Forecasting Approach – Electricity Demand Forecasting Methodology

August 2023

Applied in developing the 2023 Electricity Statement of Opportunities Forecast

Important notice

Purpose

AEMO has prepared this document as part of its Forecasting Approach, as guided by the AER's Forecasting Best Practice Guidelines (FBPG). While the FBPG relates to the National Electricity Market (NEM), this methodology concerns the forecast annual consumption and maximum and minimum demand in both WA's Wholesale Energy Market (WEM) and the NEM. This document is used for planning publications such as the Electricity Statement of Opportunities (ESOO) in both markets, and the Integrated System Plan (ISP) in the NEM. The National Electricity Rules (Rules) and the National Electricity Law (Law) prevail over this document to the extent of any inconsistency.

Disclaimer

This document might also contain information which is provided for explanatory purposes. That information does not constitute legal or business advice, and should not be relied on as a substitute for obtaining detailed advice about the Law, the Rules, or any other applicable laws, procedures or policies. AEMO has made reasonable efforts to ensure the quality of the information but cannot guarantee accuracy or completeness.

Accordingly, to the maximum extent permitted by law, AEMO and its officers, employees and consultants involved in the preparation of this document:

- make no representation or warranty, express or implied, as to the currency, accuracy, reliability or completeness of the information in this document; and
- are not liable (whether by reason of negligence or otherwise) for any statements or representations in this document, or any omissions from it, or for any use or reliance on the information in it.

Copyright

Version control

Version	Release date	Changes
1	27/5/2021	Forecasting Approach – Electricity Demand Forecasting Methodology published following consultation
1.1	21/9/2021	Update following Long-term BMM forecasts FRG Consultation
1.2	31/8/2022	Update electricity retail pricing and Residential-business segmentation
1.3	31/8/2023	Updates for 2023 ESOO

AEMO acknowledges the Traditional Owners of country throughout Australia and recognises their continuing connection to land, waters and culture. We pay respect to Elders past and present.

Contents

1	Introduction	6
1.1	Application of the Electricity Demand Forecasting methodology	6
1.2	Forecasting principles	6
1.3	Demand drivers, uncertainty and risks	7
1.4	Customer segmentation	8
1.5	Modelling consumer behaviour	9
1.6	Key definitions	10
1.7	Maintaining the methodology document	12
2	Business annual consumption	14
2.1	Large industrial load consumption forecasting	15
2.2	Hydrogen sector consumption forecasting	19
2.3	Liquified natural gas sector consumption forecasting	21
2.4	Business mass market consumption forecasting	21
2.5	Total business forecasts	26
3	Residential annual consumption	29
3.1	Step 1: Calculate the base year by weather normalising residential consumption	31
3.2	Step 2: Apply forecast trends and adjustments	33
3.3	Step 3: Scale by connections forecasts	36
3.4	Step 4: Calculate the total residential annual consumption forecast	36
4	Operational consumption	38
4.1	Small non-scheduled generation	39
4.2	Network losses	40
4.3	Auxiliary loads	41
5	Maximum and minimum demand	42
5.1	Data preparation	43
5.2	Exploratory data analysis	44
5.3	Model development and selection	45
5.4	Simulate base year (weather and calendar normalisation)	47
5.5	Forecast probability of exceedance for base year	49
5.6	Forecast probability of exceedance for long term	49
5.7	Other forecasting components	51
5.8	Structural breaks in demand forecasting models	53
6	Half-hourly demand traces	54
6.1	Growth (scaling) algorithm	55
6.2	Pass 1 – growing to OPSO-lite targets	56

6.3	Pass 2 – reconciling to the OPSO targets	56
6.4	Pass 3 – adding electrification and coordinated EV charging to OPSO	57
6.5	Reporting	57
A1.	Electricity retail pricing	58
A2.	Weather and climate	60
A2.1	Heating Degree Days (HDD) and Cooling Degree Days (CDD)	60
A2.2	Determining HDD and CDD standards	60
A2.3	Climate change	61
A3.	Rooftop PV and energy storage	64
A3.1	Rooftop PV forecast	64
A3.2	Energy storage systems forecast	65
A4.	Electric vehicles	67
A4.1	Electric vehicles charge profiles	67
A4.2	Electric vehicles annual consumption	68
A5.	Connections and uptake of electric appliances	69
A5.1	Connections	69
A5.2	Uptake and use of electric appliances	69
A6.	Residential-business segmentation	72
A6.1	Calculate distribution-connected delivered consumption	72
A6.2	Estimate residential consumption per connection based on one of two approaches	73
A6.3	Scale to a regional residential-business split	75
A7.	Demand trace scaling algorithm	77
Abbreviations		82

Tables

Table 1	Weighting for evaluation criteria for WEM LIL projects	19
Table 2	Short-term base model variable description	22
Table 3	Weather normalisation model variable description	32
Table 4	Variables and descriptions for residential consumption model	35
Table 5	Residential base load, heating load and cooling load model variables and descriptions	36
Table 6	Pricing model component summary	59
Table 7	Critical regional temperatures for HDD and CDD	60
Table 8	Prepared demand trace and targets	77
Table 9	Scaling ratios	78

Table 10	Resulting energy	79
Table 11	Check of grown trace against targets	79

Figures

Figure 1	Consumption forecasting customer segmentation	8
Figure 2	Example individual and group demand shown on one day	9
Figure 3	Scatterplot of New South Wales demand and temperature, example based on 2017 calendar year	10
Figure 4	Operational demand/consumption definition	12
Figure 5	LIL subsectors used in the NEM	14
Figure 6	LIL subsectors used in the WEM	14
Figure 7	Steps for large industrial load survey process	16
Figure 8	Segments considered for the hydrogen sector	20
Figure 9	Example of multi-sectorial electricity forecast used for calculating sectorial energy intensities for Victoria	23
Figure 10	Estimation of the energy intensity trends over time	24
Figure 11	Aggregation process for total underlying business consumption	28
Figure 12	Aggregation process for total delivered business consumption	28
Figure 13	Process flow for residential consumption forecasts	30
Figure 14	Aggregation process for total residential underlying consumption	37
Figure 15	Aggregation process for total residential delivered consumption	37
Figure 16	Delivered to the distribution network	38
Figure 17	Operational consumption (sent-out)	38
Figure 18	Converting from operational consumption (sent-out) to operational consumption (as generated)	38
Figure 19	Conceptual summer maximum demand probability density functions for three scenarios	42
Figure 20	Theoretical distribution of annual half-hourly data to derive maxima distribution	51
Figure 21	Translation from operational demand (sent-out) to operational demand (as generated)	52
Figure 22	Demand trace development process flow diagram	55
Figure 23	Electricity consumption from delivering energy services	70
Figure 24	Prepared demand trace	77
Figure 25	Day-type categories	78
Figure 26	Grown trace and targets	79
Figure 27	Adding coordinated EV charging	80
Figure 28	Example electrification daily load shape contrasting winter and summer	81

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, and maximum and minimum demand. The forecast period is up to 30 years for each region of the National Electricity Market (NEM) and up to 10 years for Western Australia's Wholesale Electricity Market (WEM).

This methodology document describes the process for forecasting regional electricity consumption, as well as the forecast regional maximum and minimum demand.

Inputs and assumptions used with these methodologies are updated at least annually in AEMO's *Inputs, Assumptions and Scenarios Report* (IASR)[1] or, in non-IASR years, AEMO's *Forecasting Assumptions Update* (FAU).

1.1 Application of the Electricity Demand Forecasting methodology

AEMO intends for the Electricity Demand Forecasting methodology to be applied for the development of electricity consumption forecasts used in the:

- NEM ESOO and Reliability Forecasts.
- NEM Medium Term Projected Assessment of System Adequacy (MT PASA).
- Energy Adequacy Assessment Projection (EAAP).
- ISP.
- WEM ESOO.

AEMO does not warrant the suitability of the methodology for other purposes.

1.2 Forecasting principles

AEMO is committed to producing quality forecasts that support informed decision-making. For decision-makers to act on forecasts, they should be credible and dependable. Forecasting principles help guide the multitude of decisions required for this goal. Principles guide choices about how the forecasts are performed, particularly where trade-offs may exist (for example, simplicity versus comprehensiveness, or speed versus insight).

In preparing its forecasts, AEMO's forecasting approach has regard to the following principles, in accordance with the Australian Energy Regulator's (AER's) Forecasting Best Practice Guidelines and based on the principles articulated in the National Electricity Rules (NER) clause 4A.B.5(b):

1. Accuracy – to adopt best practice methodologies and monitor lead indicators of change.
   – Adopt best practice techniques (subject to data availability and resourcing requirements).

[1] The most recent version of the IASR is available at https://aemo.com.au/energy-systems/electricity/national-electricity-market-nem/nem-forecasting-and-planning/forecasting-approach.

- Employ robust processes, including Quality Assurance, and use lead indicators to monitor for change.
- Apply continuous learning through monitoring the performance of past forecasts. Identify improvements to data, models and processes as documented in AEMO's Forecast Accuracy Reports[2] .

2. Transparency – to ensure inputs and forecast methodologies are well understood.
   - Publish quality information to ensure adequate stakeholder understanding of the methodologies deployed. This document in particular addresses this.
   - Provide documentation to stakeholders on inputs and assumptions, and how these are sourced.
3. Engagement – to ensure stakeholders are consulted and informed efficiently.
   - Conduct formal consultation on inputs, assumptions and methodologies.
   - Maintain regular engagement with all interested stakeholders through the Forecasting Reference Group and other forums as required.

