (such as COVID-19) is described in this report.
  - The high-level approach for adjusting the maximum/minimum demand forecasts for structural shocks (such as COVID-19) is described in this report (with the details as an appendix to the ESOO itself).
  - The COVID-19 impacts on key economic inputs is described in the IASR.

[7] See https://aemo.com.au/-/media/files/stakeholder_consultation/consultations/nem-consultations/2020/demand-side-participation/final/demand-side-participation-forecast-methodology.pdf.

2. Business annual consumption

The business sector captures all non-residential consumers of electricity in the NEM and the WEM. These have been segmented into two broad categories, recognising the different drivers affecting forecasts. This sector is further categorised into large industries and small to medium sized businesses, to apply an integrated, sectoral-based approach to business forecasts to capture structural changes in the Australian economy:

- **Large industrial loads (LIL)** – further split into subcategories:
  - **Aluminium smelting** – including Bell Bay, Boyne Island, Portland, and Tomago aluminium smelters. ***Note: This <u>does not</u> apply to the WEM.***
  - **Coal mining** – customers mainly engaged in open-cut or underground mining of bituminous thermal and metallurgical coal. ***Note: This <u>does not</u> apply to the WEM.***
  - **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. ***Note: This <u>does not</u> apply to the WEM.***
  - **Mining and minerals processing facilities –** customers mainly engaged in open-cut or underground mining of non-coal and aluminium minerals and the pre-processing of these minerals. ***Note: This <u>only</u> applies to the WEM.***
  - **Water infrastructure facilities** –all large water treatment facilities, including desalination, for potable water, wastewater treatment and water pumping.
  - **Other transmission- and distribution-connected customers** – covering any transmission- and distribution-connected loads not accounted for in the categories above.
- **Small to medium enterprises (SME)** – any distribution-connected loads not included in the LIL category.
- **Electric vehicles (EV)** – covering commercial fleet, trucks and buses.

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 for both the NEM and the WEM.

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 (Table F)		
Economic data*	ABS	External Economic Consultancy	

Data series	Source 1	Source 2	Source 3
Retail electricity price	Retail Standing Offers	AEMC Price Trend Report 2019	ISP
Wholesale electricity price	AEMO		
Energy efficiency	AEMO based on 2019 consultancy	State government departments for some regions	
Rooftop PV/battery/electric vehicle generation	External Consultancy		

* Economic data includes Gross State Product and Household Disposable Income.

2.2 Methodology

The overall approach to forecasting business consumption for both markets is to measure the energy-intensive large loads separately from broader business sector, based on the observation that each load historically is 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.

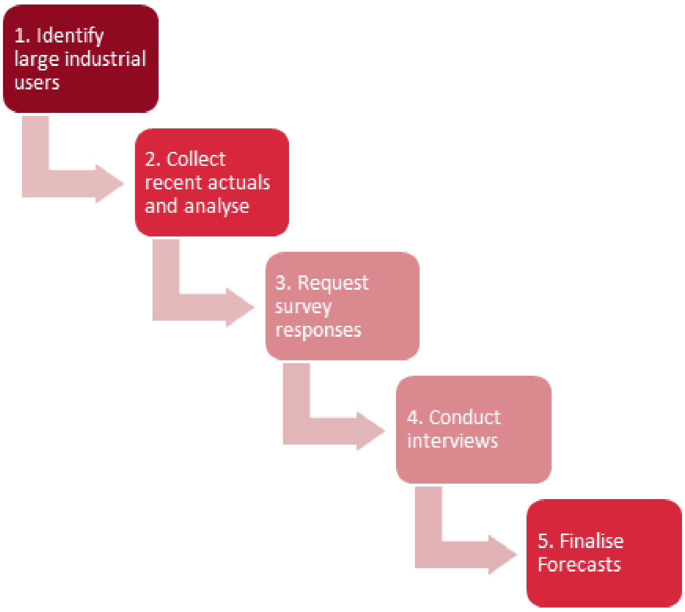
Either surveys or standard econometric methods were used to forecast consumption in these sectors:

- **Large industrial loads (LIL):** survey-based forecasts.
- **Small to medium enterprises (SME):** econometric modelling.

2.2.1 Large Industrial Load forecast

The process that produces the large industrial load (LIL) forecasts for both markets has five steps, illustrated in Figure 4. It requires AEMO to identify the LILs, collect and analyse historical data, conduct a survey (questionnaire) and interview key personnel from key LILs and incorporate the information into a final forecast for each LIL.

Figure 4 Steps for large industrial load survey process



Identify large industrial users

AEMO maintains a list of LILs identified primarily by interrogating AEMO's meter data and working with transmission network operators and distribution network operators for each region. A threshold of demand greater than 10 MW for greater than 10% of the latest financial year is used to identify those loads. This threshold aims to capture the most energy intensive consumers in each region.

The list is further validated and updated using two methods:

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

Collect historical data (recent actuals) and analyse

Updates to historical consumption data for each LIL were analysed to:

- Understand consumption trends at each site and develop targeted questions (if required).
- 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[8] requesting historical and forecast electricity consumption information by site. The survey requested annual electricity consumption and maximum demand forecasts for three scenarios in the NEM and the WEM, where the economy follows:

1. The most likely economic pathway.
2. A stronger economic pathway.
3. A weaker economic pathway.

Step 2: Detailed interviews

After the survey is issued, only prioritised large industrial users are contacted directly to expand on their survey responses. This includes 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 (such as expansion, closure, outages, cogeneration, fuel substitution).
- Their participation (if any) in Demand Side Management programs.
- Assumptions governing the scenarios.

Not all LILs were interviewed. Interviews with LILs 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.

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[8] 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 for each region.

- Year-on-year absolute variation – relative weighting of industrial load is needed to assess materiality of individual variations.
- 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.

Finalise forecasts

The following subsections detail the methodology for producing forecasts for each subsector for each region.

Aluminium smelting (this does not apply to the WEM)

The aluminium smelting forecast was based on a survey and interview process (see Section 2.2.5). To maintain confidentiality[9], AEMO aggregates forecasts with the econometric results before publishing the LIL forecast.

Coal mining (this does not apply to the WEM)

Coal mining and port service companies are surveyed, and selected operations were interviewed, to obtain a baseline for the coal industry. The consumption forecast was based on these survey result[10].

Coal seam gas (this does not apply to the WEM)

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.

AEMO surveyed the CSG consortium following the 2019 GSOO and assessed long-term global trends to update the CSG forecasts used in the 2020 GSOO. Gas to electricity conversion ratios were calculated using historical gas and electricity consumption data at the project sites and applied to the 2020 GSOO forecast to derive the CSG forecasts used in the 2020 ESOO.

Mining and minerals processing facilities (for the WEM only)

All large mining and minerals processing loads in the WEM are surveyed with selected companies interviewed by site to obtain a baseline for each facility.

Water infrastructure facilities

All large water infrastructure facilities, including desalination, for potable water, wastewater treatment and water pumping in the NEM and the WEM are surveyed with selected companies interviewed by site to obtain further information about future water requirements for each facility.

Other transmission- and distribution-connected customers

Other large users of energy that do not fall into the above categories (such as large manufacturers or large rail networks) are surveyed separately with forecasts based of these results.

2.2.2 Small to medium enterprises (SME) consumption forecast

SME consumption, with LILs removed, contains aggregate consumption data for the non-residential sector that covers a broad range of activities to which no direct information on usage behaviour is available. As such, a more detailed forecasting method is applied that accommodates time-series methods capturing the more predictable patterns in recent usage (such as seasonality, cycles and trend along with causal factors that encapsulate the long-term structural changes[11] that are explored through different scenarios for the sector. Broadly, the forecast for SME consumption can be written as:

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

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

[11] Chase, C, 2009, *Demand-Driven Forecasting: A Structured Approach to Forecasting.* John Wiley & Sons, Inc., Hoboken, New Jersey.

$$Forecast = f(seasonailty, trend, cyclical, causal\ factor(s), unexplained\ variance)$$

The seasonality is captured through the production of a short-term daily regression model trained on 24 months of data, capturing the effects of weather. A trend and cyclical component analysis is then performed against longer term data (4-6 years). Unexplained variance is captured by examining year-on-year variance, once known structural effects are accounted for and the time series is de-trended.

The causal factors are separately analysed against the Department of Energy (Table F)[12] long-term data series (10+years) with large industrial loads removed to smooth out any disjoins before correlating with economic datasets (causal factors). The data is then scaled to the AEMO SME meter data before incorporation into the forecast, with other long-term structural drivers such as energy efficiency and price.

These short-term and long-term models are then combined to produce the long-term SME model.

This shift in methodology to include a short-term trend model as well as a longer-term approach was identified as one of two key improvements from the 2019 Forecast Accuracy Report[13].

Short-term time-series model

Time-series models have been described as more applicable in short-term forecasting[14] and can be applied systematically. The short-term SME forecast uses generic time-series methods to model the trend, seasonality, cyclical and unexplained variance to form a short-term forecast (0-3 years ahead).

The short-term time-series model consists of three stages:

- Calculating a weather-normalised base year (most recent 24 months of consumption data used) capturing seasonality.
- Determining a trend or cyclical components (4-6 years of consumption data used).
- Estimating uncertainty applicable to the different scenarios.

Base year

The business sector short-term forecast was developed using a linear regression model, using approximately 24 months of consumption with ordinary least squares to estimate coefficients. The independent variables are described in Table 2 with subscript i representing days for the NEM, and months for the WEM.[15]

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

The first stage of the short-term forecast, is to produce the *Base Year*, that applies a median weather year (weather normalised) . This gives a starting point (to reflect current consumption patterns) that considers intra-year variation to seasonality, holidays and weather. Structural effects that affect the data series are also able to be captured, such as COVID-19. The following equation presents the formulation for a particular region i:

$$SME\_BaseYear_i = \beta_{Base,i} + \beta_{HDD,i}HDD_i + \beta_{CDD,i}CDD_i + \beta_{Non-workday,i}Non\_workday_{i,t} + \beta_{COVID-impact,i}COVID\_impact_{i,t} + \varepsilon_{i,t}$$

[12] Refer to Table 1 in the Business Section for details.

[13] AEMO, 2019 Forecast Accuracy Report, available at: https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/accuracy-report/forecast_accuracy_report_2019.pdf.

[14] Chase, C. Ibid.; Chambers, J, Mullick. S., Smith, D. 1971. *How to choose the right forecasting technique*. Harvard Business School. Available: https://hbr.org/1971/07/how-to-choose-the-right-forecasting-technique, Accessed 23 July 2020.

[15] AEMO only manages the Wholesale portion of the WEM and only receives monthly residential data from Synergy for modelling.

Table 2 Short-term base model variable description

Variable	Abbreviation	Units	Description
Business consumption	SME_BaseYear	GWh	Total SME 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 business activity affecting electricity consumption, for a non-work day (public holidays, Saturdays, and Sundays)
Dummy for Covid-19	COVID-impact	{0,1}	A dummy variable that captures the lower business activity, affecting electricity consumption, active from March 2020**

*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.
** Use of a dummy variable will capture an approximate average change in energy consumption compared to usage prior to the COVID-19 pandemic. As the situation is dynamic this may require a change in approach for capturing any temporary effects and structural changes.

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

Trend

To capture patterns in usage over the longer-term, such as a steady decline or growth, a rolling regression over 4-6 years using a 24 month training window was used to detect any change in usage. A linear model was then fitted (with a least squares method) to produce a trend.

Variance/dispersion

Many aspects of time-series data will not easily be matched to a pattern, nor able to be predicted with a model. The uncertainty in the fit of the trend along with the standard deviation in-detrended weather normalised annual consumption is utilised to provide dispersion around the Central scenario (similar to a simulated random walk with a deterministic drift term). The standard deviation of the annual consumption for each individual region in the NEM, and the quality of the fit of the trend (95% Confidence Interval) give approximately 2-3% difference from the Central trajectory in the first forecast year, growing to 4-5% in second forecast year and 5-7% in the third forecast year.

Long-term causal model

The long-term SME forecast was developed using a causal model for the various components estimated to have a material impact on electricity consumption. The following equation describes the model used. The subscript i represents years for the NEM and the WEM.

$$SME\_Cons_i = GSP\ impact_i + electricty\ price\ impact_i + energy\ efficiency\ impact_i + climate\ change\ impact_i + shock\ factor\ impact_i$$

GSP Impact

The growth for the long-term SME forecast was developed using a linear regression model with ordinary least squares to estimate coefficients[16]. The variables are described in Table 3 with subscript i representing years for the NEM and the WEM.

$$SME\_Cons_i = \widehat{\beta}_0 + \widehat{\beta}_1(GSP_i)$$

Table 3 SME model variable description

Variable names	Abbreviation	Units	Description
SME consumption	SME_Cons	GWh	SME business consumption.
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.

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

Price impact

Adjustments are made to the forecast consumption to capture the negative impact of price increases. An asymmetric response of consumers to price changes is used, with price impacts being estimated in the case of increases, but not for price reductions.

Energy efficiency adjustment

AEMO engaged a consultant (in 2019, *Strategy. Policy. Research. Pty Ltd*) to develop forecasts of energy efficiency savings for the Commercial and Industrial sectors. The 2020 energy efficiency adjustment is based on the 2019 forecasts, updated with the latest input data on GSP, and the split between baseload, heating and cooling load elements derived from meter data.

The forecasts estimate savings from a range of Federal and state government measures, including the National Construction Code (NCC), building disclosure schemes, the Equipment Energy Efficiency (E3) Program, and state schemes[17]. AEMO adjusted the forecasts to fit with the SME model by:

- Removing savings from Commercial and Industrial LILs[18].
- Rebasing the consultant's forecast to the SME model's base year.
- Removing the estimated future savings from activities that took place prior to the base year.
- Extending the savings attributed to state schemes beyond legislated end dates, on the assumption that a significant percentage (at least 75%) of activities would continue as business as usual depending on scheme.
- Reviewing energy savings calculations for state schemes and where possible consulting with state government departments.

AEMO applied a discount factor of approximately 20% to the adjusted energy efficiency forecasts, to reflect the potential increase in consumption that may result from lower electricity bills. The discount factor also reduces, in addition to steps taken by the consultant, the risk of overestimating savings from potential double-counting and non-realisation of expected savings from policy measures.

[16] These coefficients represent elasticity responses.

[17] For 2019, the consultant modelled the NSW Energy Savings Scheme, Victorian Energy Upgrade Program, and the SA Retailer Energy Efficiency Scheme.

[18] The consultant's forecasts include savings from the LIL sector. AEMO surveys LILs separately and assumes that savings activities would be factored into the consumption data obtained through the surveys, and as such removed LIL savings from the consultant's forecasts.

For more details on trends and drivers on energy efficiency see the 2019 energy efficiency report produced by *Strategy. Policy. Research. Pty Ltd*[19].