1.3 Demand drivers, uncertainty and risks

Drivers of electricity consumption and demand forecasts can be split into two different types:

- Structural drivers, which can be estimated based on past trends and expert judgement, but which cannot be assigned a probability.
- Random drivers, which can be modelled as probability distributions.

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

- Numerous scenarios are developed to test uncertainty in structural drivers. Examples of structural drivers include:
  - Population.
  - Economic growth.
  - Electricity price.
  - Technology adoption such as consumer energy resources (CER) uptake.
  - Energy efficiency.
  - Fuel switching.
- Maximum and minimum demand forecasts use probability distributions to describe uncertainty in random drivers, including:
  - Weather-driven coincident customer behaviour.
  - Weather-driven embedded generation output.
  - Non-weather-driven coincident customer behaviour.

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

1.4 Customer segmentation

Consumption forecasts are developed by customer segments (see Figure 1), because the demand drivers affect these customer segments differently. The aggregated customer segments are:

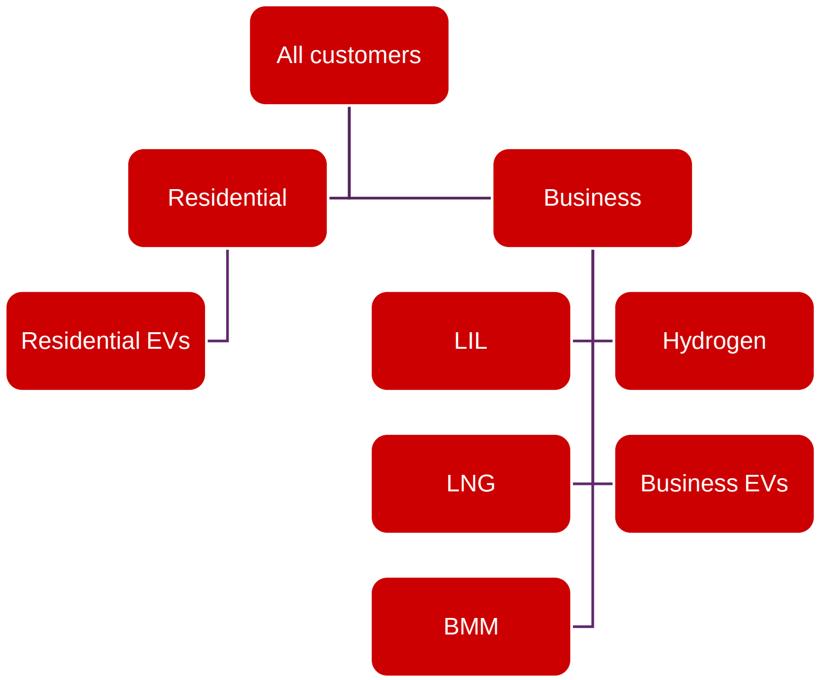
- **Residential** – residential customers only.
- **Business** – includes industrial and commercial users. This sector is subcategorised further (in accordance with Section 2) as follows:
  - Large industrial loads (LIL).
  - Hydrogen.
  - Liquified natural gas (LNG).
  - Electric vehicles (EVs).
  - Business Mass Market, covering those business loads not included in the subcategories above.

Specifically, residential electricity consumption is defined as electricity used in a place of permanent abode. This excludes, for example, hotels and boarding houses. Technically, the forecast depends on customer type in the Market Settlement and Transfer Solutions (MSATS) system as tagged by the local distribution network service provider (DNSP).

Business electricity use is defined as all other electricity use, apart from that needed to generate and distribute electricity (generation and losses).

While annual consumption can reasonably be split into residential and business consumption, this cannot be done at the half-hourly level. Therefore, the maximum and minimum demand forecast will only consider LIL (where half-hourly data is available) and aggregate the remainder into one segment.

Figure 1 Consumption forecasting customer segmentation

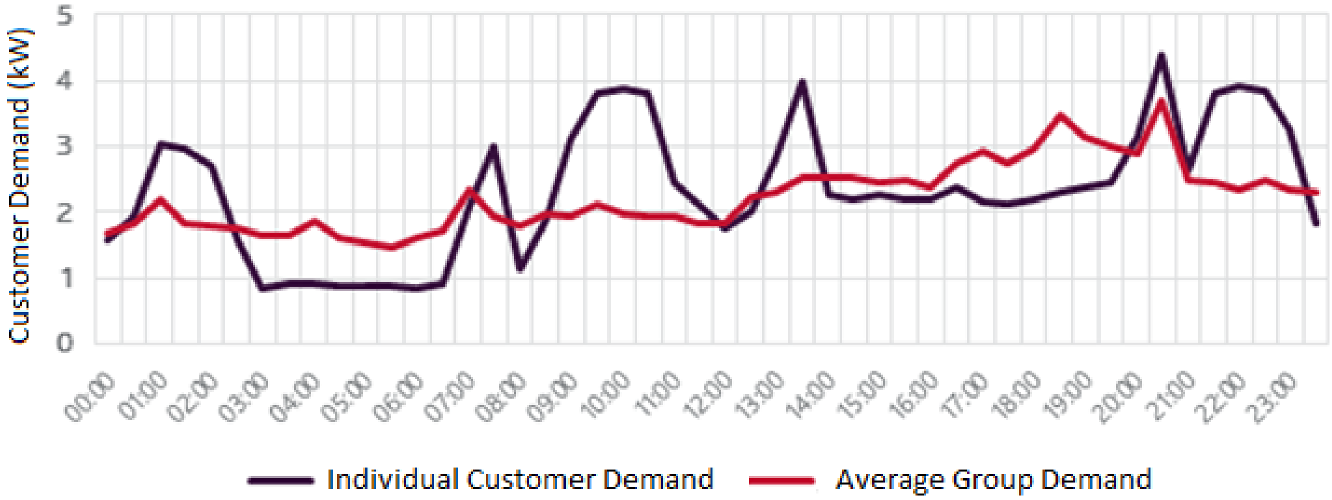


1.5 Modelling consumer behaviour

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. Electrical demand becomes more predictable as the size of the aggregation group grows, because random idiosyncratic behaviour of individuals tends to cancel out.

Figure 2 shows the load profile of an individual customer, compared to the average of a group of similar customers (in this case, eight). While the load profile of the individual is spikey and erratic, the group profile has smoothed out some of idiosyncrasies of individual customers. If larger groups are considered, this profile would smooth out even further.

Figure 2 Example individual and group demand shown on one day

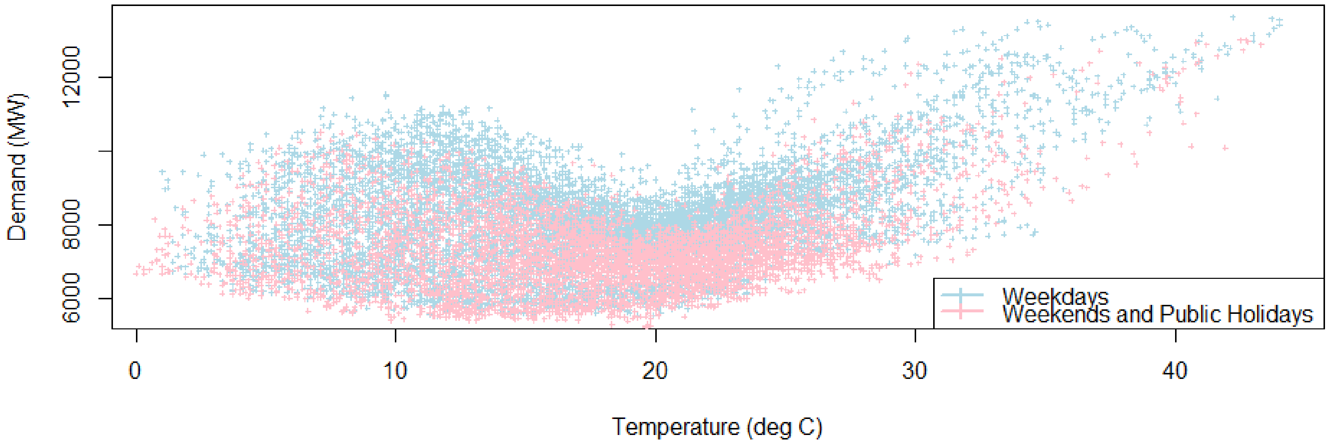


Although demand becomes more predictable when aggregated, it remains a function of individual customer decisions. Periods of high demand exist because individual customers choose to do the same things at the same time. Peak demand is therefore driven by the degree of coincident appliance use across customers, across larger geographical areas. There are many factors that drive customers to make similar choices regarding electricity consumption 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 3 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 3 Scatterplot of New South Wales demand and temperature, example based on 2017 calendar year



1.6 Key definitions

AEMO forecasts are reported based on a number of various definitions describing specific characteristics of the parameter that is presented. Several of these key definitions are described below[3]:

- **Operational** – electricity demand is measured by metering supply to the network rather than what is consumed. 'Operational' refers to the electricity used by residential and business customers, 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 are:
  - Non-scheduled generators, which due to size or location in the network are important to reflect in dispatch, including constraint equations[4].
  - 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[5].
  - For the WEM, intermittent loads are excluded[6].
- **Consumption** – consumption refers to power used over a period of time, conventionally reported as megawatt hours (MWh) or gigawatt hours (GWh) depending on the magnitude of power consumed. It is reported on a "sent-out" basis unless otherwise stated (see below for definition).
- **Demand** – demand is defined as the amount of power consumed at any time. Maximum and minimum demand is measured in megawatts and averaged over a 30-minute period. It is reported on a "sent-out" basis unless otherwise stated (see below for definition).