Climate change adjustment

Heating and cooling load is expected to vary as the climate changes and the SME sector is adjusted to reflect this. 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[20] forecast for the SME sector.

The SME consumption, split into Heat, Base, and Cool elements for the base year, is then adjusted in subsequent forecast years by the estimated climate change impact on the number of HDDs and CDDs.

Shock factor (structural break) adjustment

Economic shocks are noted to historically disrupt business activity and electricity consumption. For example the Australian recession in 1990 and the Global Financial Crisis (GFC) in 2007 both resulted in reductions in electricity consumption. The period after the GFC in particular, has been characterised by slower industrial production output[21].

AEMO has previously used factors to account for the disruption in long-term relationship with electricity demand and economic indicators from the GFC. In 2020, due to the COVID-19 pandemic AEMO has applied a shock-factor to the SME sector, to canvas the potential downside impact from the more energy-intensive manufacturing sector.

The energy intensity of manufacturing was calculated by dividing the 2019 Department of Energy (Table F) manufacturing sector annual electricity consumption by the actual 2019 manufacturing sector GVA provided by AEMO's economic consultant. Electricity consumption and GVA attributed to the aluminium sector was removed prior to determining the energy intensity to mitigate overstating the size of the shock, as these users are accounted for in the LIL forecasts. This factor was then multiplied by the forecast drop in GVA between 2019 and 2021 from the economic forecast for each scenario (excluding Step Change) provided by the economic consultant, producing the amount of load deemed at risk.

The impact was proportionally applied to the regional forecasts (based on the comparative size of each regions' manufacturing sector) with the size of the impact determined by the respective economic GVA forecast for the manufacturing sector in each scenario. The shock factor was applied elastically in the Central scenario, with the load returning after four years (a U-shaped recovery), while in the Slow Change scenario the adjustment is applied with a proportion of load not being recovered (an L-shaped recovery), reflecting the risk that some industrial consumption may not return.

Combining the short- and long-term models

There are several methods that can be used to combine different forecasting models. AEMO adopts a weighted method for combining the forecast models; literature suggests an equal weight should apply where there is uncertainty on what weights are appropriate.[22] As the uncertainty of time-series methods increases as the forecast horizon expands, yet time-series models are generally more accurate in the short-term, AEMO has adopted an equal weighting of 50% for combing the short-term series model with the long-term causal model (excluding the shock factor), in the first forecast year then decaying to 25% in the second forecast year, 12.5% in the third forecast year, then 0% afterwards, for the short-term component.

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[19] *Strategy. Policy. Research. Pty Ltd. Energy Efficiency Forecasts: 2019 - 2041*. July 2019, at https://www.aemo.com.au/-/media/Files/Electricity/NEM/Planning_and_Forecasting/Inputs-Assumptions-Methodologies/2019/StrategyPolicyResearch_2019_Energy_Efficiency_Forecasts_Final_Report.pdf.

[20] 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.

[21] Langcake, S. *Conditions in the Manufacturing Sector* RBA Bulletin June Quarter 2016, at https://www.rba.gov.au/publications/bulletin/2016/jun/4.html.

[22] Chase, C, 2009, *Demand-Driven Forecasting: A Structured Approach to Forecasting.* John Wiley & Sons, Inc., Hoboken, New Jersey.

The shock factor has been applied on top of the combined short and long-term models to preserve the quantum of shocks forecast.

2.2.3 Electric vehicles

Projections for EV uptake and electricity consumption associated with electric vehicles were produced by CSIRO[23] in 2020. Charging of non-residential electric vehicles is considered to add to the consumption of the SME category. For more detail refer to Appendix A4.

2.2.4 Battery storage loss adjustment

Battery losses were accounted-for by applying 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 consultant reports, the latest of which is by CSIRO[24] and Green Energy Markets[25].

2.2.5 Rooftop PV adjustment

This adjustment was made to translate energy consumption forecasts from an underlying consumption basis to a delivered consumption basis. 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. For more details on trends and drivers see the afore-mentioned consultant reports.

2.2.6 Total business forecasts

The aggregation of all sector forecasts is used to obtain the total business underlying consumption forecasts.

$$Total\ Business\ Underlying\ Consumption =$$
$$LIL\ consumption + SME\ consumption + Electric\ Vehicles\ consumption$$

Total business delivered consumption can be found as shown in Figure 5.

Figure 5 Aggregation process for final delivered forecast

[23] CSIRO, 2020 projections for small-scale embedded technologies report, at https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/inputs-assumptions-methodologies/2020/csiro-der-forecast-report.pdf?la=en.

[24] CSIRO, 2020 projections for small-scale embedded technologies report, at https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/inputs-assumptions-methodologies/2020/csiro-der-forecast-report.pdf?la=en.

[25] GEM, 2020 Projections for distributed energy resources – solar PV and stationary energy battery systems report, at https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/inputs-assumptions-methodologies/2020/green-energy-markets-der-forecast-report.pdf?la=en.

3. Residential annual consumption

This chapter outlines the methodology used in preparing residential annual consumption forecasts for each NEM and WEM 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 4 and Table 5.

Table 4 Historical input data sources for residential sector modelling

Data series	Reference
Total daily residential connections for each region*	AEMO metering database and from Synergy for the WEM.
Total daily underlying consumption for all residential customers for each region**	AEMO metering database
Daily actual weather measured in HDD and CDD***	BoM temperature observations

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

Table 5 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	Consultancy (Strategy. Policy. Research. Pty Ltd*in 2019)
Forecast gas to electric appliance switching	2020 GSOO**
Forecast annual rooftop PV generation	Consultancy (CSIRO*** and Green Energy Markets**** in 2020) and Appendix A3

Data series	Reference
Forecast electric appliance uptake	Appendix A5
Forecast electric vehicles	Consultancy (CSIRO in 2020)***

* *Strategy. Policy. Research. Pty Ltd. Energy Efficiency Forecasts: 2019 - 2041*. July 2019. Available at: https://www.aemo.com.au/-/media/Files/Electricity/NEM/Planning_and_Forecasting/Inputs-Assumptions-Methodologies/2019/StrategyPolicyResearch_2019_Energy_Efficiency_Forecasts_Final_Report.pdf
** AEMO *2019 Gas Demand Forecasting Methodology Information Paper*. Available at: https://www.aemo.com.au/-/media/Files/Gas/National_Planning_and_Forecasting/GSOO/2019/Gas-Demand-Forecasting-Methodology.pdf
*** CSIRO, 2020 projections for small-scale embedded technologies report, available at https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/inputs-assumptions-methodologies/2020/csiro-der-forecast-report.pdf?la=en,
**** GEM, 2020 Projections for distributed energy resources – solar PV and stationary energy battery systems report, available at: https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/inputs-assumptions-methodologies/2020/green-energy-markets-der-forecast-report.pdf?la=en

3.2 Methodology

3.2.1 Process overview

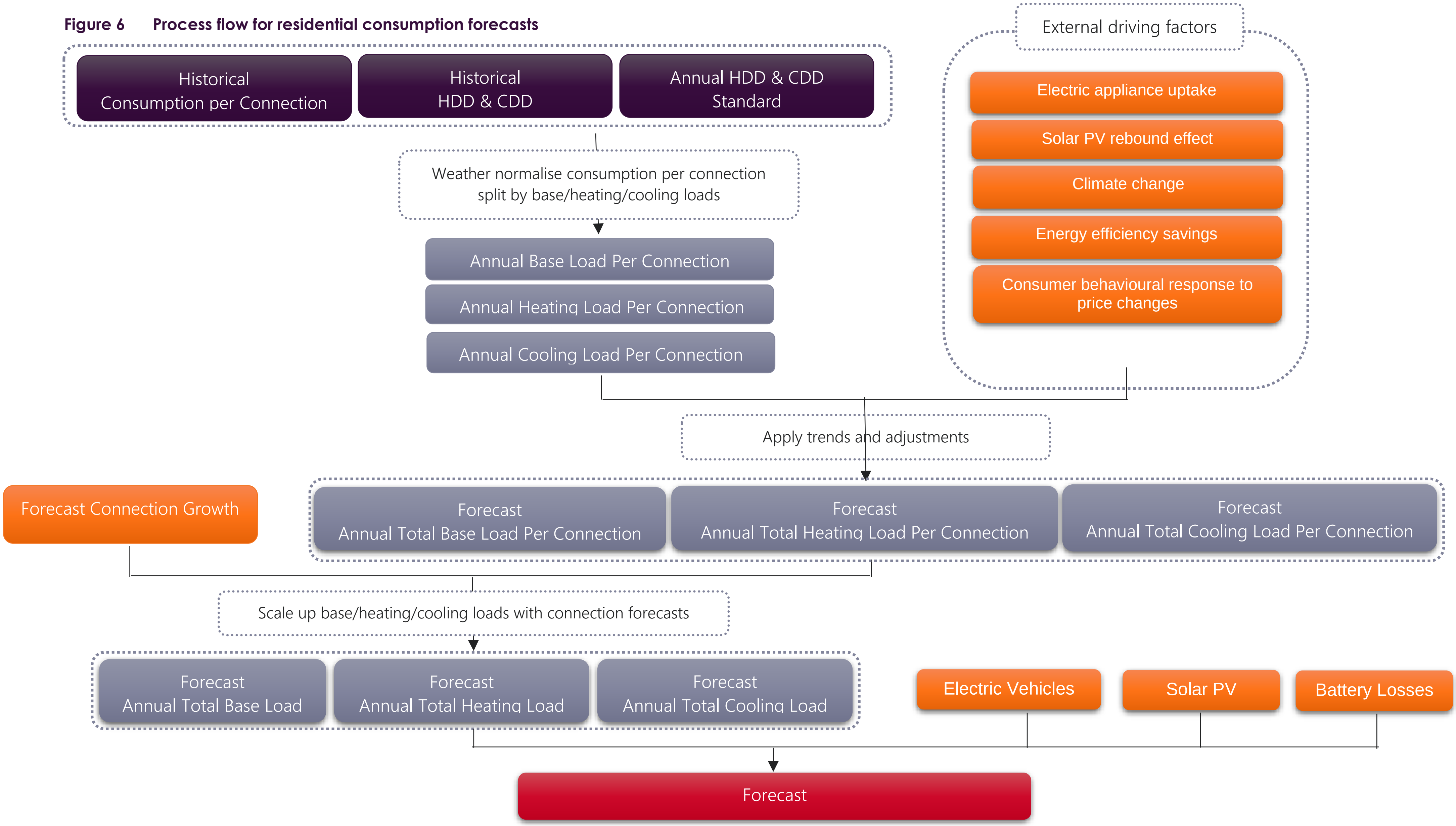
AEMO applied a "growth" model to generate 20-year annual residential electricity consumption forecasts. At the core of the forecast were the following stages:

- 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[26].
- 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.

[26] 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. Due to the availability of data, the WEM applied the same model below using monthly data. For this section, the subscript i for the WEM denotes month and the differences for the WEM are outlined in brackets.

Step 1.1: Analyse historical residential consumption

Daily (monthly) 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 (monthly) average underlying consumption in each region.
- Estimating the daily (monthly) underlying consumption per residential connection by dividing by the total connections.

A daily (monthly) regression model is used to calculate the daily (monthly) average consumption split between baseload, cooling and heating load.

COVID-19 has altered the energy consumption pattern of the residential sector due to stay-at-home restrictions and a higher utilisation of appliances in the home. In order to account for that AEMO has introduced a dummy variable to canvas the impact of COVID-19 on the energy consumption of residential sector.

Daily (monthly) regression model

Daily (monthly) 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 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. This model also has the capability to account for other drivers impacting the consumption of the residential sector such as non-working days and COVID-19 period.

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:

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

Regression model applied to Tasmania:

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

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 6.

Table 6 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.
$COVID\_impact_{i,t}$	Dummy variable to flag COVID period for region i on day t.
$CoolingLoadPerCDD_i$	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. Appliance growth is modified for policy-induced fuel switching from gas to electrical appliances. See Appendix A5 for more detailed discussion of appliance uptake.

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 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 2.3: Estimating impact of climate change

The BoM 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 2.4: 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.

Step 2.5: Estimating impact of energy efficiency savings

Ongoing improvements in appliance efficiency and thermal performance of dwellings drive energy savings in the residential sector. AEMO engaged a consultant (in 2019, *Strategy. Policy.* changes *Research. Pty Ltd*) to forecast residential energy savings from a range of government measures, including the NCC, E3 program and state schemes. Fuel switching between gas and electricity for space heating arising from changes to the NCC is embedded in the EE forecasts and detailed in the consultant's report[27]. Other fuel switching policies are captured by the appliance growth indices.

The consultant apportioned energy savings by load segment using ratios developed by AEMO for each NEM region, considering the total annual consumption that is sensitive to cool weather (heating load) and to hot

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[27] At https://www.aemo.com.au/-/media/Files/Electricity/NEM/Planning_and_Forecasting/Inputs-Assumptions-Methodologies/2019/StrategyPolicyResearch_2019_Energy_Efficiency_Forecasts_Final_Report.pdf.

weather (cooling load). The residual consumption is considered temperature-insensitive and is apportioned to baseload.

AEMO used the 2019 forecasts as the basis for the 2020 ESOO, including a discount factor (20%) on the consultant's forecast, and updated with the latest data on population growth, residential building stock growth and National Meter Identifier (NMI) connections. See Appendix A5 for more detailed discussion on the residential building stock model and NMI connections forecast.

Step 2.6: 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.

$$TOTBaseload\_Con_{i,j} = Baseload\_Con_i + API\_BL\_Con_{i,j} + PVRB\_BL\_Con_{i,j} - EEI\_BL\_Con_{i,j}$$

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

$$TOTCoolingload\_Con_{i,j} = Coolingload\_Con_i + API\_CL\_Con_{i,j} + PVRB\_CL\_Con_{i,j} - EEI_{CL_{Con\,i,j}} + CCI\_CL\_Con_{i,j} + PI\_CL\_Con_{i,j}$$

Variables and their descriptions are detailed in Table 7.

Table 7 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*
$PVRB\_BL\_Con_{i,j}$	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.

Variable	Description
$EEI\_BL\_Con_{i,j}$	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:

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

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

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

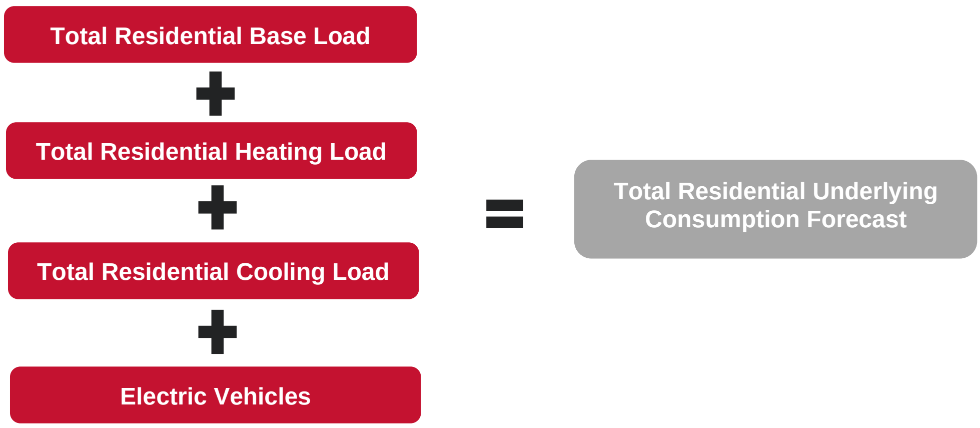
Table 8 Residential base load, heating load and cooling load model variables and descriptions

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, as shown in Figure 7.

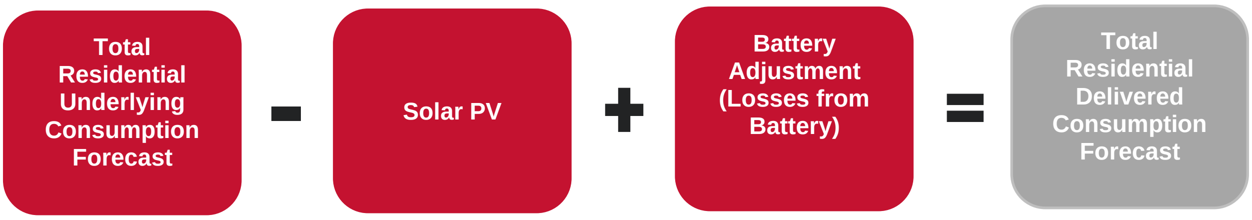
Figure 7 Aggregation process for final residential underlying forecast



External advice is obtained from consultancies (in 2019 this was CSIRO and Energeia) for estimates of historical and forecast electric vehicle uptake[28].

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

Figure 8 Aggregation process for final residential delivered forecast

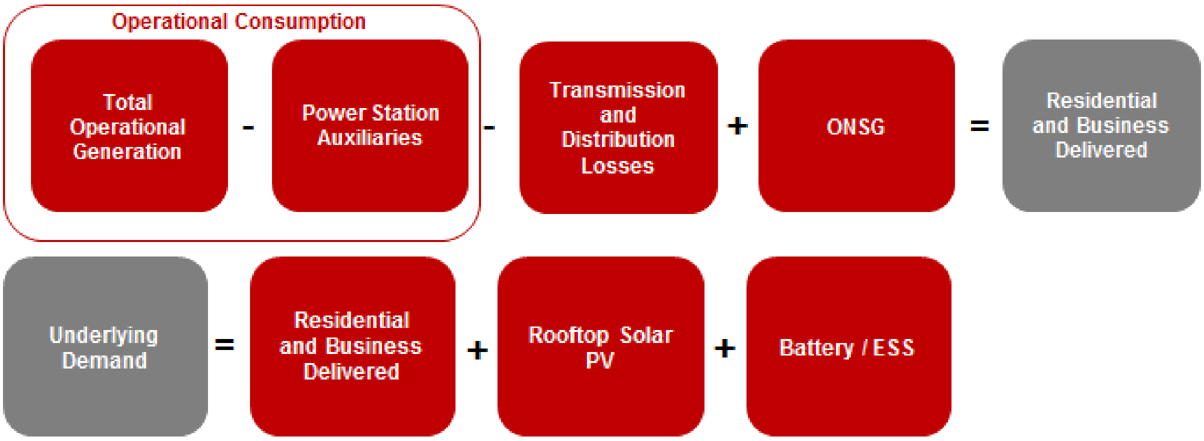


[28] See Appendix A4 for more information.

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[29]. 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.

Figure 9 Demand relationships



4.1 Small non-scheduled generation

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

4.1.1 Data sources

AEMO forecast small NSG based on the following data sources:

- Publicly available information.
- Data provided by network businesses.
- Projection of PV uptake (as forecast by the consultants, in 2020 CSIRO and Green Energy Markets).

[29] Operational definition at https://aemo.com.au/-/media/files/stakeholder_consultation/consultations/nem-consultations/2019/dispatch/demand-terms-in-emms-data-model---final.pdf.

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, although based on growth rates for commercial rooftop PV. From 2018, this sector has been forecast with a different approach; larger projects require special purpose financing and their uptake has been forecast by AEMO's consultants 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:

- Obtaining solar insolation data at 30-minute granularity from Solcast to estimate PVNSG historical generation from 2001.
- Determining regional normalised generation traces by combining this with historical PVNSG installed capacity data.
- 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 PVNSG generation in each forecast year.

The historical traces were used to update historical underlying demand based on installed capacity in the given years.

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 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 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.

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 uses the transmission loss factors to calculate historical losses across the transmission network for each region.

AEMO forecasts 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 average per region, generally based on recent losses reported to the 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*[30] for the generation station such that:

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

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.

[30] See https://www.aemo.com.au/-/media/Files/Electricity/NEM/Planning_and_Forecasting/Inputs-Assumptions-Methodologies/2019/2019-Input-and-Assumptions-workbook.xlsx.

Auxiliary loads (forecast)

The annual auxiliary loads in each region were forecast using the auxiliary loads from a future generation forecast that have a mix of technologies. Forecasts of the future generation mix are currently based on the 2020 Integrated System Plan (ISP) auxiliary load forecasts with each of the 2020 scenarios modelled in the ISP. As the 2020 ISP was based on earlier consumption forecasts than the 2020 forecasts (broadly based on 2019 forecasts, but for one Updated Demand sensitivity), they needed to be rebased to preserve the auxiliary load proportion of energy consistent with the 2020 ESOO forecasts. To arrive at this adjustment, the forecast auxiliary factor for each financial year and for each NEM region in the 2020 ESOO was defined as:

$$\text{Auxiliary Load Factor (2020 ESOO)} = \frac{\text{Total Auxiliary Load (ISP)}}{\text{Operational Consumption Forecast as sent out (ISP)}}$$

The annual auxiliary load forecast was then determined by first calculating the operational consumption forecast (as generated) by dividing the 2020 ESOO operational consumption forecast (as sent-out) by the 2020 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).

5. Maximum and minimum demand

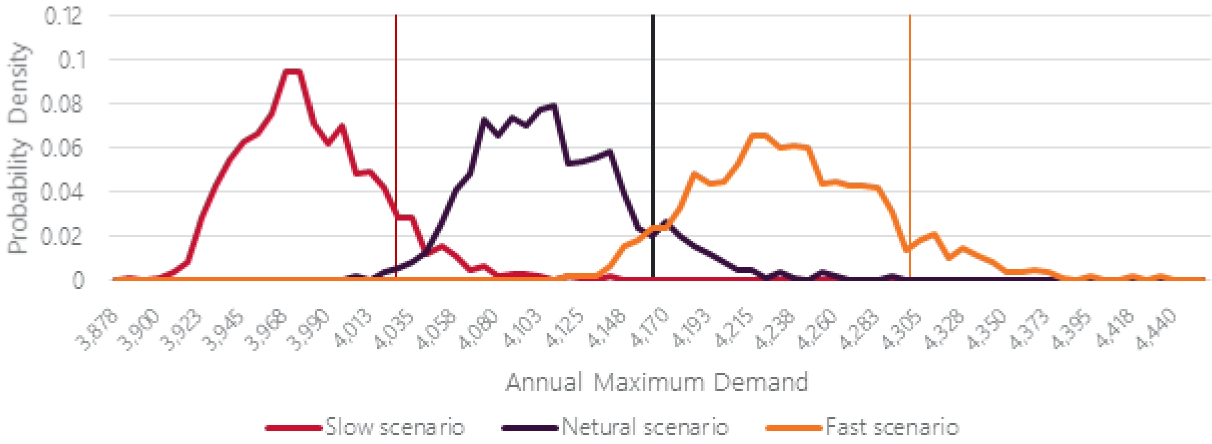
Regional minimum and maximum demand forecasts are developed by season using a probabilistic methodology. Demand is dependent on both structural drivers as well as random drivers including weather conditions, seasonal effects and random stochastic volatility.

To model this uncertainty, several scenarios are developed to capture uncertainty in structural drivers, while uncertainty attributable to random drivers is expressed as an interval, probability of exceedance (POE) forecast from a forecast distribution. As such, forecast maximum demand (MD) is not a single point forecast. For any given season or year:

- A 10% POE MD value is expected to be exceeded, on average, one year in 10.
- 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 10.

Figure 10 shows modelled probability density functions that represent possible maximum demand outcomes for a typical southern region. Three probability density functions are shown, one for each of the scenarios with unique structural drivers. The 10% probability of exceedance (POE) estimates are sampled from the probability distributions, shown by the vertical lines.

Figure 10 Conceptual summer maximum demand probability density functions for three scenarios



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.

AEMO forecasts operational demand 'sent out' as defined in Section 1.3. In the following it will be referred to as OPSO. Based on estimates of auxiliary load, this can be converted into forecast operational 'as generated' (OPGEN) maximum and minimum demand.

Maximum demand is forecast as Season Year to prevent any of the seasons (summer/winter) being arbitrarily split by the year definition. Season Year is from 1 September to 30 August. For instance, 1 September 2018 to 30 August 2019 would be season year 2019.

The WEM maximum demand is forecast based on capacity year which is from 1 October to 30 September the following year.

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 for more thorough data cleaning and to consider the daily shape 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 and normalised generation.
- Historical and forecast PVNSG installed capacity and normalised generation.
- Forecast electric vehicles numbers and charge profile.
  - A proportion of EV is considered using coordinated charging with the proportion varying by scenario.
- 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.
- NMI data for the top 100 large industrial loads (loads over 10 MW, 10% of the time).
- Historical and forecast LILs.
- Historical underlying demand.
- Projected climate change adjusted dry temperature.

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.

5.2 Exploratory data analysis

Exploratory data analysis (EDA) was used to detect outliers and identify important demand drivers and multicollinearity 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 greater than 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 were 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 data was removed unless there was cause to remove it, because by definition maximum demand is an outlier more than three standard deviations from the mean and the purpose is not to remove legitimate data. 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).
  - Dry bulb temperature – both instantaneous and heatwave/coolwave.
  - 'Instantaneous' temperature may be transformed 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.
  - Apparent temperature[31] – both instantaneous and heatwave/coolwave.
  - EHF – excess heating factor is a measure of heatwave intensity. When maximum daily temperatures are above the 95th percentile[32] for three consecutive days, then these days are deemed to be in heatwave conditions with the variable increasing with the intensity.
  - Heat index[33] – both instantaneous and heatwave.
  - Higher order terms of the above variables, for example $Instant\mathrm{Temperature}^2$ and $DailyTemperature^2$, to capture changing dynamics between temperature and demand at different ends of demand.
- Calendar/seasonal variables, including weekday/weekend and public holiday Boolean (true/false) variables.

The Calendar/seasonal variables and other indicator variables in practise work to stratifies the data in different seasons, weekends and weekdays. The fixed effects model effectively models different seasons, months, weekdays and hours separately within the same model.

The EDA process assessed multicollinearity of the explanatory variables by consider the Variance Inflation Factor[34] caused by collinear variables.

5.3 Model development and selection

AEMO developed three models for each region, a half-hourly model, a maximum Generalized Extreme Value (GEV) model and a minimum GEV model. Models for each region were specified using the variables identified as statistically significant during the EDA process.

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

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

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

[34] 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.

The half-hourly models simulate half-hourly demand and perform well in modelling the impact of disruptive technology such as PV, ESS and EV. These technologies have a half-hourly shape and cause demand to shift over the day. The GEV models are seasonal (or monthly) minimum and maximum models that produce interval forecasts for minimum and maximum demand. AEMO used the GEV models to estimate the intervals of minimum and maximum demand in the first year of the forecast. Then AEMO used the half-hourly model to grow demand out 20 or 30 years.

Half-hourly model

The half hourly 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 as well as weather effects (such as $Instant\mathrm{Temperature}$, and $Instant\mathrm{Temperature}^2$ and daily rolling average of temperature).

AEMO used a Machine Learning algorithm to derive a model with good fit and strong predictive power. The Least Absolute Shrinkage and Selection Operator (LASSO)[35] regularization algorithm, a special case of Elastic Net, selects the best model from the range of variables available and all the interactions between the variables. The model was developed trading off the model bias[36] and model variance[37] to derive a parsimonious model with strong explanatory power.

AEMO then performed additional in-sample and out-of-sample model diagnostic checks on the best model selected by LASSO. Where the best model failed these checks AEMO adjusted the LASSO algorithm iteratively. AEMO:

- Performed k-folds out-of-sample cross validation[38] to find the optimal model that trades off between bias and variance.
- Inspected the QQ-plots, the residual diagnostics over time and against the x variables to ensure the residuals were random with no discernible patterns that could indicate missing explanatory factors.
- Inspected residuals at the relevant ends of demand to ensure that the assumptions for residuals when simulating minimum and maximum demand are relevant and that there is no bias at either ends of extreme demand.
- Compared actual against predicted from the half-hourly model.
- Compared actual detrended historical minima and maxima against simulated minima and maxima from the model.

Table 9 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 rather than derived weather variables such as apparent temperature. These variables were then used in the final half-hourly demand model.

Table 9 List of variables included for half-hourly demand model

Variable	Description
Public holiday	Dummy flag for public holiday
Half-hour factor	A factor variable with values for each half hour of the day

35 AEMO fit the LASSO regularization path for linear regression using cyclical coordinate descent in a path-wise fashion.

36 Under-fitting the model results in a model with high bias.

37 Over-fitting the model result in a model with high variance.

38 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
temperature	Transformation of dry temperature ie rolling average, weekly average, daily average or half-hourly as well as quadratic or cubic transformation depending on model fit.

Generalise extreme value model

AEMO specified a separate model for minimum and maximum demand. The GEV is based on extreme value theory to capture the distribution of rare events or the limit distribution of normalized minima and maxima. The GEV model aimed to model the distribution of extreme values (minima and maxima) for operational demand less large industrial load. As such the extreme value model was trained on weekly operational minima and maxima less large industrial loads.

The GEV models found the relationship between minimum and maximum demand and PV Capacity, PVNSG capacity and weekly weather metrics. AEMO developed the GEV models by iteratively selecting variables to explain demand and testing the performance of the model through in-sample and out-of-sample diagnostics.

The explanatory variables are detailed in Table 10. The GEV model was fit using weekly operational minima and maxima as a function of PV capacity, PVNSG capacity, customer number count (NMIs), calendar effect variables and average weather. Similar to the half-hourly model, AEMO then assessed the in-sample performance by:

- Inspecting the QQ-plot, the residual diagnostics over time and explanatory power of the x variables to ensure the residuals were random with no discernible patterns that could indicate missing explanatory factors, and
- Inspecting that degree of serial correlation in the residuals, where no serial correlation is desired.