[3] More definition information is at https://www.aemo.com.au/-/media/Files/Electricity/NEM/Security_and_Reliability/Dispatch/Policy_and_Process/Demand-terms-in-EMMS-Data-Model.pdf.

[4] For the exceptions, see https://www.aemo.com.au/-/media/Files/Electricity/NEM/Security_and_Reliability/Dispatch/Policy_and_Process/Demand-terms-in-EMMS-Data-Model.pdf.

[5] Registering a Battery System in the NEM – Fact Sheet is at https://aemo.com.au/-/media/files/electricity/nem/participant_information/new-participants/registering-a-battery-system-in-the-nem.pdf.

[6] 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.

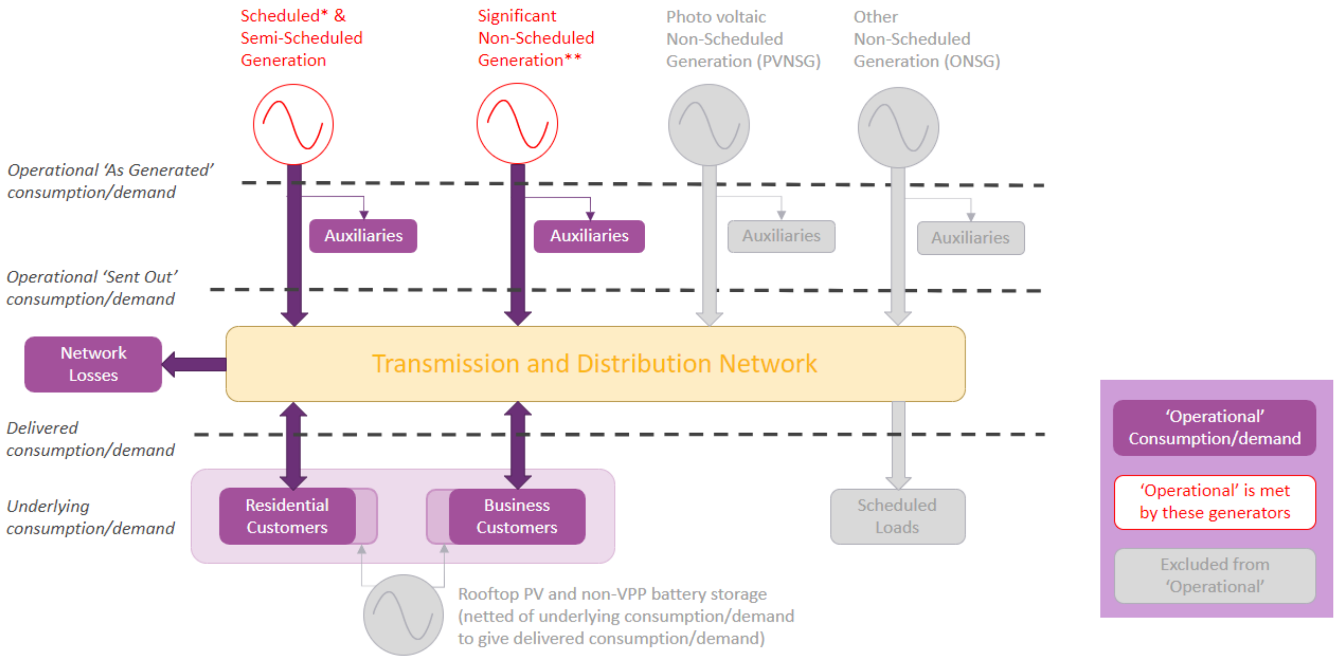
- **Delivered** – delivered consumption or demand refers to the electricity supplied to electricity customers from the grid. It therefore excludes the part of their consumption that is met by behind-the-meter (typically rooftop photovoltaic (PV)) generation.
- **Underlying** – underlying consumption or demand refers to the total consumption by electricity users from their power points, regardless of whether it is supplied from the grid or by behind-the-meter (typically rooftop PV) generation.
- **"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, but also adds auxiliary loads, or electricity used by a generator, to represent the gross electricity generation on site.
- **Auxiliary loads** – auxiliary load, also called 'parasitic load' or 'self-load', refers to energy generated for use within power stations, excluding 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.
- **Distributed PV** – distributed PV is the term used for rooftop PV and PV Non-Scheduled Generators combined.
- **Rooftop PV** – rooftop PV is defined as a system comprising one or more PV panels, installed on a residential building or business premises (typically a 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 non-scheduled PV generators larger than 100 kW but smaller than 30 MW.
- **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 systems for residential and business consumers.
- **Virtual power plants (VPP)** – VPPs refer to embedded battery devices that are available to be operated by an aggregator. Unlike un-aggregated ESS, VPPs may operate on occasion in a coordinated manner, similar to a scheduled, controllable form of generation, much like a traditional form of grid-generated electricity supply. The frequency of this form of aggregated behaviour, as opposed to un-aggregated behaviours which target the minimisation of the individual customer's energy costs, will depend on the technical and commercial terms of each specific VPP scheme.
- **Electric vehicles (EVs)** – EVs are electric powered vehicles, ranging from small residential vehicles such as motor bikes or cars, to large commercial trucks. EVs typically refer to battery electric vehicles (BEV) or plug-in hybrid electric vehicles (PHEV), although may also include fuel-cell electric vehicles (FCEV) which are fuelled through hydrogen fuel cells, rather than batteries.

Figure 4 provides a schematic of the breakdown and links between demand definitions. Operational demand "sent out" is computed as the sum of residential and business customer electricity consumption plus distribution and transmission losses minus rooftop PV, PVNSG and ONSG.

Figure 4 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/Demand-terms-in-EMMS-Data-Model.pdf

1.7 Maintaining the methodology document

This Electricity Demand Forecasting Methodology forms part of AEMO's Forecasting Approach – the collection of methodologies applied for AEMO's longer-term forecasting studies, including the ESOO and ISP for the NEM. While the Australian Energy Regulator's (AER's) Forecasting Best Practice Guidelines (FBPG)[7] provide guidance on AEMO's Forecasting Approach and only apply for the NEM, AEMO intends to use a common approach for forecasting electricity consumption and demand for both the NEM and the WEM where practicable and will maintain this forecasting methodology as a single document.

In accordance with the FBPG, AEMO must consult on the Forecasting Approach at least every four years, but may stagger the review of the components that make it up. This is to facilitate transparency around methodologies used in AEMO's key forecasting publications and allow stakeholders to engage with AEMO's forecasting team on the appropriateness of methods and possible improvements.

In addition, AEMO will assess forecast accuracy annually:

- For the NEM, the previous year's ESOO forecast will be assessed against actuals for the past year in the annual Forecast Accuracy Report[8]. That report outlines forecast improvements planned to mitigate issues

[7] At https://www.aer.gov.au/system/files/AER%20-%20Forecasting%20best%20practice%20guidelines%20-%2025%20August%202020.pdf.

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

found. The improvement opportunities can include input data, but also methodologies. AEMO will consult on such changes and update this and other methodology documents accordingly.

  – Non-material changes are consulted on as part of the Forecast Improvement Plan, included in the FAR.
  – Material changes will be consulted on using the applicable FBPG consultation process.

- For the WEM, the forecast accuracy of the past ESOO forecast will be assessed in the following ESOO.

The FBPG consultation processes guide the Forecasting Approach (including this Electricity Demand Forecasting Methodology) as it applies to the NEM. Accordingly, AEMO may vary any aspect of the Forecasting Approach (including this Electricity Demand Forecasting Methodology) as it applies to the WEM without complying with the FBPG consultation procedures.

2 Business annual consumption

The business sector captures all non-residential consumers of electricity. The forecast is based on an integrated, sectoral-based approach to capture structural changes in the Australian economy, and the impacts of these changes to commercial and industrial customers.

Business sector split by subsector

At a high-level, the business sector is forecast using the following subsectors:

- **Large industrial loads (LIL)** – these can be either transmission or distribution connected.
- **Hydrogen** – any loads associated with the production of hydrogen.
- **LNG** – any loads associated with the production of LNG.
- **Electric vehicles (EVs)** – covering commercial fleet, trucks and buses, and
- **Business Mass Market (BMM)** – any business sector loads not included above.

The LIL sector is further subdivided into subsectors. This allows them to be differentiated between various forecast scenarios. This is summarised in Figure 5 (for the NEM) and Figure 6 (for the WEM) below.

Figure 5 LIL subsectors used in the NEM

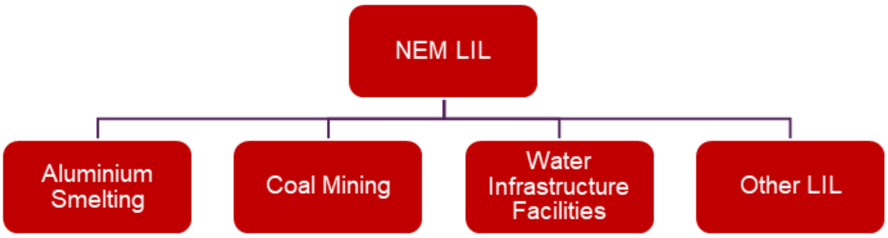
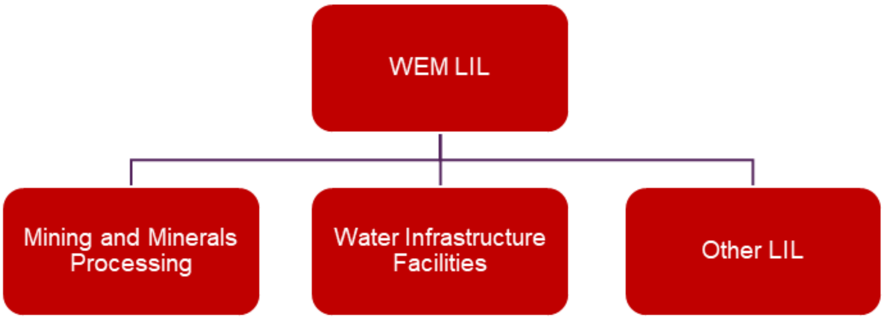


Figure 6 LIL subsectors used in the WEM



The definitions of the LIL subsectors are outlined in the following:

- **Aluminium smelting** – including all aluminium smelters in the NEM. *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.*

- **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 only 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.