Finally, AEMO assessed the out-of-sample performance by comparing:

- Actual against predicted from the GEV model, and
- Actual historical minima and maxima against simulated minima and maxima from the GEV models.

Table 10 List of variables included for half-hourly demand model

Variable	Description
Month factor	A factor variable with values for each months of the year
PV capacity	The sum in MW of the all the rooftop PV panels in a region
PVNSG capacity	The sum in MW of the all the PV non-scheduled generators in a region
NMI count	The number of NMIs within a region
Dry temperature	Transformation of dry temperature ie rolling average, weekly average, daily average or half-hourly as well as quadratic or cubic transformation depending on model fit.
Solar irradiance	Some transformation of Solar irradiance ie rolling average, weekly average, daily average or half-hourly depending on model fit

5.4 Simulate base year (weather and calendar normalisation)

The half-hourly and GEV models selected from the above process were used to simulate demand for each region. All three models were used to simulate, the half-hourly models were used to simulate every half-hour hour and aggregate to the season. The GEV models were used to simulate minima and maxima for each week which were aggregate to the season. Such that for each season and region we had minima and maxima from the half-hourly model and minima and maxima from the GEV models (two set of minima and maxima). The GEV was used for the first forecast year then transitioned to the half-hourly model for the long-term forecast horizon.

Demand was simulated using calendar effects, stochastic volatility and weather. Historical weather events were simulated to develop a weather distribution to normalise demand then stochastic volatility was applied:

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

$$MaxOpso_{week} = f(x_{week}) + g(x_{week}) + \mu_3 + \varepsilon_{week}$$

$$MinOpso_{week} = f(x_{week}) + g(x_{week}) + \mu_3 + \varepsilon_{week}$$

Where:

- $f(x_{hh})$ is the relationship between demand and the demand drivers such as weather and calendar effects.
- $f(x_{week})$ is the relationship between weekly minima/maxima demand and the weekly demand drivers such as PV or PVNSG capacity and NMI count.
- $g(x_{week})$ the second moment scale parameter as a function of x variables.
- μ_3 the third moment shape parameter which was found to be a constant.
- ε_{hh} represents random normally distributed[39] changes in demand not explained by the model demand drivers.
- ε_{weekly} represents random normally distributed[39] changes in demand not explained by the model demand drivers from the GEV models.

Half-hourly model simulation

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") and stitching together the 26 fortnights to construct one weather year. The fortnights were stitched together in order to ensure that they corresponded to the correct time of year, summer fortnights to summer and winter fortnights to winter.

The weather data was block bootstrapped from 20 historical weather years warmed to future climates[40]. A total of 3,000 weather simulations were created to derive 3,000 weather years of data (at half-hourly observations)[41].

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.

The above mentioned half-hourly 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, the stochastic volatility was simulated to account for the component of demand

[39] 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.

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

[41] 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 unexplained by other demand drivers captured in the models (ε_{hh}) which is a feature of all statistical models. The synthetic half-hourly demand traces were estimated for 3,000 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 the natural stochastic volatility of a statistical model. The process also preserved the probabilistic relationship between demand and its key drivers.

GEV model simulation

The GEV model was simulated in a similar process as the half-hourly model. However, the GEV model is less reliant on weather and is more reliant on capturing and understanding the distribution of the extreme values. The simulation process constructed synthetic weather years by sampling daily weather data from history. While the GEV model was specified as a weekly model, daily data was used to increase the number of simulations. The GEV model was then applied to the synthetic weather years to estimate the point forecast component of the GEV.

The GEV distribution was simulated using the same synthetic weather years. In the GEV model the variance of the model is a function of the x variables. The variance of the GEV model was simulated using the x variables from the synthetic weather years.

Finally, the simulation process simulated random normally distribution stochastic volatility of demand. The stochastic volatility was simulated to account for the component of demand variability unexplained the demand drivers captured in the linear model (ε_{hh}) which is a feature of all statistical models.

5.5 Forecast probability of exceedance for base year

The GEV simulation estimates demand for the base year of the forecast. The base year of the ESOO MD demand forecast is the last year of summer actuals. For instance, if the last summer actual demand was 31 March 2019, then base year for the purpose of the forecast is financial year end 2019.

The minimum and maximum demand values were pulled for each synthetic weather year of the GEV simulation. Then the distribution of the minima and maxima was established to calculate the probability of exceedance for operational demand for the base year of the forecast.

5.6 Forecast probability of exceedance for long term

Once the base year was established from the GEV simulation, the half-hourly model then forecast the year-on-year change in demand accounting for shifts in time of day for minimum and maximum demand.

The half-hourly 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 in the half-hourly model and to each forecast year. The process grows half-hourly underlying demand by annual or seasonal growth indices such as population growth, economic factors and price.

This process yields demand values for each half-hour over a simulated year. This represents the half-hourly prediction of the 17,520 half-hours forecast in a given year, for each year in the forecast horizon. The prediction values, as explained previously, represent Underlying demand less LIL.

At this point, the process converts this to operational demand 'sent out' and 'as generated'. This is done by subtracting other forms of generation (rooftop PV, PVNSG and ONSG), adjusting for daily profiles for ESS and EV operation, and adding LIL, distribution and transmission losses back on. As a result, the load factor between maximum demand and annual energy changes over time. For more information on translating Underlying demand to Operational demand, see Figure 3 in Section 1.3.

See below for more information on the LIL, losses, ONSG and auxiliary (needed for 'as generated') forecasts at time of minimum and maximum demand.

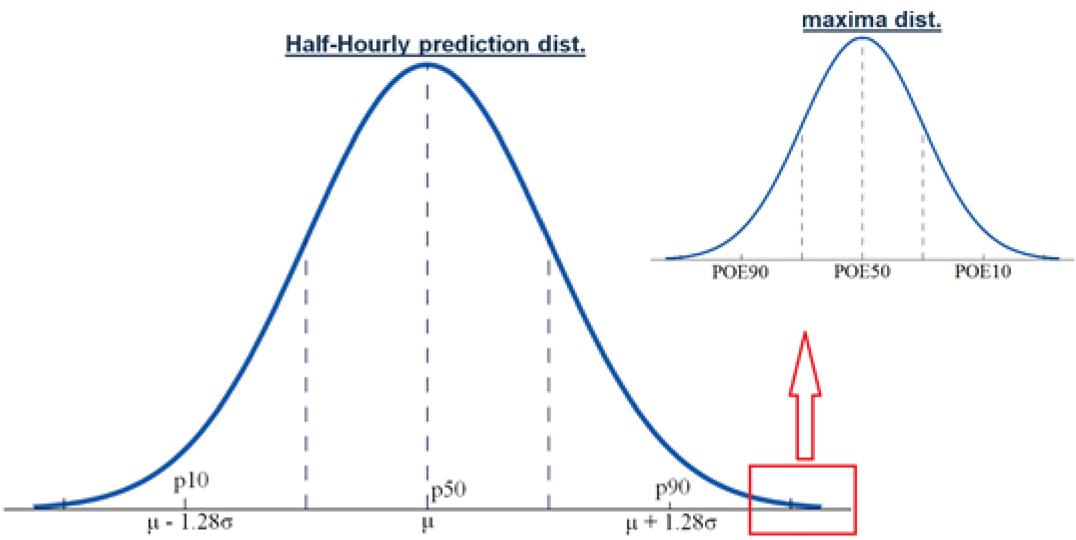
AEMO then extract the seasonal minima and maxima from the simulations. The number of simulations is chosen to be large enough to obtain a smooth distribution of predictions, subject to computational resource limits. For example, if 3,000 simulations are performed, there will be 3,000 maximum and 3,000 minimum values for each scenario-season-year combination. From the 3,000 simulated minima/maxima, AEMO then extracts the necessary POE levels 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 11:

- 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[42].

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.

Figure 11 Theoretical distribution of annual half-hourly data to derive maxima distribution



AEMO then transitioned from the minima and maxima from the GEV model in the base year to the minima and maxima of the half-hourly model for the 20-year forecast horizon.

Transmission and distribution losses

AEMO forecast transmission and distribution losses using transmission and distribution loss factors as provided by the AER.

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

[42] 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.

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, LILs 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.

Other non-scheduled generation

As for annual consumption, the ONSG forecast is done by technology categories, such as small-scale wind farms. The forecast impact on maximum and minimum demand is calculated based on the different technologies' historical generation at time of maximum or minimum demand[43], grown proportionally with any forecast growth in installed capacity.

Generation from peaking-type ONSG is not consider at time of maximum demand. These peaking generators are considered as a form of DSP. As a result, more of the demand at time of maximum demand is modelled as met by operational generators

Auxiliary load forecast

AEMO provides forecast auxiliary load at time of maximum demand. This forecast is based on generator dispatch across hundreds of Monte-Carlo simulations with different thermal generator outages using the PLEXOS simulation software. The forecast uses the average modelled auxiliary load at time summer/winter peak demand.

Structural breaks in demand forecasting models

Similar to the discussion in Section 2.2.2, AEMO deals with structural breaks in the maximum/minimum demand forecast models by including a factor variable to account for it when training the models. This allows AEMO to develop and train models with good forecast accuracy in the presence of structural breaks.

These structure breaks, in the case of the Global Finance Crises, may impact annual energy consumption while having only a minor impact on the daily load profile, or, in the case of COVID-19, impact both the long-term consumption and the short-term daily load profile.

AEMO accounts for these in its forecasts through both the long-term drivers of demand captured in the annual consumption forecast which drives minimum and maximum demand as well as adjustments to the daily demand profile. The details of how a specific structural break has been modelled will accompany the publication where it is used.

An example of this can be seen in Appendix A2 of the 2020 ESOO, which discusses the methodology for accounting for the impact of COVID-19.

[43] For maximum demand, the top 10 highest demand half-hours in each of the last five years were used to calculate the average generation at time of maximum demand. For minimum demand, the bottom 10 demand periods were used.

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 (financial-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.

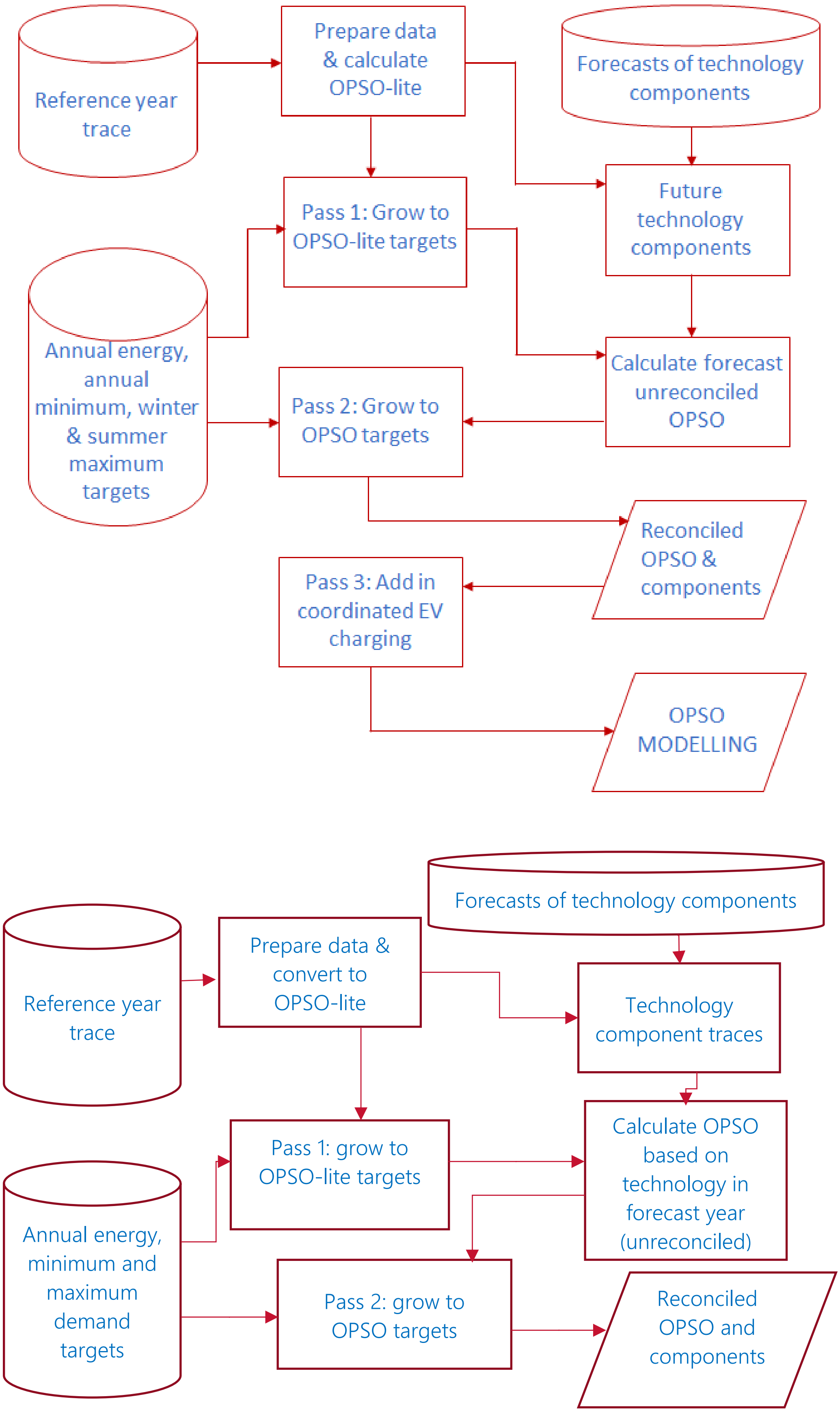
For the purposes of load traces used in market modelling, AEMO have developed an additional demand definition – operational demand sent out modelling (OPSO-modelling) – to capture the effects of future coordinated EV charging.

The trace development process was conducted in three passes for each combination of NEM region, historical reference year, target year, scenario and POE level:

- Pass 1. Growing the reference year trace on an OPSO-lit*e* basis to meet OPSO-lite targets (demand trace has forecasts of technology components removed, refer to Section 6.2 for full description).
- Pass 2. Reinstating forecasts of technology components and reconciling the time series to meet the OPSO targets.
- Pass 3. Add coordinated EV charging to OPSO.

The trace development process is summarised as a flow diagram in Figure 12. A worked example of the growth scaling algorithm (discussed in section 6.1) is also provided in Appendix A8.

Figure 12 Demand 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. The first two passes of the three-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 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. 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.
2. Categorised each day in the reference year into day-type groups:
   – High-demand days in summer to target the summer maximum demand target.
   – High-demand days in winter to target the winter maximum demand target.
   – Low-demand half-hour periods to target the annual minimum demand target.
   – Other which is used to target the annual consumption target.

A threshold number of days or periods in each group was nominated as an input parameter.

3. Scaled the half-hourly demands across all summer high-demand days such that only the highest demand point exactly matched the summer maximum demand target.
4. Scaled the half-hourly demands across all winter high-demand days such that only the highest demand point exactly matched the winter maximum demand target.
5. Scaled the minimum demand across all low-demand half-hour periods such that only the minimum demand point exactly matched the annual minimum demand target.
6. Determined the scaling factor for each day-type group such that the energy across the year matched the annual energy target.
7. Calculated future annual energy for each day-type group by multiplying the energy in each day-type group with demand scaling factors.
8. The "other" day type had no scaling factor for the purpose of meeting a demand target. As such, the algorithm allocated the remainder of future energy to the 'other' day-type category for the purpose of meeting the annual energy target.
9. 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 8 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 – growing to OPSO-lite targets

As highlighted in Figure 12, 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 Pass 2 – 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, PVNSG, ESS, EV and CSG were taken into account, as well as DSP. This is because the OPSO targets were based on simulating weather, 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 Pass 3 – adding coordinated EV charging to OPSO

The third phase adds coordinated EV charging to OPSO.

For each day in the demand trace, a daily amount of coordinated EV charging energy is added to the daily OPSO profile such that the coordinated EV charging fills up the daily half-hourly OPSO troughs. The result is OPSO-modelling. The approach for each day:

1. Orders the OPSO power profile from lowest to highest.
2. Calculates the corresponding accumulated OPSO energy.
3. Calculates the minimum OPSO power level such that this value adds the necessary energy to OPSO to match the daily coordinated EV charging energy amount.
4. The new OPSO-modelling power profile is the maximum of the minimum OPSO power level (calculated from the previous step) and the original OPSO power profile.
5. A stochastic component is added to the OPSO-modelling power profile.
6. Reorders the OPSO-modelling power profile according to time.

6.5 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:

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

The retail price structure followed the Australian Energy Market Commission (AEMC) 2019 Residential Electricity Price Trends[44] report. The wholesale price forecasts are based on AEMO's Draft 2020 Integrated System Plan (ISP). Network, environmental and retail components are based on the AEMC's report. Additional transmission development costs associated with AEMO's ISP central development plan also impact the total cost. The process of residential pricing modelling is summarised in Table 11.

Commercial and industrial pricing models were developed using the residential pricing model as a baseline. Each component is then adjusted based on methodology from Jacob's 2017 Retail Electricity Price History and Projected Trends Jacobs Report[45] and updated using Bloomberg NEF 2019 Australia Behind the Meter Forecast. 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.

[44] AEMC, 2018 Residential Electricity Price Trends, at https://www.aemc.gov.au/market-reviews-advice/residential-electricity-price-trends-2018.

[45] Jacobs, Retail Electricity Price History and Projections, 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.

Table 11 Residential pricing model component summary

Component	Process summary
Wholesale costs*	Wholesale price forecasts based on AEMO's Draft 2020 Integrated System Plan.
Network costs	Use 2019 Residential Electricity Price Trends AEMC Report. Extrapolate the trajectories based on AEMO's 2019 ISP Central Optimal Development Path Scenario. Benchmark against published network tariffs
Environmental costs	Use 2019 Residential Electricity Price Trends AEMC 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 2019 Residential Electricity Price Trends AEMC Report for the base year (FYE 2019) and hold constant across the forecast period.

* The wholesale costs component of retail price consists of wholesale price, hedging cost, and market charges.

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[46].

Table 12 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 BoM 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[47] is:

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

The formula for CDD[48] is:

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

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 and is specific to the 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[49] and the stations used are given below.

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

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

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

[49] BoM Climate Data, http://www.bom.gov.au/climate/data/.

Table 13 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)*	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

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

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:

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

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

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.

- 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 to transform the historical temperatures to the distribution of projected temperatures.
- 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 eight 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 eight 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 midpoint 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.
- 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 2020 forecast of installed capacity for rooftop PV (installations with a capacity < 100 kW) was based on advice from two external consultants, Green Energy Markets (GEM) and CSIRO.

Table 14 below provides details on the scenario mapping used for the 2020 ESOO scenarios; the forecast methodologies are available in CSIRO's and GEM's published reports[50,51]. This scenario mapping was developed after consultation with stakeholders in the March 2020 Forecasting Reference Group (FRG)[52] meeting and considers the relationship between the PV and battery forecasts to capture a broad range of scenario possibilities.

Table 14 Mapping of consultant trajectories used for DER forecasts

	ESOO scenarios			ISP scenarios	
	Slow Change	Central	Step Change	Fast Change	High DER
PV	CSIRO Slow Change	Average of CSIRO Central and GEM Central	GEM Step Change	Average of CSIRO Fast Change and GEM Fast Change	GEM High DER
Embedded battery systems	CSIRO Slow Change	Average of CSIRO Central and GEM Central	GEM Step Change	Average of CSIRO Fast Change and GEM Fast Change	GEM High DER
Electric Vehicles	CSIRO Slow Change	CSIRO Central	CSIRO Step Change	CSIRO Fast Change	CSIRO High DER

The main drivers behind the forecast rooftop PV uptake are:

- 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.

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50 CSIRO, 2020 projections for small-scale embedded technologies report, at https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/inputs-assumptions-methodologies/2020/csiro-der-forecast-report.pdf?la=en.

51 GEM, 2020 Projections for distributed energy resources – solar PV and stationary energy battery systems report, at https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/inputs-assumptions-methodologies/2020/green-energy-markets-der-forecast-report.pdf?la=en

52 For FRG minutes and presentation see https://aemo.com.au/en/consultations/industry-forums-and-working-groups/list-of-industry-forums-and-working-groups/forecasting-reference-group-frg#:~:text=The%20Forecasting%20Reference%20Group%20(FRG,AEMO%20and%20industry's%20forecasting%20specialists.&text=It%20is%20an%20opportunity%20to,not%20a%20decision%20making%20body.

- The payback period considering forecast retail electricity prices and feed-in tariffs.
- Population growth in Australia, allowing for more rooftop PV systems to be adopted before saturation is reached.
- Complementary uptake of other technologies that can be used to leverage the energy from PV systems for increased financial benefit (for example, energy storage systems).

The impact of the COVID-19 pandemic is also considered to different extents depending on the scenario over the short term[53].

This year, CSIRO updated their approach to the short-term (two years) projections to consider the recent historical trend, blending these into the technology adoption curve method applied in 2019 for the long-term forecast. This shift in methodology to include a short-term trend model as well as a longer-term approach was identified as the second of two key improvements from the 2019 Forecast Accuracy Report[54].

The forecasts used in the energy and demand models are effective (degraded) panel capacity, which is the DC panel capacity adjusted for degradation of panels over time. AEMO rebased this forecast so the forecast starts from the most recent CER data up to the end of April 2020. It should be noted that:

- The CER data has a lag in it due to installers not necessarily submitting their STC applications to the CER in the same month that a given PV system is installed in. Due to this lag the last two months are projections based on previous month's uptake.
- CER data is based on the installed PV panel capacity (DC), which may be up to 33% higher than the installed inverter capacity in some cases.
- CER data currently does not capture the removal of old PV systems.
- CER data does not make any adjustment for the degradation of PV capacity over time.

A3.1.2 Rooftop PV generation

AEMO obtained estimates of historical 30-minute generation of installed rooftop PV systems for each NEM region. The primary dataset, procured from Solcast, supplements data derived from AEMO's in-house model (developed with the University of Melbourne, covering the period 2000-2008). The resulting historical generation is a time series for each NEM region from 1 January 2000. It is based on solar irradiance from satellite imagery and weather from ground-based observing stations.

The historical PV generation is first obtained in the form of a normalised measure representing average (30-minute) AC power output for a notional 1 kW DC unit of installed capacity. For the energy forecast, a climatological mean of normalised generation for each market period in a year is applied to the effective capacity projections[55]. The resulting normalised generation values for the outlook period are verified against the historical annual and monthly capacity factors.

For each region, an additional profile is calculated for west-facing PV panels by using clear-sky estimates to manipulate the actual normalised generation profiles.

The generation profiles are used to calculate total rooftop PV generation in future years, by multiplying with the forecast of effective rooftop PV capacity. The generation profiles are blended to account for the AEMO assumption that over time there will be a shift towards a larger proportion of panels installed with a westerly orientation, reaching a predefined percentage of the forecast effective capacity after 20 years. This reflects AEMO's consideration 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.

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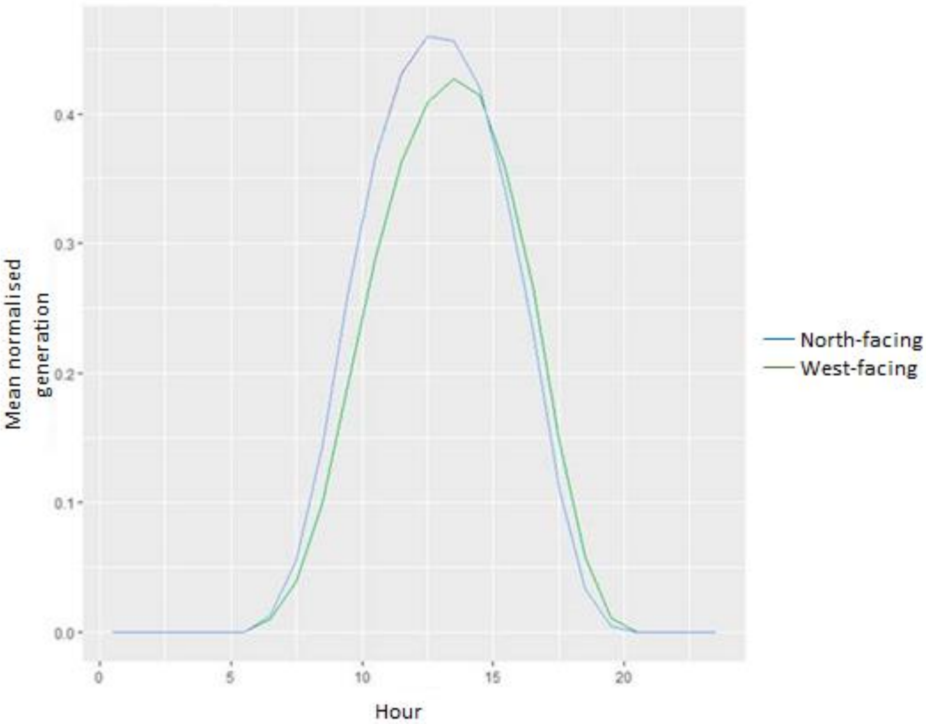
[53] See CER and GEM reports for further information on COVID 19 adjustments.

[54] AEMO, 2019 Forecast Accuracy Report, at https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/accuracy-report/forecast_accuracy_report_2019.pdf.

[55] The climatological mean was based on a 30-day rolling means of data back to 2000, designed to impart smoothness throughout the year into the normalised generation values.

- 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 13, west-facing panels have the potential to generate around 15% less power at midday and 15% more power towards sunset relative to north-facing panels. The proportion of west-facing panels, in the 2020 ESOO was set to reach 10% by 2029-30 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 13 Example of north-facing vs west-facing PV generation



Source: AEMO

A3.2 Energy storage systems forecast

A3.2.1 Installed capacity forecast

The GEM and CSIRO forecasts are used to inform AEMO's forecast of energy storage systems (ESS). The ESS forecast is behind-the-meter residential and business batteries integrated with PV systems. These forecasts do not include grid-connected batteries associated with small solar power stations.

The main drivers for the ESS installed capacity forecast are:

- 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).

The assumptions for each scenario have been updated to capture recent observations and Consultant advice. These include the following changes to the scenario assumptions:

- The FYE 2019 estimated actual data has been revised upwards by 55 MW, based on updated battery estimated actuals information[56].
- The degradation adjustment has been removed from battery MW and is only applied to MWh in line with industry advice received by the consultants.
- Updated population and economic forecasts.
- Development of state specific representative customer load profiles[57], which are linked to the 19 years of estimated historic rooftop PV generation by state described in A3.1.
- Updates to the battery and balance of plant installed costs based on Draft GenCost 2019-20[58] forecasts.
- Revised retail tariff assumptions, with a smaller proportion of customers accessing smart tariffs in the Central scenario based on low historical consumer interest in opt-in time-of-use tariffs.
- Updated CSIRO forecast approach, using the recent historical trend to inform the short term forecast before blending into the technology adoption curve approach used in 2019.
- A revised scenario mapping approach, combining both GEM and CSIRO battery forecasts as detailed in Table 14.

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 is assumed to primarily charge from excess rooftop PV generation) 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.

The demand forecasts consider two types of battery operation:

- Shift Solar, where the battery will charge when excess solar PV generation is available and discharge whenever solar PV generation is insufficient to cover household demand
- Time of Use tariff (TOU), where the battery is optimised to take advantage of a time of use tariff, top up charge at off peak times to maximise avoidance of peak time tariffs.

A third operating type, control of battery by an aggregator, commonly referred to as a virtual power plant (VPP), with the battery operation optimised to reduce overall system costs and operated as a scheduled, controllable form of generation, much like a traditional form of grid-generated electricity supply.

The proportions of each battery operating type are provided in Table 15 below.

Table 15 New South Wales Central scenario tariff and associated battery operating type shares

Customer Class	Shift solar		TOU		Virtual Power Plant (VPP)	
	2030	2050	2030	2050	2030	2050
Residential	76%	68%	6%	2%	18%	30%
Commercial	14%	12%	56%	48%	30%	40%

[56] Average battery size information was sourced from market intelligence provided by a third party consultant to CSIRO (SunWiz).