High level business sector forecast 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 are used to forecast consumption in these sectors:

- **LIL** – survey-based forecasts.
- **Hydrogen** – scenario based assumptions supported by consultant inputs.
- **LNG** – survey-based forecasts, extended across the scenario collection by applying assumed global trends for each scenario.
- **Electric vehicles** – scenario based assumptions supported by consultant inputs.
- **BMM** – econometric modelling.

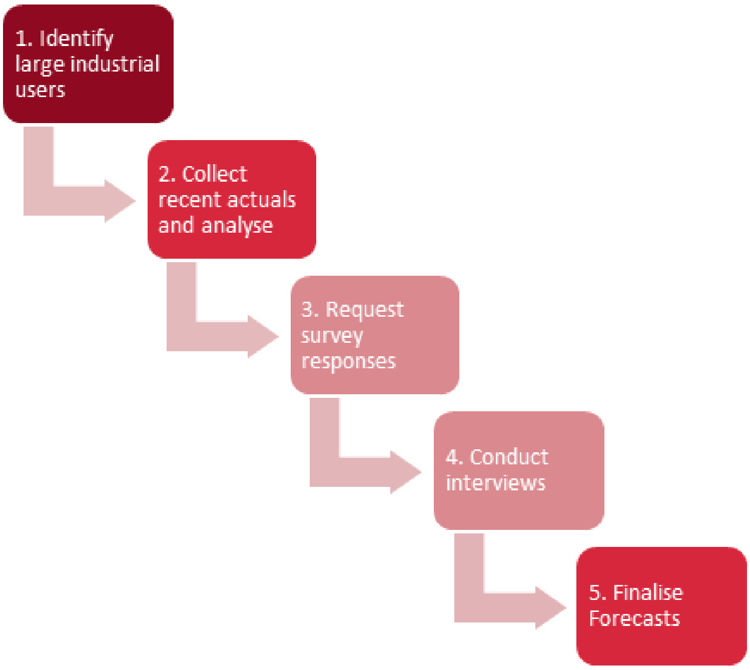
The detailed approaches applied are explained in the following section.

2.1 Large industrial load consumption forecasting

The process that produces the LIL forecasts for both the NEM and WEM has five steps, illustrated in Figure 7. It requires AEMO to identify the LILs, collect and analyse historical data, conduct a customer survey (questionnaire) and interview personnel from key LILs and incorporate the information into a final forecast for each LIL.

The individual LIL survey results are confidential, with the end of this section noting the process to conserve confidentiality prior to publishing LIL forecasts.

Figure 7 Steps for large industrial load survey process



Step 1: Identify large industrial users

For the NEM, any customers connected directly to the transmission network will be considered an LIL. For distribution connected loads, AEMO maintains a list of LILs identified primarily by interrogating AEMO's meter data for each region. A demand threshold of greater than 10 MW for more 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 network service provider surveys – requesting information on existing 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.

In the WEM, AEMO engages with a range of stakeholders, including Western Power, in deciding to include prospective and committed LILs in the electricity forecasts.

Step 2: Collect historical data (recent actuals) and analyse

Updates to historical consumption data for each LIL are 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.

Step 3: Request survey responses

AEMO surveys all identified LILs by requesting historical and forecast electricity consumption information by site. The survey requests annual electricity consumption, maximum demand and minimum demand forecasts for scenarios in the NEM and the WEM that can be mapped to scenarios developed with stakeholders as part of the IASR development, while considering the burden to industrial customers providing this information. This will include a central scenario. If the IASR is undergoing re-development, which for scenarios occurs biennially, the most recent finalised scenario collection is provided for LIL surveying purposes.

Step 4: Conduct 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 (PPAs) and hedging options.
- Impact of current and future prices on consumption.
- Potential drivers of major change in electricity consumption (such as expansion, closure, outages, cogeneration, fuel substitution – including electrification, hydrogen production or energy efficiency measures).
- Involvement (if any) in Demand Side Participation programs.
- Variations in observed electricity demand relative to previous expectations.
- Assumptions governing the scenarios.

Not all LILs are interviewed. Interviews with LILs are prioritised based on the following criteria:

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

Step 5: Finalise forecasts

The following subsections describe the LIL forecast development for each scenario and for each subsector in each region.

Develop a single scenario forecast:

- AEMO produces a forecast for a scenario, which reflects a future energy system based around current state and federal government environmental and energy policies and best estimates of all key drivers. This is used as input into AEMO’s reliability forecast published in the ESOO and in MT PASA.

- For each subsector, AEMO will review the survey responses[9] and assess the reasonableness of the forecasts (if necessary, verify with the respondents).
- For each region, the aggregated forecasts by subsector for this scenario (Step 3) becomes a scenario forecast, accounting for any committed load additions (including electrification of processes) or site closures.

Develop the scenario spread:

Alternate scenarios are developed based on likely opportunities and risks for the LILs, which is formed using survey responses. This can be driven by the overall economic conditions of the scenarios, and any specific, defined purpose of the scenario. Overall, this may include modelling closures of large loads, in addition to any committed closures. For example, a scenario's purpose may be to test the power system's ability to operate under low demand conditions, and to identify efficient investments to maintain power system security in low load conditions. In such a scenario, AEMO may close the largest industrial loads in a reasonable timeframe, taking into account any known contracted load positions. In this way, closures of the largest industrial loads may progressively appear in scenarios examining this purpose, across the regions as appropriate considering the operational risks that exist in each region.

In other scenarios, new industrial loads may be assumed, for example electrolyser loads in scenarios that examine the potential operational impact and investments needed to support an emerging hydrogen economy, or electrification of processes currently relying of fossil fuels to lower carbon emissions.

NEM LIL evaluation

For the single scenario that represents the best estimates of all key drivers, AEMO will only include a new LIL if:

- The project has obtained the required environmental approvals.
- The project has obtained approvals from the network service provider to connect to their system.
- The project proponent has publicly announced that it has taken a positive Final Investment Decision (FID) and/or the project has commenced construction.

A scenario that reflects slower demand growth may assume a delay in commissioning, or even that the project doesn't eventuate. Similarly, for scenarios that reflect a higher demand growth future, new LILs may be included even when only a subset of the criteria above are met.

WEM LIL evaluation

For the WEM, the scenarios are typically consistent with a subset of the scenarios in the IASR and are required to include a higher, a central (expected) and a lower demand growth scenario[10]. The WEM adopts a scoring system for new LILs which differs from the NEM's criteria-based approach. The WEM's scoring system differentiates between projects expected to connect within the next four years compared to those likely to connect beyond this period. This distinction allows for the fact that proponents typically apply for environmental approvals within three to four years in advance of their expected Financial Investment Decision (FID).

The new LIL projects are evaluated on a graded scale using weighting summarised in Table 1 according to:

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

[10] As required by clause 4.5.10 of the Wholesale Electricity Market Rules (WEM Rules).

- Western Power's assessment of the likelihood of the project connecting to the South West Interconnected System (SWIS).
- Whether the project proponent has publicly announced that it has taken a positive FID and/or the project has commenced construction.
- Whether the project is a carbon reduction project. This criterion gives weight to projects that align with policy-driven decarbonisation ambitions. Examples include projects that involve hydrogen production, or the extraction and processing of critical minerals such as lithium, nickel, cobalt and rare earth elements.
- The project's current state of progress through environmental approval stages. The stages are scored from 0% for "no application submitted" through to 100% for "Stage 5 (approved)". For projects that are expected online within four years, the system gives a weight to EPA approval, which is needed for a project to progress. No weight is given for EPA application for projects expected online more than four years ahead.

Table 1 Weighting for evaluation criteria for WEM LIL projects

Criteria	Projects expected online within four years	Projects expected online more than four years ahead
Western Power active stage	30%	33.3%
Status of EPA approval	30%	-
Likelihood of Final Investment Decision	30%	33.3%
Carbon reduction project	10%	33.3%

Publish forecasts

To maintain confidentiality[11], AEMO aggregates all subsector forecasts with the other LILs before publishing the LIL forecast. The LNG forecasts are published separately, as there are sufficient sites within a region to maintain confidentiality.

2.2 Hydrogen sector consumption forecasting

An emerging sector within Australia's economy that is gaining significant interest and investment is the development of a renewable hydrogen industry to support the transformation of existing and new industrial processes, and potential export to international consumers. Momentum is building in the industry as the development of a hydrogen economy may provide a means to achieve carbon emission reduction objectives. If established, hydrogen production has the potential to support provide a transformative influence on Australia's energy systems, and as such AEMO's methodologies are incorporating this potential development within its scenario analysis approach.