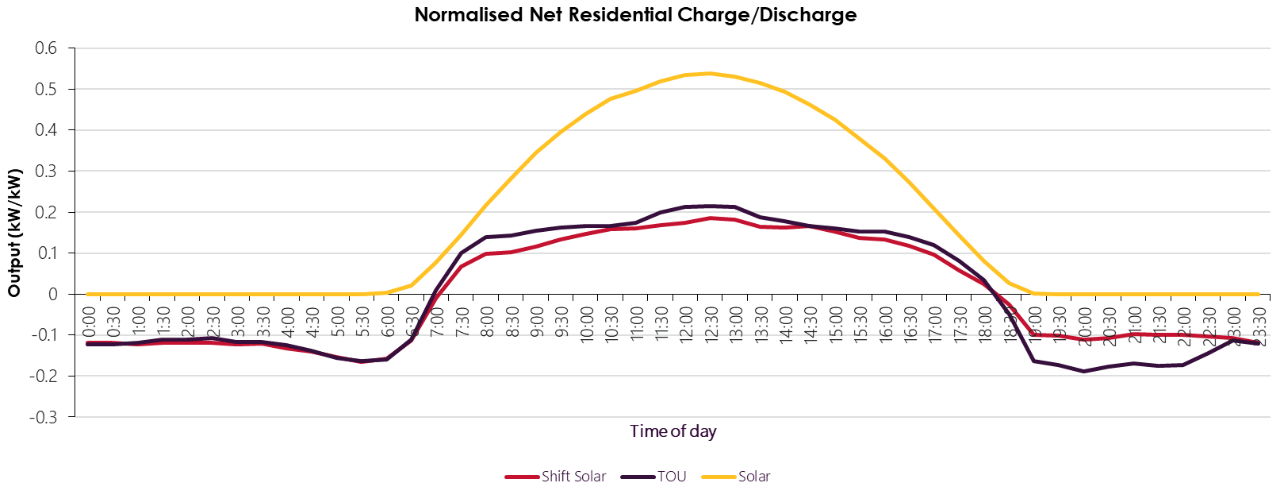
[57] See Appendix A.2 of Projections for small-scale embedded technologies, 2019.

[58] Graham, Paul; Hayward, Jenny; Foster, James; Havas, Lisa. GenCost 2019-20. CSIRO publications repository: CSIRO; 2020, at https://doi.org/10.25919/5eb5ac371d372.

To calculate the effect of batteries contribution to the 2020 ESOO demand profile forecasts, CSIRO developed a detailed set of normalised battery charge/discharge profiles. These profiles were developed using New South Wales customer load profile data for from the Smart Grid Smart Cities program run by Ausgrid. CSIRO provided load profiles for each region based from these profiles, with regions other than NSW adjusted based on zone substation data.

Figure 14 compares the charge/discharge profiles of the two battery operating types for New South Wales for February . Actual charge/discharge profile will depend on a range of factors including the actual availability of solar resources to charge the battery system, household consumption, and battery size.

Figure 14 New South Wales average daily February profile



The charge/discharge profiles have the effect of smoothing out demand across the day and reducing maximum demand, however for shift solar and shift peak battery operating types, the effect per battery at reducing the operational demand at peak times in summer is relatively small given that battery operations are targeting residential load reductions, rather than whole-of-grid reductions.

A3.2.3 ESS in annual consumption

ESS stores energy for later use, but in so doing incurs electrical losses as indicated by a battery's round-trip efficiency. In the 2020 forecasts, the round-trip efficiency is assumed to be 85%. That is, for each 1 kWh of energy stored in the battery, 15% of that energy is lost in the process of charging and then discharging the battery. This lost energy is accounted for in business and residential consumption forecasts as an additional form of energy consumption applying the expected level of battery operation. These losses are small relative to NEM operational consumption, accounting for <0.01 % of total electricity consumption by 2038-39 in the Central scenario.

A4. Electric vehicles

A4.1.1 Electric vehicles forecast

CSIRO developed AEMO's forecast of EVs, including residential, light commercial, and heavy commercial vehicles such as buses and trucks. The most recent CSIRO report is available on AEMO's website[59].

The main drivers for the EV forecast are:

- 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.
- Limiting factors such as renter's access to external household charging points.
- Full decarbonisation of transport by 2050 (considered in Step Change scenario only).

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

Consultancies also provided AEMO the daily charge and discharge profile for EVs used in the minimum and maximum demand modelling.

Four different charge profiles are applied in the 2020 forecasts:

- Convenience charging – vehicles assumed to have no incentive to charge at specific times, resulting in greater evening charging after vehicles return to the garage.
- Daytime charging – vehicles incentivised to take advantage of high PV generation during the day, with available associated infrastructure to enable charging at this time. For 2020 this was further split so that a proportion of day time charging EV was assumed to be managed by a VPP or charging aggregator to minimise peak demand events driven by EV charging (See Table 16).
- Night-time charging – vehicles incentivised to take advantage of low night-time demand. For 2020 this was further split so that a proportion of night time charging EV was assumed to be managed by a VPP or charging aggregator to minimise peak demand events driven by EV charging (See 0). Highway fast charging – vehicles that require a fast charging service while in transit, based on a mix of simulated and actual arrivals of vehicles at public fast charging from CSIRO research.

The charge profiles are used in the minimum and maximum demand simulation process and load trace growing algorithm.

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[59] At https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/Inputs-Assumptions-and-Methodologies.

Table 16 Assumed proportion of daytime charging that is managed, by scenario

FYE	Central	Fast Change	High DER	Slow Change	Step Change
2030	0%	0%	0%	0%	0%
2040	40%	40%	50%	0%	50%
2050	80%	80%	100%	0%	100%

Table 17 Assumed proportion of night-time charging that is managed, by scenario

FYE	Central	Fast Change	High DER	Slow Change	Step Change
2030	0%	0%	0%	0%	0%
2040	30%	30%	50%	0%	50%
2050	60%	60%	100%	0%	100%

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.

A5. Connections and uptake of electric appliances

A5.1 Connections

As the retail market operator for most Australian electricity retail markets (except the Northern Territory and Tasmania), AEMO has access to historical connections data for these markets; historical connections data for the other markets are acquired from a confidential survey. AEMO forecasts 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 household projections, which is determined by 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[60].

For the 2020 ESOO, AEMO engaged Conach to develop a residential building stock model that forms the basis of the connections forecast. The building stock model takes actual household numbers from the Australian Bureau of Statistics (ABS) 2016 census and grows the household numbers from 2017 to 2019 using the NMI connections growth rate, due to both the updated data for connections since the ABS census and the stable growth rate making the use of a trend variable appropriate.

From 2020 to 2023, the building stock model transitions from using the NMI connections growth rate to the ABS household projections (Cat. No. 3236.0) on a sliding scale of 0% to 100%. The ABS Household Projections data provides three series – Series 1 (upper), Series II (middle) and Series III (lower) – that have been applied to the Step Change, Central and Slow Change scenarios. From 2024 onwards, the building stock model applies only the ABS Household Projections. AEMO used recent data on connections per household to convert the building stock model for each scenario into connections forecasts. Further spread between the scenarios is drawn from construction sector activity (Division E) per capita relative to the Central scenario, based on the economic consultants economic and population forecasts.

It is anticipated that COVID-19 will reduce the demand for new building construction, and AEMO has adjusted the connections forecast based on published housing industry reports[61].

[60] Residential connections forecasts are available on AEMO's Forecasting Data Portal, at http://forecasting.aemo.com.au.

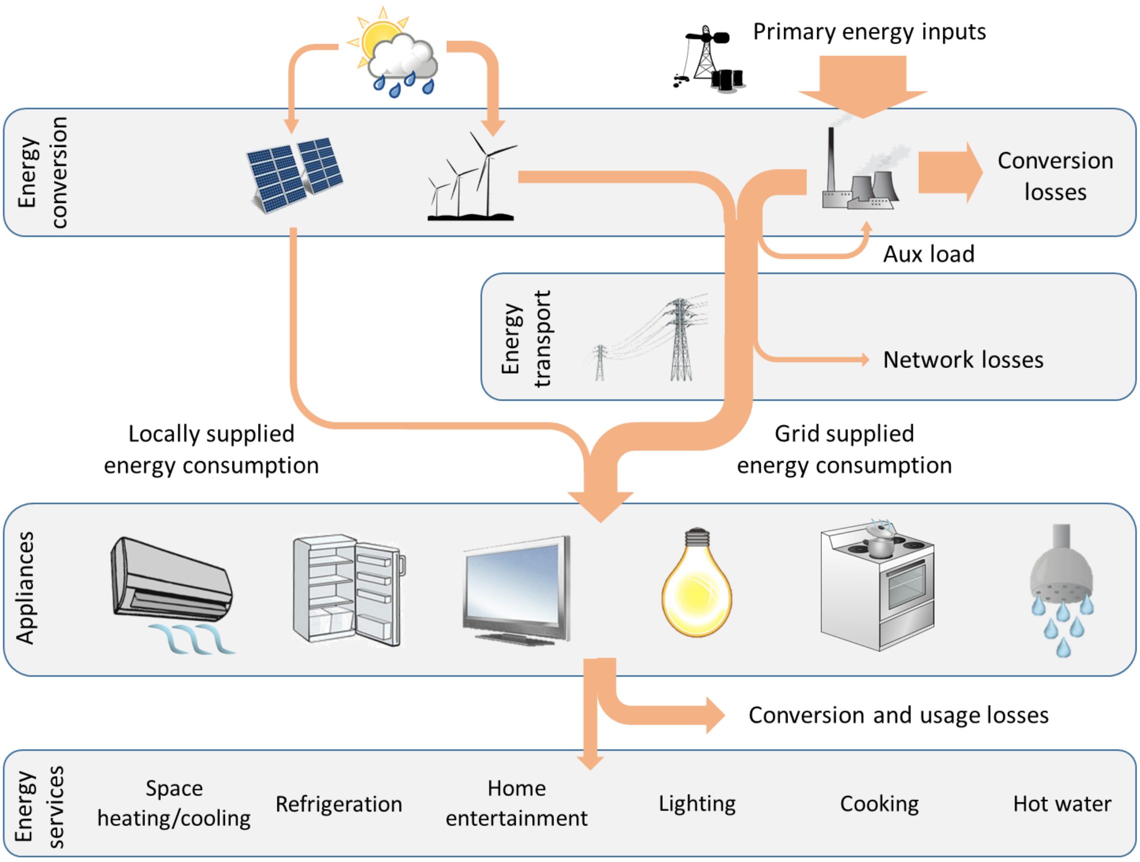
[61] See https://hia.com.au/-/media/HIA-Website/Files/Media-Centre/Media-Releases/2020/national/half-a-million-jobs-at-risk.ashx.

A5.2 Uptake and use of electric appliances

AEMO uses appliance data from the former Australian Government Department of the Environment and Energy[62] 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 15 illustrates the difference between energy services and energy consumption.

Figure 15 Energy services vs energy consumption



A5.2.1 Appliance growth calculation

The following lists how AEMO calculates energy services by appliance group.

- Heating/cooling: Number of appliances × output capacity of appliance × hours used per year.
- White goods: Number of appliances × 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: Number of appliances x hours used per year.
- Hot water: Number of appliances x hours used per year.

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

The calculated demand for energy services by appliance group is converted into a growth index for each load type, with the reference year of the consumption forecast being the base year (index = 100). For baseload, the relevant appliance groups are combined into a composite index based on their relative estimate energy consumption in the base year. AEMO divides the appliance growth indices by the number of households[63] in a forecast year.

The table below shows the appliances covered by the calculations.

Table 18 List of appliance categories used in calculating the appliance growth index

Load type	Category	Group
Heating/cooling load	Combined space heating/cooling	AC ducted AC non-ducted (split and window/wall units)
Heating/cooling load	Space cooling	Evaporative (mostly central) Fans
Heating/cooling load	Space heating	Electric resistive Mains gas non-ducted Mains gas ducted LPG gas non-ducted Wood Heaters
Base load	White goods	Refrigerators Freezers Dishwashers Clothes washers Clothes dryers
Base load	IT & Home Entertainment	Television – composite average Set-top box – free-to-air Set-top box – subscription Video players and media recorders Home entertainment – other (mostly audio) Game consoles Computers – desktop (and associated monitors) Computers – laptop Wireless/Wired networking device Miscellaneous IT equipment
Base load	Lighting	MV incandescent MV halogen ELV halogen CFL Linear fluorescent LED
Base load	Cooking Products	Upright – Electric Cooktop – Electric

[63] AEMO uses household data from RBS 2015 for consistency

Load type	Category	Group
		Oven – Electric Upright – Gas Cooktop – Gas Oven – Gas Upright – LPG Cooktop – LPG Oven – LPG Microwave
Base load	Hot water heaters	Electric water heater, storage – small Electric water heater, storage – medium/large Electric water heater, instant Gas water heater, storage (mains) Gas water heater, storage (LPG) Gas water heater, instant (mains) Gas water heater, instant (LPG) Solar electric Solar gas Heat pump Wood, wetbacks
Base load	Other Equipment	Pool Equipment – Electric Pool Equipment – Gas Pumps Battery chargers Miscellaneous 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 18), 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.

AEMO made further adjustments to the number of appliances in the space heating and hot water heating categories, to account for policy-induced fuel switching behaviour from gas to electricity. In 2020, the policies considered were the National Construction Code 2022 for water heating, the Victorian Solar Homes Program for solar electric water heating, the ACT Gas Heater Rebate, and the planned E3 Zoned Space Heating Label Program. Adjustments vary by scenario and reflect similar adjustments in the 2020 GSOO fuel switching model. AEMO also estimated the potential impact of the ACT Government's Climate Change Strategy, which is legislated to achieve net zero emissions from gas use by 2045[64].

[64] ACT Government, ACT Climate Change Strategy 2019-2025, at https://www.environment.act.gov.au/__data/assets/pdf_file/0003/1414641/ACTClimate-Change-Strategy-2019-2025.pdf.

AEMO provides further dispersion across the scenarios by applying a per capita Household Disposable Income (HDI) index to the Slow Change and Step Change scenarios, relative to the per capita HDI for the Central scenario.

A5.2.3 COVID-19 adjustments

AEMO considered the impact of significant restrictions in movement outside of the household and the likely effect on the appliance growth indices. While the economic downturn reduced household spending, particularly for displaced workers, a sizeable portion of the workforce rapidly transitioned to work from home arrangements. This is supported by observations of residential meter data, that indicates a 10 to 15% increase in consumption for the sector.

AEMO applied a short-term bounce in consumption of approximately half this value in the Step Change, should six months of this sustain usage remain, with a lower level applied to the Central and Slow Change scenarios. AEMO assumed a smaller adjustment in the 2022, as mobility is expected to increase towards pre-COVID levels. In the Central and Step Change scenarios, a modest adjustment is applied in the longer term to account for some working from home practices persisting. Table 19 lists the COVID adjustments made to the appliance growth indices.