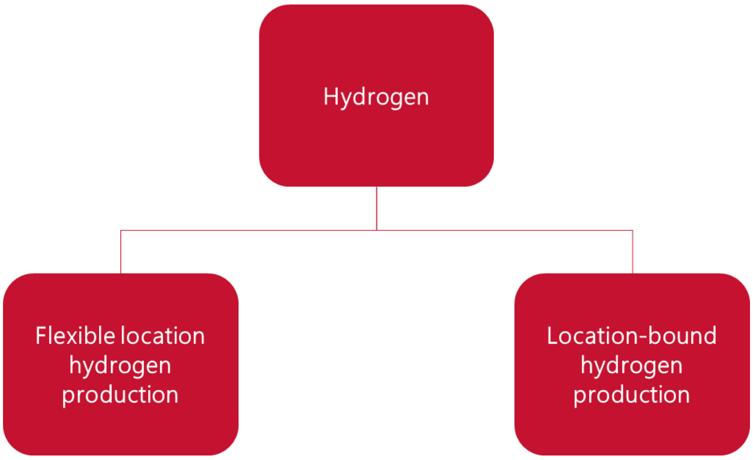
The hydrogen sector within AEMO's demand forecasting methodology captures all grid supplied electricity consumption used to produce hydrogen within the Australian economy.

As illustrated in Figure 8, the hydrogen sector covers two components:

- production for existing consumers, and location-specific
- production that has locational flexibility to service new customers, influenced by the availability of resources.

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

Figure 8 Segments considered for the hydrogen sector



As Australia's hydrogen economy is still emerging, AEMO considers the most prudent means of capturing potential hydrogen production within its electricity demand forecasting is to consider it as a scenario parameter, allowing the scale and type of hydrogen production to vary across scenarios. The level of hydrogen production is therefore an input into the forecasting process, based on scenario design and where required consultant advice. This will be converted into electricity consumption required to produce this amount of hydrogen based on an assumed efficiency of the conversion[12].

AEMO's methodology assumes that hydrogen production will be provided by electrolysers.

2.2.1 Flexible location hydrogen production

Flexible location hydrogen production relates to the potential hydrogen production to be consumed by new industrial processes or export industries, where there is no fixed existing location.

The preferred location of these facilities will be influenced by the quality and availability of input resources, particularly of variable renewable energy (VRE) generators and electricity transmission infrastructure. With no locational requirement, the location of electrolyser loads is optimised within the modelling as per AEMO's ISP methodology[13].

By treating these facilities as dispatchable loads, with production constraints as needed, the seasonal and daily operation of these assets considers the cost of supply and other system constraints. Given the assumed ability to store hydrogen, dispatch can be assumed to be flexible. The ISP methodology provides greater detail on the optimisation approach, including any constraints that apply to the operation of these assets.

The outcomes of the simulations will be used to calculate combined impacts on electricity consumption and load from producing hydrogen at times of maximum and minimum demand.

2.2.2 Location bound hydrogen production

Location-bound hydrogen production refers to hydrogen produced for existing industrial processes that are connected to existing infrastructure, particularly the gas distribution systems. To service these customers,

[12] This will be subject to consultation through the *Inputs, Assumptions and Scenarios Report*, see https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/Inputs-Assumptions-and-Methodologies.

[13] Large-scale located wherever the capacity outlook modelling deems 'best' and modelled as a dispatchable load with an overall monthly production target.

hydrogen facilities will require access to existing gas distribution networks for gas-blending, or proximity to the specific loads that may directly consume hydrogen. This sector includes, for example, small distributed units producing hydrogen for transport refuelling. This forecast component is developed based on scenario assumptions supported where required by AEMO analysis or consultancy inputs. Unlike the flexible location production, this component is not optimised within AEMO's ISP modelling, and is reflected as a demand component within consumption, demand and electricity traces.

2.3 Liquified natural gas sector consumption forecasting

The LNG forecasts estimate the expected electricity consumption of the operations of coal seam gas (CSG) fields in the NEM by considering survey data provided by the LNG consortia. This data considers the anticipated operating range of CSG facilities over the short to medium term. The longer-term forecast is developed by extending the surveyed trend across the scenario collection, applying assumed global trends for each scenario.

2.4 Business mass market consumption forecasting

BMM consumption contains aggregate consumption data for the non-residential sector that covers a broad range of activities which is not covered by the LIL, Hydrogen or LNG sector forecasts. Given the much higher number of customers in this segment, the forecasting approach combines a statistical method – which employs time-series methods capturing the more predictable patterns in recent usage (such as seasonality and trend) – with a structural approach that incorporates long-term causal factors[14] under the various forecast scenarios. Broadly, the forecast for BMM consumption can be written as:

$$\text{Forecast} = f(\text{seasonality}, \text{trend}, \text{causal factor(s)}, \text{residual}).$$

Weather-driven seasonality and trends are estimated through a regression model trained on five years of monthly data. The long-term structural model is driven by economic and climatic causal factors as well as projections of energy efficiency and price. The data is then scaled to the AEMO estimate of BMM consumption based on meter data analysis before incorporation into the forecast. These short-term and long-term models are then combined to produce the long-term ensemble BMM model.

2.4.1 Short-term time-series model

Time-series models have been described as more applicable in short-term forecasting[15] and can be applied systematically. The short-term BMM forecast uses generic time-series methods to model the trend and weather-driven seasonality to form a short-term forecast (0-5 years ahead).

AEMO uses a monthly regression model based on five years (60 months) of historical data. The choice of five years strikes a balance between ensuring that the model considers only relatively recent consumption trends and behaviours, while being long enough to capture seasonality and contain enough observations to be statistically meaningful. At this stage, structural shocks which affect the data series (such as COVID-19) can also be captured using dummy variables, where applicable.

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

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

First, for each region i, trend and weather sensitivities are estimated from the model:

$$BMM\_cons_{i,m} = \beta_i + \beta_{\mathrm{Trend,i}} m + \beta_{HDD,i} HDD_{i,m} + \beta_{CDD,i} CDD_{i,m} + \beta_{shock} Shock\_impact_{i,m} + \varepsilon_{i,m},$$

where $m = 1,2,\ldots,60$ is a month counter. The coefficients to be estimated are the intercept (β_i), trend ($\beta_{\mathrm{Trend},i}$), Heating Degree Days (HDD) sensitivity ($\beta_{HDD,i}$), and Cooling Degree Days (CDD) sensitivity ($\beta_{CDD,i}$). This method decomposes the load into a trend, weather-driven seasonality, and a residual ($\varepsilon_{i,m}$). The independent variables are described in Table 2. More detail on critical temperatures applied in the calculation of HDD and CDD is provided in Appendix A2.

Table 2 Short-term base model variable description

Variable	Abbreviation	Units	Description
Business consumption	BMM_BaseYear	GWh	Total BMM business consumption including rooftop PV (i.e., excluding any LIL both existing and closed).
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 shock effect	Shock-impact	{0,1}	Dummy variable(s) that captures the changed business activity from external shock(s) affecting electricity consumption**

* 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 shock. As the situation is dynamic this may require a change in approach for capturing any temporary effects and structural changes.

Then, forecasts are generated using coefficients estimated from the regression model, replacing historical actual HDD and CDD values with weather standards as described in Appendix A2.2, and extending the date variable, m, to cover the months within the five-year forecast horizon.

2.4.2 Long-term causal model

The long-term BMM forecast is developed using a causal model for the various components understood to have a material impact on electricity consumption. The following equation describes the model used. The subscripts i and t represent regions and years, respectively[16].

$$BMM\_cons_{i,t} = economic\_impact_{i,t} + electrification\_impact_{i,t} + energy\_efficiency\_impact_{i,t}$$
$$+ price\_impact_{i,t} + climate\_change\_impact_{i,t}$$

Estimate economic impact

AEMO estimates the impact of economic factors on BMM electricity consumption forecasts by:

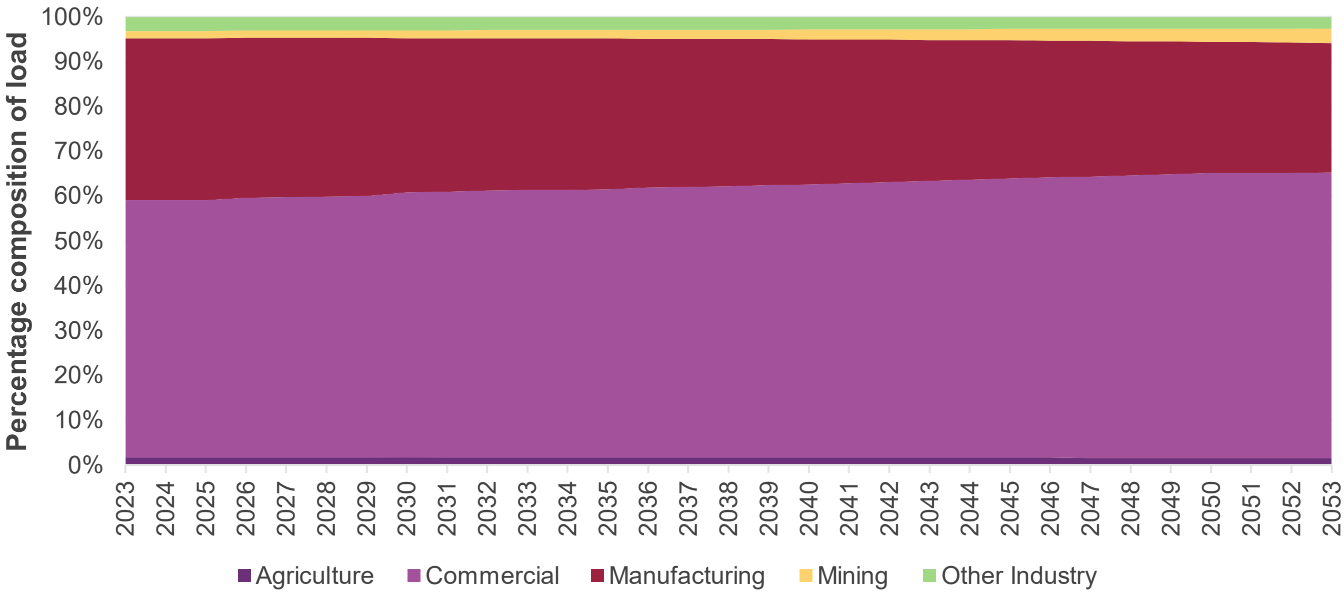
1. Modelling the multi-sector forecasts as energy intensity forecasts.
2. Applying economic forecasts to the energy intensity forecasts.