Table 19 COVID adjustments to the appliance growth indices

Financial year	Central	Step Change	Slow Change
2020-21	3.5%	6%	2%
2021-22	1.0%	2%	0.5%
2022-23 and beyond	0.5%	1%	0%

A6. Data sources

Table 20 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 21 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
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/http:.	
Weather & Climate Change Data	CSIRO	https://www.csiro.au/	
Weather & Climate Change Data	Climate Change Australia	https://www.climatechangeinaustralia.gov.au/	
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 Household Projections	ABS	https://www.abs.gov.au/ausstats/abs@.nsf/mf/3236.0	AEMO uses household projections series I (Step change scenario); series II (Central scenario); series II (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 (BIS Oxford Economics)	Original: https://www.aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/inputs-assumptions-methodologies/2020/bis-oxford-economics-macroeconomic-projections.pdf?la=en COVID-19 update:	Economic projections were developed by an economic consultant, according to AEMO's scenario requirements

Data series	Data sources	Reference	Notes
		https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/inputs-assumptions-methodologies/2020/bis-oxford-economics-macroeconomic-central-scenario-and-downside-scenario-forecast.pdf?la=en	
Wholesale Electricity Price	AEMO ISP	https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/Integrated-System-Plan	Wholesale price forecasts by AEMO
DER forecasts	CSIRO and GEM	https://aemo.com.au/-/media/Files/Electricity/NEM/Planning_and_Forecasting/Inputs-Assumptions-Methodologies/2020/CSIRO-DER-Forecast-Report https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/inputs-assumptions-methodologies/2020/green-energy-markets-der-forecast-report.pdf?la=en	
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	
Auxiliary Factors	GHD 2018-19 Costs and Technical Parameters	https://www.aemo.com.au/-/media/Files/Electricity/NEM/Planning_and_Forecasting/Inputs-Assumptions-Methodologies/2019/GHD-AEMO-revised---2018-19-Costs_and_Technical_Parameter.xlsb	
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
Energy data by Industry Code	Department of Environment and Energy Data Statistics	https://www.energy.gov.au/publications/australian-energy-update-2019	Table F

A7. Data segmentation

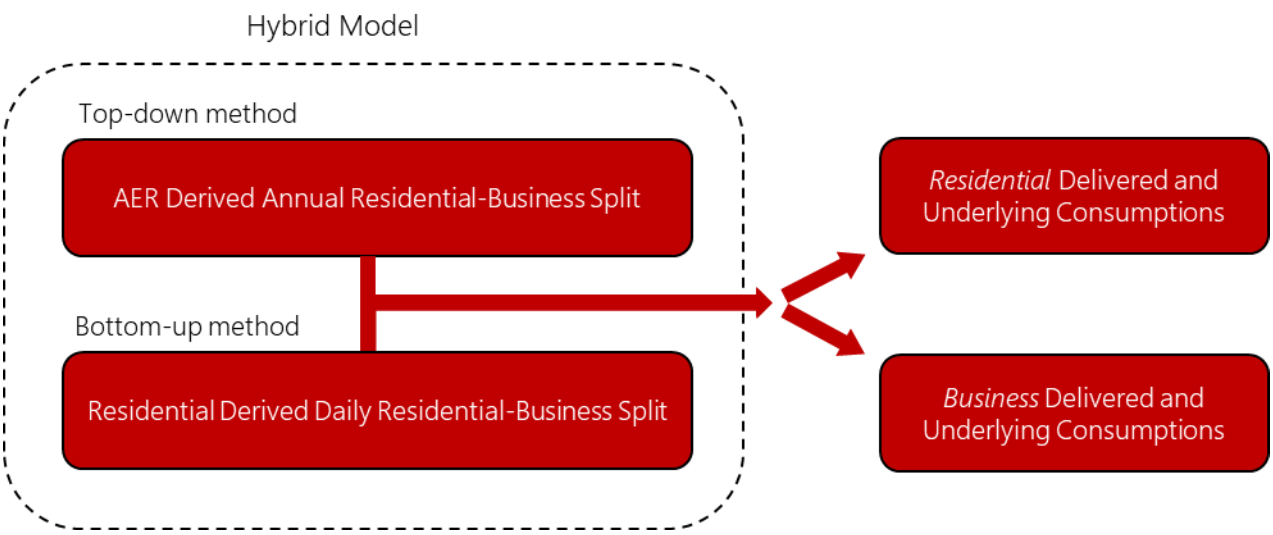
AEMO used a hybrid model, a combination of two different methods, to calculate the half-hourly Residential and Business split for the latest year of actual consumption, which forms the starting point for the forecasting process. As illustrated in Figure 16, this hybrid method utilises the combination of AER Derived Annual Residential-Business Split (top-down) and Residential Derived Daily Residential-Business Split (bottom-up) methods to calculate the half-hourly Residential and Business consumptions. Herein the names top-down and bottom-up to denote the two approaches. This process provides:

- Delivered consumption.
- Underlying consumption.

For the definitions of the consumption types, see Section 1.3.

The bottom up method is used for all NEM regions, except Tasmania which has lower amount of smart meter connection. As a result, Tasmania is based on the top-down approach.

Figure 16 Hybrid model used to calculate the half-hourly residential and business split



A7.1 AER-derived annual residential-business split: top-down method

The top-down method used a combination of Residential to Business annual percentage splits (provided to AEMO by the AER) and its own meter data classification to calculate the half-hourly residential and business split for the latest year of actual consumption.

A7.1.1 AER residential to business splits

The AER annually surveys distribution network service 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.

A7.1.2 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.

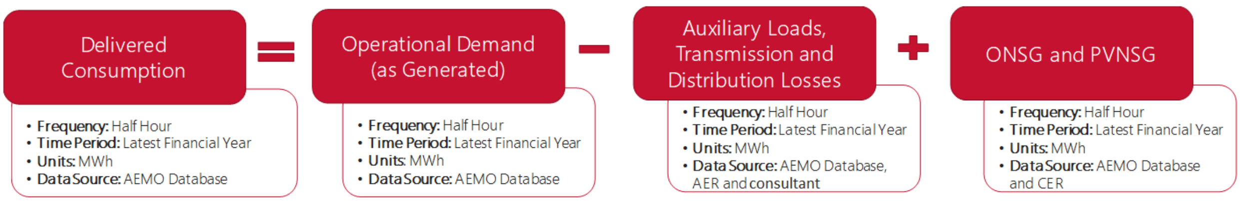
Business half-hourly data

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.

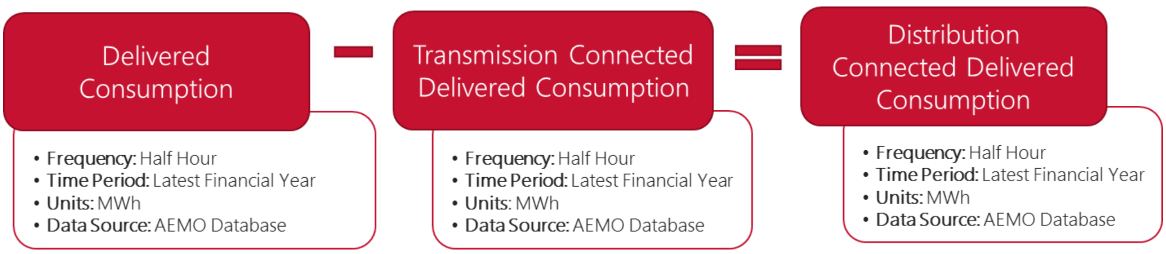
A7.1.3 Methodology

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:

Distribution Connected Delivered Consumption

- **Frequency:** Annual
- **Time Period:** Latest Financial Year
- **Units:** MWh
- **Data Source:** AEMO Database

✖

AER Residential-to-Business Split

- **Frequency:** Annual
- **Time Period:** Latest Financial Year
- **Units:** %
- **Data Source:** AER

=

Distribution Connected Delivered *Business* Consumption Target

- **Frequency:** Annual
- **Time Period:** Latest Financial Year
- **Units:** MWh

Distribution Connected Delivered *Residential* Consumption Target

- **Frequency:** Annual
- **Time Period:** Latest Financial Year
- **Units:** MWh

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

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

- **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

- **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

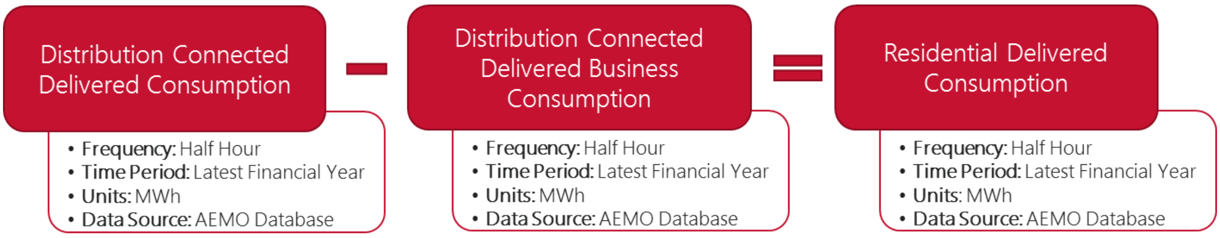
=

Business Delivered Consumption

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

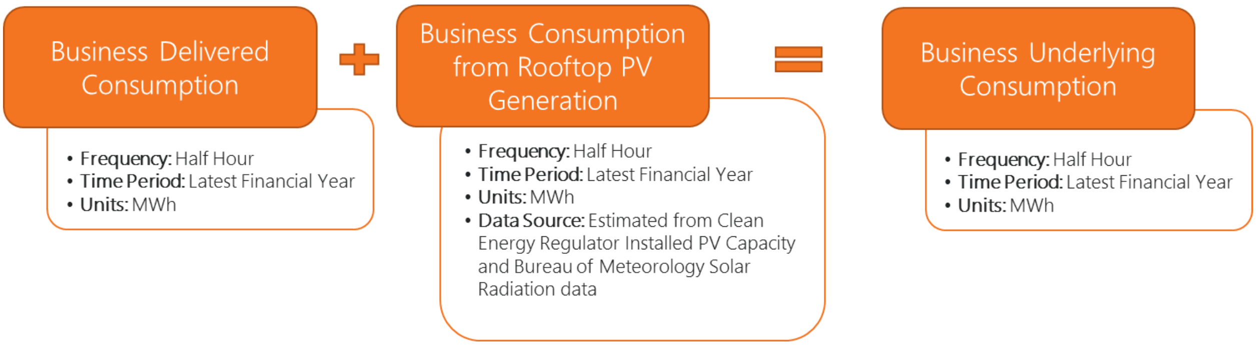
Note that all transmission-connected loads are heavy industrial users and fall in the business category.

Calculate residential half-hourly delivered consumption:

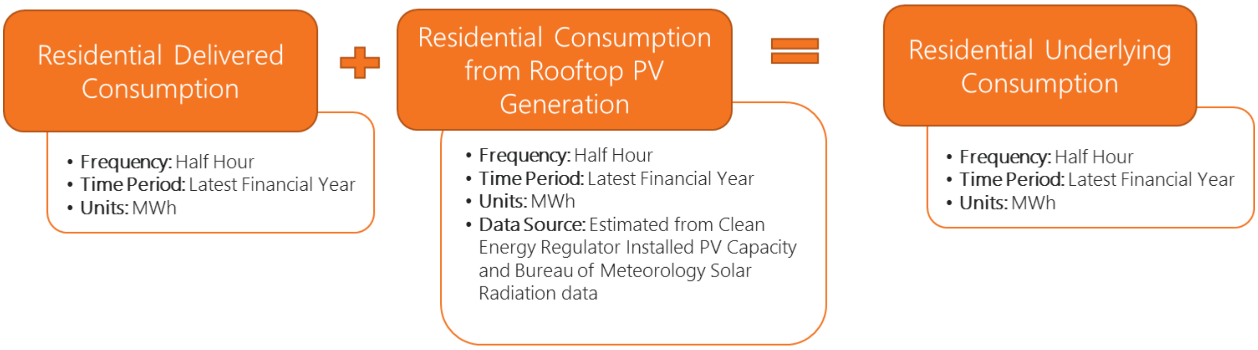


Stage 2: Developing Residential to Business Underlying Consumption Split

Calculate business underlying consumption:



Calculate residential underlying consumption:



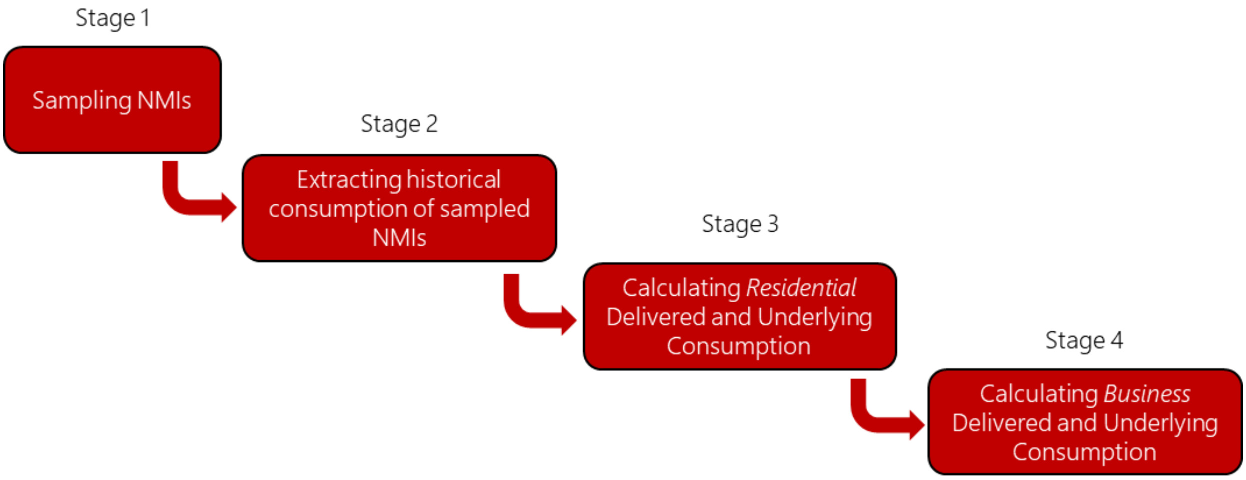
A7.2 Residential delivered daily residential-business split: bottom-up method

The bottom-up method uses AEMO's smart meter data to calculate the half-hourly Residential and Business split for the latest year of actual consumption. Residential metered load, when sampled representatively, are more likely to display similar usage patterns to a population than business consumers (that have a broad industry and usage profile) and is the preferred method for splitting out the total grid consumption. However, as the number of smart meters in the population of meters has been historically small (outside of Victoria) this method could not be fully utilised until higher counts in other jurisdictions could be obtained.

A7.2.1 Methodology

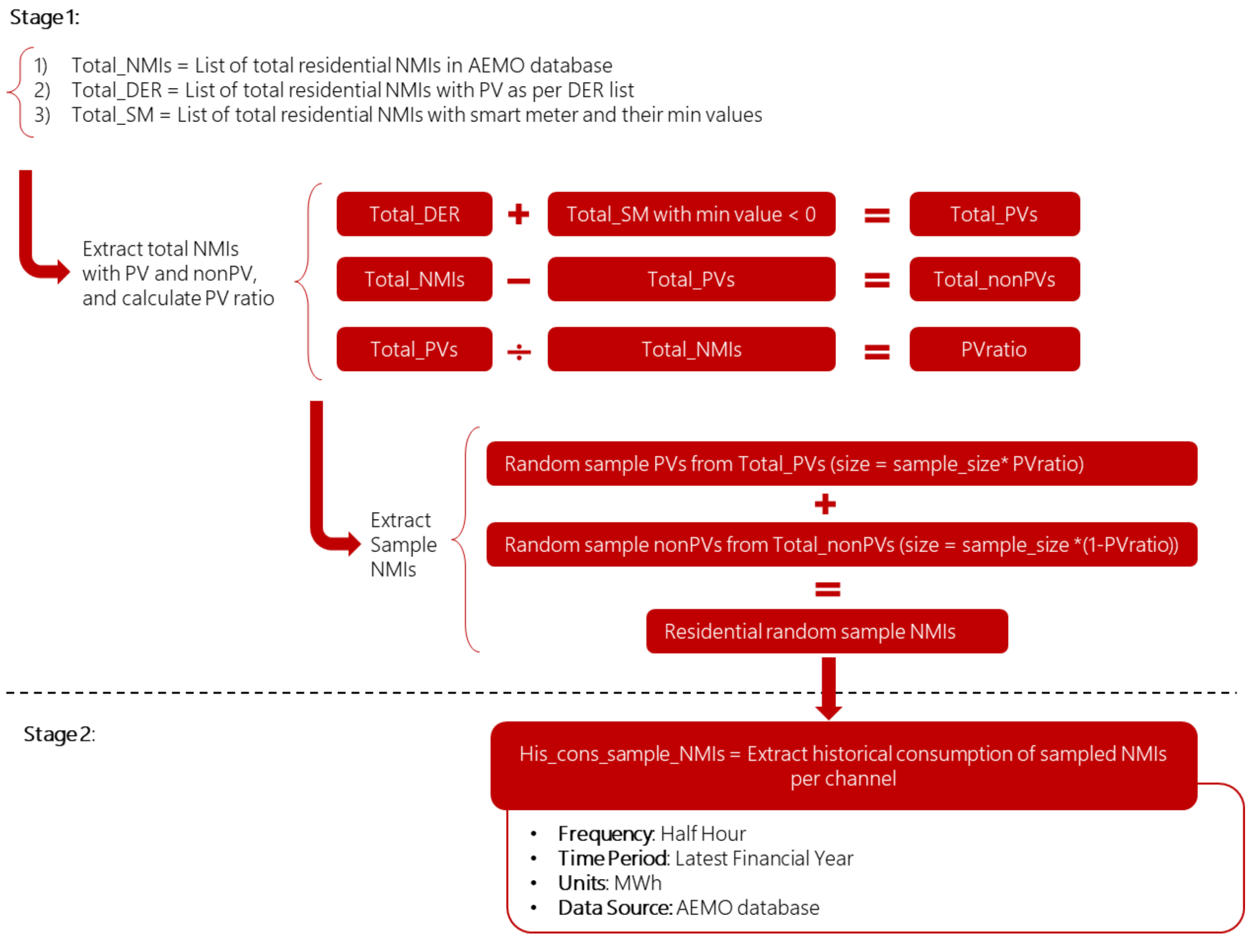
The methodology of this method is depicted in Figure 17. This method consists of four stages for calculating the half-hourly delivered and underlying consumptions for both residential and business sectors.

Figure 17 Workflow of the bottom-up method for residential-business split



Stage 1: Sampling NMIs

Extracting a representative sample of NMIs that represents the whole region is carried out in this stage. This is done by randomly sampling among residential NMIs that contain the correct proportion of those with PV and those without PV (denoted as 'non PV') systems and combining them to form the residential random sample of NMIs preserving the ratio of those with PV and those without PV (denoted as the 'PV ratio'). This PV ratio is calculated by dividing the total number of the residential NMIs with PV systems extracted from AEMO's list of households (demoted as DER List) that have solar PV to the total number of the residential NMIs in each region. The amount of NMIs in each sample is also calculated to be at least a 95% confidence interval in each region (approximately 20,000 NMIs are used for each region).



Stage 2: Extracting historical consumption of sampled NMIs

In this stage, the historical consumption from the sampled NMIs is extracted from AEMO's database at the half-hourly level.

Stage 3: Calculating residential delivered and underlying consumptions

The residential delivered and underlying consumption are calculated in this stage. The usage per NMI is initially calculated from the sampled NMIs and then, using the count of connected residential NMIs (number of households) in each region, the usage per NMI is scaled to produce the sample-derived regional residential delivered consumption. Lastly, the residential underlying consumption is calculated by adding residential PV generation as estimated for each region (refer to Appendix A3) to the residential delivered consumption.

Total consumption of NMIs in His_cons_sample_NMIs
- **Frequency**: Half Hour
- **Time Period**: Latest Financial Year
- **Units**: MWh

÷

Total number of NMIs in His_cons_sample_NMIs
- **Frequency**: Half Hour
- **Time Period**: Latest Financial Year

=

Usage per NMI
- **Frequency**: Half Hour
- **Time Period**: Latest Financial Year
- **Units**: MWh

Usage per NMI
- **Frequency**: Half Hour
- **Time Period**: Latest Financial Year
- **Units**: MWh

×

Total residential connected NMIs
- **Frequency**: Monthly
- **Time Period**: Latest Financial Year
- **Data Source**: AEMO database

=

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

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

+

Residential Sector PV Generation
- **Frequency**: Half Hour
- **Time Period**: Since first time
- **Units**: MWh
- **Data Source**: AEMO database

=

Residential Underlying Consumption
- **Frequency**: Half Hour
- **Time Period**: Latest Financial Year
- **Units**: MWh

Stage 4: Calculating business delivered and underlying consumptions

In this stage, the business delivered consumption is calculated by first taking the half-hourly distribution connected delivered consumption (refer to Section 4 for its derivation) and then deducting off the sample-derived regional residential delivered consumption. Similarly, using the same method as for the residential consumers, the business PV generation is added on, so the business underlying consumption can be calculated.

Distributed Connected Delivered Consumption
- **Frequency**: Half Hour
- **Time Period**: Financial year
- **Units**: MWh
- **Data Source**: AEMO database

−

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

=

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

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

+

Business Sector PV Generation
- **Frequency**: Half Hour
- **Time Period**: Since first time
- **Units**: MWh
- **Data Source**: AEMO database

=

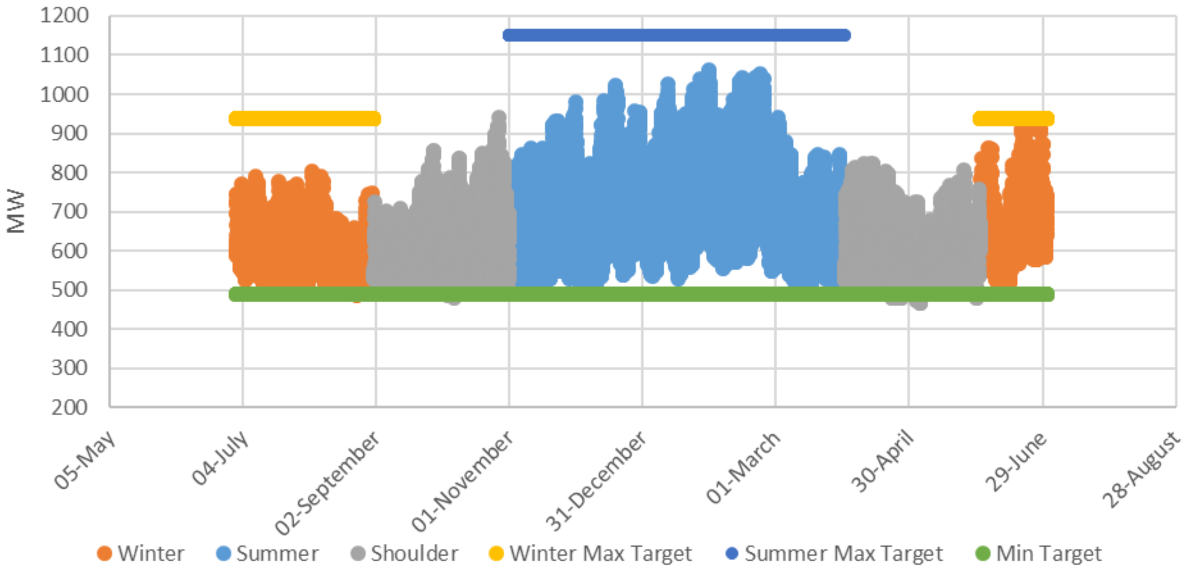
Business Underlying Consumption
- **Frequency**: Half Hour
- **Time Period**: Latest Financial Year
- **Units**: MWh

A8. Demand trace scaling algorithm

This appendix provides a worked example of how half-hourly demand traces are scaled for the outlook period. This covers the first two passes of the method 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 18.

Figure 18 Prepared demand trace



Day swapping is 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.

The targets are summarised in 0. All targets represent an increase to the reference trace in this example.

Table 22 Prepared demand 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

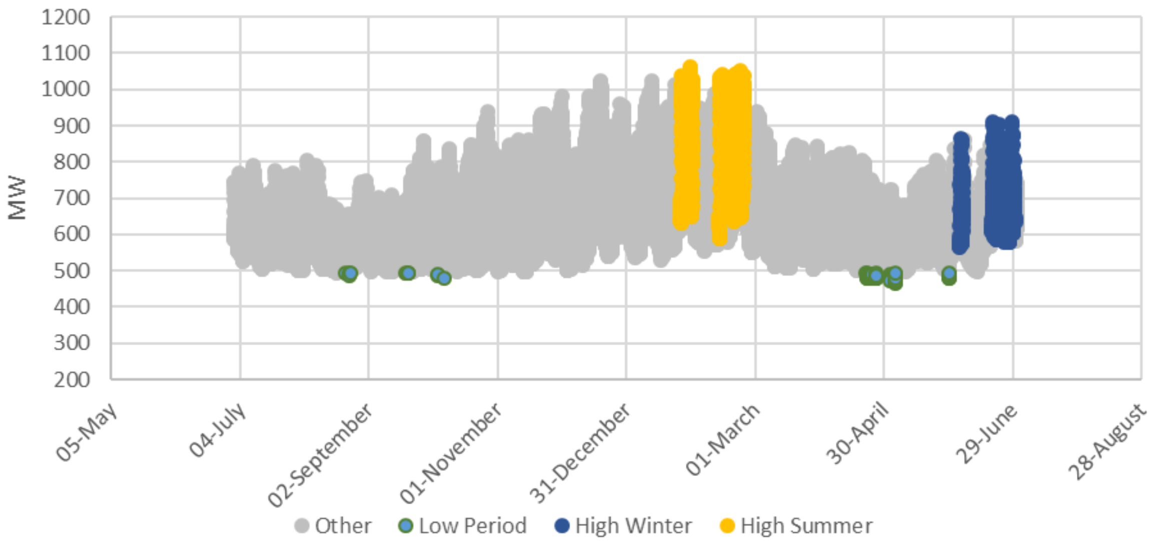
The series is categorised into *n* highest-demand days in summer (using daily maximum as the reference), *n* highest demand days in winter, *p* lowest demand half-hour periods. In this example,

n = 10 days

p = 70 half-hour periods

The day-type categorisation (High Summer, High Winter, Low Period and Other) is displayed in Figure 19.

Figure 19 Day-type categories



Scaling then commences. The demand, categorised into day-types, is scaled according to the ratios in Table 23. The ratios are calculated as *target / prepared trace* using the information from 0.

Table 23 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. Note that the energy target still needs to be addressed. Application of the scaling factors results in the energy presented in Table 24 and the remaining energy difference is calculated as the *target minus the current grown total*.

Table 24 Resulting energy

	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 24 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 in Table 25 and the grown trace is plotted in Figure 20.

Figure 20 Grown trace and targets

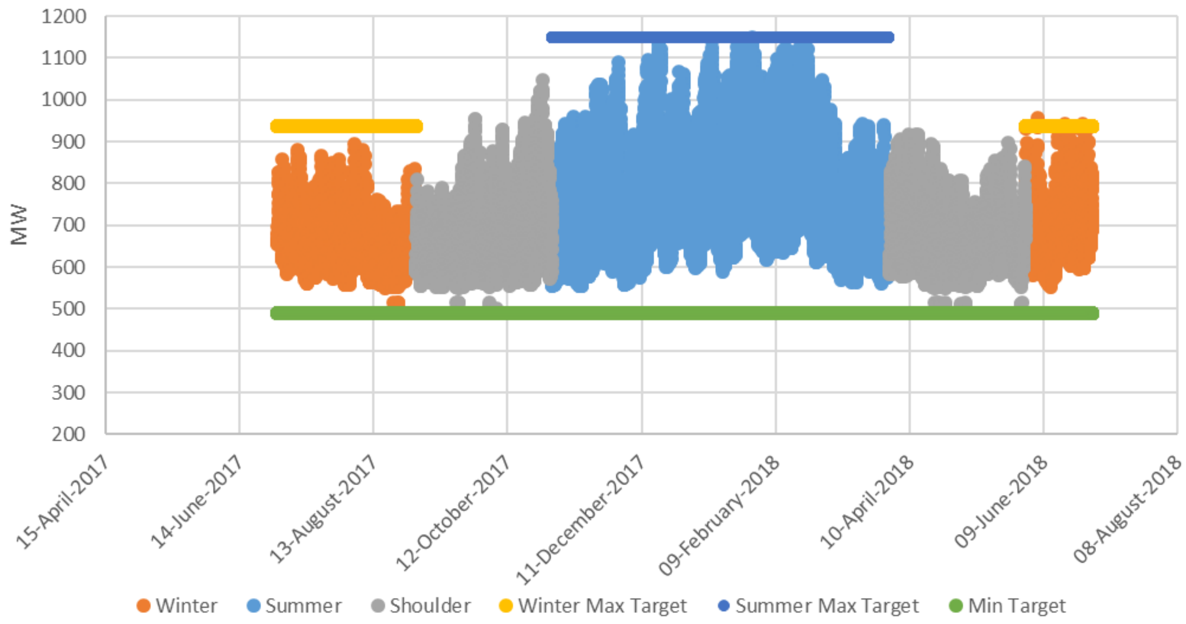


Table 25 Check of grown trace against targets

	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 25 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 forecast 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.

EVs that can act as home batteries were modelled for the first time in the 2019 Step Change scenario. To model this, a certain proportion of the residential vehicle fleet are modelled to have their EVs discharge in the home (termed vehicle-to-home) to serve the users energy requirements. This discharge profile is included in the demand trace growing algorithm in a similar way as the other behind the meter technologies. The charge profile is not captured within the demand traces but is instead optimally charged within the supply model, similar to VPP charging. In this way, the EV fleet charges from the grid at times of low system cost, avoiding contribution to maximum demand.

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
HIA	Housing Industry Association
HDD	Heating degree day
ISP	Integrated System Plan
KW	Kilowatts
LIL	Large industrial loads
LNG	Liquefied natural gas

Abbreviation	Full name
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