[16] In contrast with electricity forecasts from previous years, price impact is included after combining the short- and long-term forecasts into a single ensemble forecast. This approach was adopted to avoid diluting the short-term effect of upcoming price changes, which are not reflected in the short-term regression model.

In the first step, for each scenario, the multi-sector modelling outputs describe the long-term dynamics of energy consumption, driven from causal factors such as to industry activity changes, trade, import substitution and sectorial changes in the economy.

Figure 9 shows an example of different sectors forecast in proportion to the total sectorial forecast.

Figure 9 Example of multi-sectorial electricity forecast used for calculating sectorial energy intensities for Victoria



Energy intensity, defined as the energy consumption of a sector divided by the sector's gross economic product, is a means to reflect how economic factors impact electricity consumption[17]. AEMO uses energy intensities for modelling multi-sector forecasts, although periodically reviews the denominator, choosing whichever economic metric best fits and reasonably explains the data.

AEMO has observed, through meter data exploration, a decrease in energy intensity in the last decade across all regions. As logically the reduction cannot continue indefinitely, it is modelled as a decay function over time rather than a linear function over time. The empirical model is:

$$\text{Energy intensity} = A \times t^{-B},$$

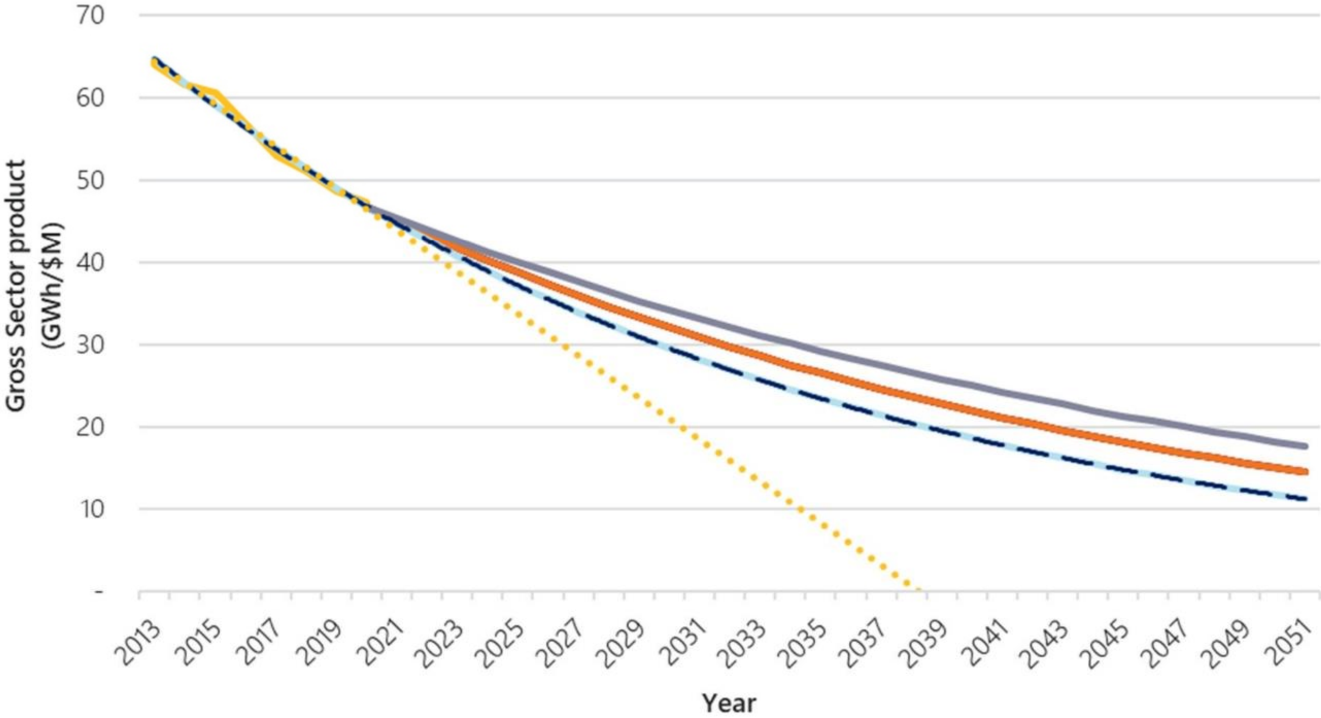
where A and B are the parameters fitted to the multi-sectoral forecast with ordinary least squares, and t is time in financial years. For scenarios where no multi-sectorial modelling outputs are available, historical data informs the parameter values.

Figure 10 is an example of energy intensity forecasts based on the multi-sector forecasts, where the dotted yellow linear trend serves to highlight the decay function shown in various hypothetical scenario curves.

In the second step, for each scenario, the economic impact to energy consumption is calculated by multiplying the energy intensity forecast by the economic forecast with the appropriate economic metric.

[17] See https://www.energy.gov/eere/analysis/energy-intensity-indicators. Accessed 24 August 2021.

Figure 10 Estimation of the energy intensity trends over time



Reflect price impact

As with any normal commodity, electricity consumption is expected to respond to price changes – price increases reduce consumption and vice versa. The impact of price variation is captured in the long-term model using the concept of price elasticity of demand[18].

Adjust for electrification

Forecast scenarios targeting net zero carbon emissions may include significant extra electricity consumption from fuel switching in sectors across the entire Australian economy where the most cost-effective strategy to reduce emissions is conversion of fossil fuel use to consumption of renewable electricity.

Annual electricity consumption arising from these electrification activities will be based on consultancy inputs and added to the overall BMM forecast.

Note that certain fuel switching will happen though energy efficiency programs. To the extent this happens, they will generally be captured though the adjustment for energy efficiency (below), to ensure these are not double counted.

Adjust for energy efficiency

AEMO obtains forecast energy efficiency savings either through consultants or its own analysis of federal and state-based energy efficiency programs, including the National Construction Code (NCC), building disclosure schemes, the Equipment Energy Efficiency (E3) Program, and state schemes[19]. This may include schemes that

[18] The price elasticities used in the forecast are documented in the IASR.

[19] For example, the New South Wales Energy Savings Scheme, Victorian Energy Upgrade Program, and South Australia Retailer Energy Efficiency Scheme.

promote fuel switching from gas (or other fuels) to electricity. AEMO also considers the impact of market-led energy efficiency investment, which occurs without policy incentives.

The energy efficiency savings are then split between base load, heating and cooling load elements derived from meter data.

AEMO adjusts the forecast energy efficiency savings to fit with the BMM model by:

- Removing savings from LILs[20].
- Rebasing the consultant's forecast to the BMM model's base year.
- Removing the estimated future savings from activities that took place prior to the base year.
- Reviewing energy savings calculations for state schemes and where possible consulting with state government departments. This includes identifying potential overlaps with what is delivered from federal initiatives and making adjustments where relevant to avoid double-counting savings.
- Applying a discount factor[21] to the adjusted energy efficiency forecasts, to reflect the potential increase in consumption that may result from lower electricity bills (knows as the "rebound" or "take back" effect[22]) and the potential non-realisation of expected savings from policy measures.

Adjust for climate change

Heating and cooling load is expected to vary as the climate changes, and the BMM sector is adjusted to reflect this. While the forecasts are produced assuming normalised weather standards, the weather standards change over the forecast period due to climate change (see Appendix A2).

A climate change index is used to adjust heating and cooling load[23] forecast for the BMM sector.

The BMM consumption, split into base load, heating and cooling elements for the base year, is then adjusted in subsequent forecast years by the estimated climate change impact on HDDs and CDDs.

2.4.3 Shock factor (structural break) adjustment

Throughout history, various economic or structural shocks have disrupted 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.

AEMO may apply shock factors to account for the disruption in the long-term relationship between electricity demand and economic indicators, as needed. This applied following the GFC, and in 2020 AEMO re-introduced a shock factor variable to account for the impact of the COVID-19 pandemic on the BMM sector.

[20] 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.

[21] The factor used in the forecast is documented in the IASR, at https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/Inputs-Assumptions-and-Methodologies.

[22] See for instance S. Sorrell (2007): "The Rebound Effect: an assessment of the evidence for economy-wide energy savings from improved energy efficiency". UK Energy Research Centre, Online, at http://www.ukerc.ac.uk/programmes/technology-and-policy-assessment/the-rebound-effect-report.html.

[23] Cooling and heating load is consumption that is temperature-dependent (for example, electricity used for cooling in warm weather or heating in cold weather). Load that is independent of temperature (such as electricity used in cooking) is called base load.

As the nature of shocks, by definition, varies depending on the circumstances of the shock itself, any adjustment will be customised based on available impact estimates, and will include considerations of:

- Impact on observed consumption data (training data) which will affect the future forecast.
- Impact on future consumption not captured through training data.
- Recovery from the shock/duration of impact.

Scenarios and sensitivities may be used to address the uncertainty in outcomes from structural shocks to the economy, where appropriate.

2.4.4 Combining the short-term and long-term BMM 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[24].

Time-series models are generally more accurate in the short term, so generally AEMO adopts:

- a short-term weighting of 100% in the first year,
- a short-term weighting of 80% in the second year,
- a short-term weighting of 60% in the third year,
- a short-term weighting of 40% in the fourth year,
- a short-term weighting of 20% in the fifth year, and
- a short-term weighting of 0% thereafter,

with the remainder coming from the long-term causal model.

AEMO may adopt different weightings when the near-term outlook differs from the short-term trend. Cases which could warrant a different blending of short- and long-term forecasts include:

- An anticipated recovery of the economy following a recession.
- A major policy announcement impacting from a specific year.

Reflect price impact

Adjustments to capture the impact of price changes are applied to the long-term models. Appropriate adjustments are then made to ensure that the full effects of large projected short-term price changes are not diluted in the process of combining the long-term and short-term models. The projected price changes used for these forecasts are described in Appendix A1. Price elasticities used are documented in the IASR.

2.5 Total business forecasts

AEMO forecasts the consumption impacts of CER that are related to business consumers. These are used to calculate the total underlying business consumption as well as the delivered business consumption, as explained in the following sections.

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

2.5.1 Consumer energy resources

AEMO typically obtains CER forecasts – including distributed PV, EVs and battery storage – from appropriately skilled consultants. Details on these forecasts will be available in the consultant reports, referred to in the IASR.

Electric vehicles

EV projections are split into the business and residential forecasts, based on the vehicle type and functionality. Consumption from the business sector EVs is combined with other sectors, such as LIL, LNG and BMM, to give the total underlying business consumption as per Section 2.5.2. For more detail on the EV forecast, refer to Appendix A4.

Rooftop PV adjustment

Forecast PV generation from commercial or industrial customers is subtracted from underlying consumption to translate this into delivered consumption (see Section 2.5.3), as it offsets the need for electricity supplied from the grid. This step covers commercial or industrial PV installations up to 100 kW. (Note that while AEMO uses the term ‘rooftop PV’, installations of this size may not be physically on rooftops). Larger systems (up to 30 MW) are accounted for in Section 4.

Battery storage loss adjustment

Batteries are not 100% efficient in the charging and discharging cycle, and AEMO must take this into account when incorporating the use of battery storage into the consumption forecast. The round-trip efficiency of batteries is documented within the IASR’s supporting material. Combined annual battery losses are found by multiplying the number of storage systems, the loss factor (1 minus the round-trip efficiency), and the capacity of each of the storage systems. It is assumed that each battery performs a full cycle each day.

$$\text{Loss per battery} = (1 - \text{Round trip efficiency}) \times \text{Capacity per battery (degraded)} \times \text{Cycles per day} \times \text{Days per year}$$

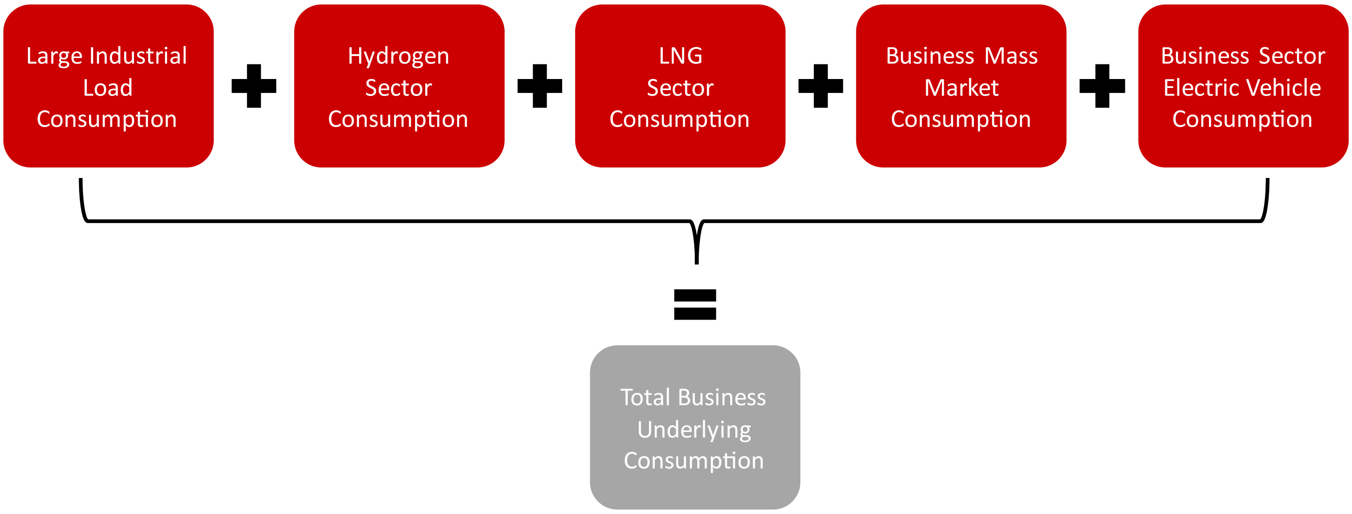
$$\text{Total Battery Losses} = \text{Number of batteries} \times \text{Loss per battery}$$

This is used to calculate delivered consumption from underlying consumption (see Section 2.5.3), as factoring in battery losses increases the amount of electricity that must be supplied from the grid.

2.5.2 Total underlying business forecasts

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

Figure 11 Aggregation process for total underlying business consumption



2.5.3 Total delivered business forecasts

Total business delivered consumption is the metered business consumption from the electricity grid and is derived by netting off distributed PV generation from underlying consumption and adjusting for battery storage losses as discussed above. This is illustrated in Figure 12.

Figure 12 Aggregation process for total delivered business consumption

3 Residential annual consumption

This section outlines the methodology used in preparing residential annual consumption forecasts for each region (including all NEM regions, and the WEM).

High level residential sector methodology

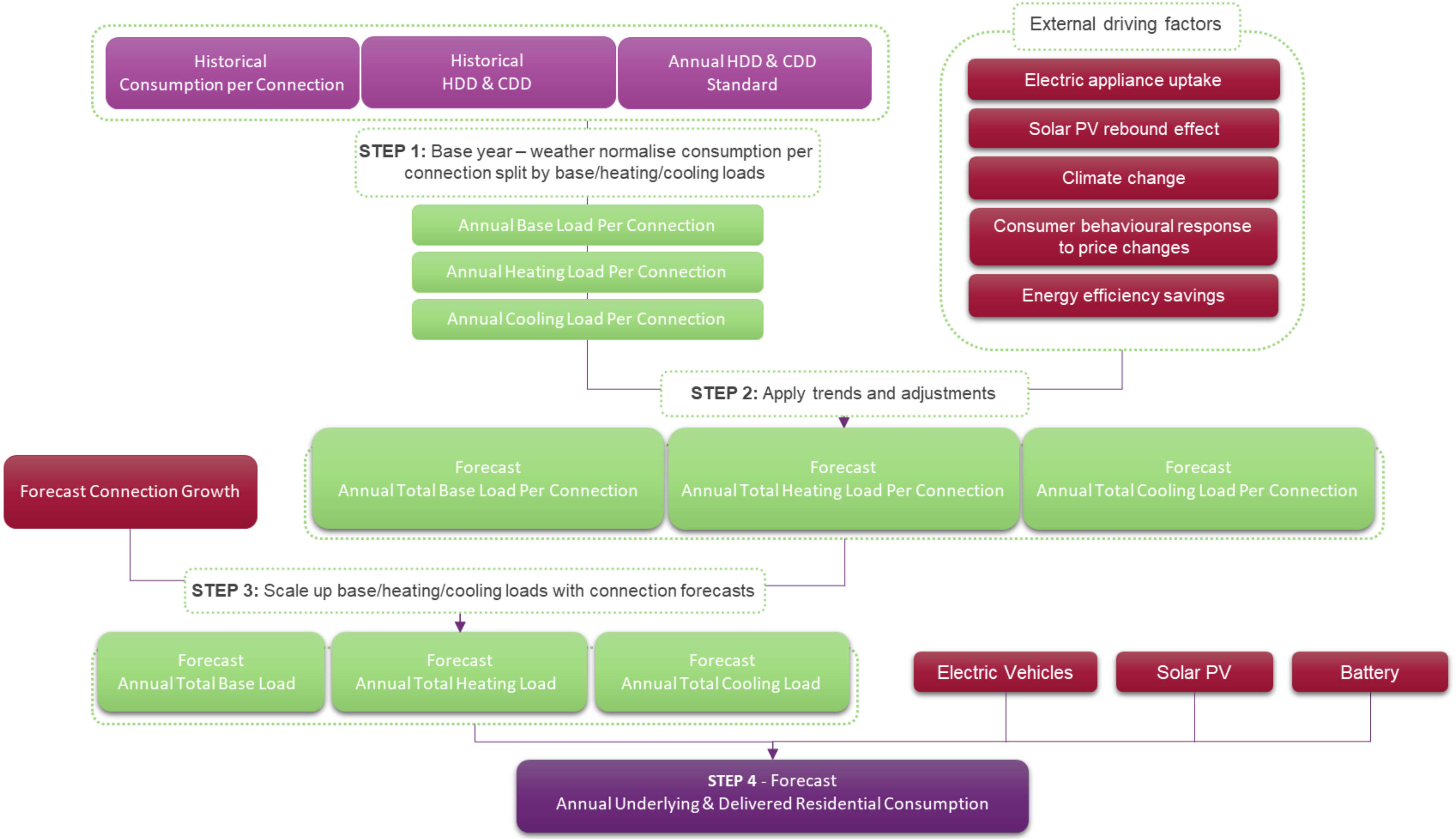
AEMO applies a “growth” model to generate 30-year annual residential electricity consumption forecasts. The key four steps are summarised below and detailed further in the rest of the chapter:

- Step 1: Calculate the base year by weather normalising residential consumption – estimate the average annual base load, heating load, and cooling load at a per-connection level. This is based on projected annual HDDs and CDDs under ‘standard’ weather conditions.
- Step 2: Apply forecast trends and adjustments (per connection) – account for the impact of the modelled consumption drivers including changing appliance penetration, energy efficiency savings, changes in retail prices, climate change impacts, electrification, and any rebound effects of consumer investments, particularly in rooftop PV.
- Step 3: Scale by the connections forecasts – scale the per connection consumption forecasts by the connections growth forecasts to result in the projected base load, heating load, and cooling load by region over the forecast period[25].
- Step 4: Calculate the total residential annual consumption forecast – develop the underlying residential consumption by summing the base load, heating load, and cooling load as well as the forecast consumption from electric vehicles. Delivered consumption is then determined by subtracting rooftop PV and adding back the losses incurred in operating battery systems.

Figure 13 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.

[25] 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 13 Process flow for residential consumption forecasts



3.1 Step 1: Calculate the base year by weather normalising residential consumption

Historical residential daily consumption is 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 are 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 applies the same model below using monthly data instead. For this section, the subscript t 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 is determined by:

- Estimating the underlying consumption by adding 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). Where material, other CER devices, including batteries and EVs, will be included in the same manner.
- 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 base load, cooling and heating load.

If appropriate, AEMO applies a dummy variable to capture the impact of structural shocks, such as COVID-19, on the energy consumption of the residential sector.

Daily (Monthly) regression model

Daily (Monthly) consumption per connection is regressed against temperature measures (namely, CDD and HDD) using ordinary least squares estimates based on the four-year time series leading up to the reference year as training data.

The four-year window is chosen to reflect current usage patterns (for example, dwelling size and housing type mix) but to be 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 shocks leading to structural breaks.

A similar regression approach is 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:

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

Regression model applied to Tasmania:

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

The above parameters are 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:

$$CoolingLoadPerCDD_i = 0$$

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

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

The variables of the model are defined in Table 3.

Table 3 Weather normalisation model variable description

Variable	Description
$\boldsymbol{Res\_Con_{i,t}}$	Daily average underlying consumption per residential connection for region i on day t.
$\boldsymbol{HDD_{i,t}}$	Average heating degree days for region i on day t.
$\boldsymbol{CDD_{i,t}}$	Average cooling degree days for region i on day t.
$\boldsymbol{HDD_{i,t}^2}$	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.
$\boldsymbol{Non-workday_{i,t}}$	Dummy variable to flag a day-off for region i on day t. This includes public holidays and weekends.
$\boldsymbol{Shock\_impact_{i,t}}$	Dummy variable to flag shock impact (such as COVID-19) for region i on day t.
$\boldsymbol{CoolingLoadPerCDD_i}$	Estimated cooling load per CDD for region i.
$\boldsymbol{HeatingLoadPerHDD_i}$	Estimated heating load per HDD for region i.
$\boldsymbol{AnnualHDD_i}$	Projected annual HDD in standard weather conditions for region i.
$\boldsymbol{AnnualCDD_i}$	Projected annual CDD in standard weather conditions for region i.
$\boldsymbol{Baseload\_Con_i}$	Estimated average annual base load per connection for region i.
$\boldsymbol{Heatingload\_Con_i}$	Estimated average annual heating load per connection for region i.
$\boldsymbol{Coolingload\_Con_i}$	Estimated average annual cooling load per connection for region i.

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

The daily (monthly) consumption estimates are scaled to give average annual base load, heating load and cooling load per connection, excluding impacts from weather conditions and installed rooftop PV generation based on the following:

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

$$HeatingLoad\_Con_i = HeatingLoadPerHDD_i \times AnnualHDD_i$$

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

Refer to Table 3 for description of variables.

3.2 Step 2: Apply forecast trends and adjustments

The average annual base load, heating load and cooling load per connection estimated in Step 1 (base year value) will not change over the forecast horizon, being unaffected by the external driving factors. The adjustment that accounts for external impacts, is 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: Estimate 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 (and other residential fuel switching, for example to solar hot water heating). 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: Estimate the impact of solar PV rebound effect

It is assumed that households with installed rooftop PV are likely to increase consumption due to lower electricity bills and less behavioural diligence to reduce energy consumption. The PV rebound effect[26] is allocated proportionally to base load, heating load, and cooling load per connection.

[26] AEMO assumes a rebound of energy consumption equal to 20% of the energy generated by the PV systems, as lower future bills may change consumption behaviour or trigger investments in equipment that uses more electricity. This rebound effect is supported by analysis carried out by CSIRO Energy on AEMO's metering data using open-source package OpenEEmeter. Refer to N. Mahdavi, "Solar PV Rebound Effect on Regional Demand," 2022 IEEE Sustainable Power and Energy Conference (iSPEC), Perth, Australia, 2022, pp. 1-5, doi: 10.1109/iSPEC54162.2022.10032991.

Step 2.3: Estimate the impact of climate change

Based on historical observed weather data, and projected future climate scenarios, AEMO adjusts 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: Estimate the impact of consumer behavioural response to retail price changes

Changes in electricity prices impact consumers' use of electricity.

Prolonged price increases typically drive capital investments to lower energy consumption. AEMO's residential consumption forecast captures most of this through forecast energy efficiency savings and rooftop PV uptake.

The response to shorter-term retail price increases is modelled through consumer behavioural response. Consumers' assumed asymmetric response 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.

Price movements are measured relative to the start year, as an index. For each forecast year, the change in index from the previous year times the price elasticity[27] gives the percentage change in consumption applied to the forecast.

Step 2.5: Estimate the impact of energy efficiency savings

Ongoing improvements in appliance efficiency and the thermal performance of dwellings drive energy savings in the residential sector. AEMO accounts for energy efficiency through consultants or its own assessment of residential energy savings from a range of government measures, including the NCC, E3 program and state schemes.

Fuel switching between gas and electric appliances for space heating arising from changes to the NCC is typically embedded in the energy efficiency forecasts. Other fuel switching policies are captured by the electrification adjustment.

Energy savings are apportioned by load segment using ratios developed by AEMO for each region, considering the total annual consumption that is sensitive to cool weather (heating load) and to hot weather (cooling load). The residual consumption is considered temperature-insensitive and is apportioned to base load.

AEMO then applies a discount factor[28] to the forecast energy efficiency savings to reflect the potential increase in consumption that may result from lower electricity bills (knows as the "rebound" or "take back" effect[29]) and the potential non-realisation of expected savings from policy measures. This is applied equally to heating load, cooling load and base load savings.

---

[27] The price elasticities used in the forecast are documented in the IASR.

[28] The factor used in the forecast is documented in the IASR.

[29] See for instance S. Sorrell (2007): "The Rebound Effect: an assessment of the evidence for economy-wide energy savings from improved energy efficiency". UK Energy Research Centre, Online: http://www.ukerc.ac.uk/programmes/technology-and-policy-assessment/the-rebound-effect-report.html.

Step 2.6: Estimate the forecast consumption 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 2.5. 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 4.

Table 4 Variables and descriptions for residential consumption model

Variable	Description
$\boldsymbol{TOTBaseload\_Con_{i,j}}$	Forecast total base load per connection for region i in year j .
$\boldsymbol{TOTHeatingload\_Con_{i,j}}$	Forecast total heating load per connection for region i in year j.
$\boldsymbol{TOTCoolingload\_Con_{i,j}}$	Forecast total cooling load per connection for region i in year j.
$\boldsymbol{API\_BL\_Con_{i,j}}$	Impact of electrical appliances uptake on annual base load per connection for region i in year j.
$\boldsymbol{API\_HL\_Con_{i,j}}$	Impact of electrical appliances uptake on annual heating load per connection for region i in year j.
$\boldsymbol{API\_CL\_Con_{i,j}}$	Impact of electrical appliances uptake on annual cooling load per connection for region i in year j.
$\boldsymbol{PVRB\_BL\_Con_{i,j}}$	Impact of rooftop PV rebound effect on annual base load per connection for region i in year j.
$\boldsymbol{PVRB\_HL\_Con_{i,j}}$	Impact of rooftop PV rebound effect on annual heating load per connection for region i in year j.
$\boldsymbol{PVRB\_CL\_Con_{i,j}}$	Impact of rooftop PV rebound effect on annual cooling load per connection for region i in year j.
$\boldsymbol{CCI\_HL\_Con_{i,j}}$	Impact of climate change on average heating load per connection for region i in year j.
$\boldsymbol{CCI\_CL\_Con_{i,j}}$	Impact of climate change on average cooling load per connection for region i in year j.
$\boldsymbol{PI\_HL\_Con_{i,j}}$	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.
$\boldsymbol{PI\_CL\_Con_{i,j}}$	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.
$\boldsymbol{EEI\_BL\_Con_{i,j}}$	Impact of energy efficiency savings on annual base load per connection for region i in year j.
$\boldsymbol{EEI\_HL\_Con_{i,j}}$	Impact of energy efficiency savings on annual heating load per connection for region i in year j.
$\boldsymbol{EEI\_CL\_Con_{i,j}}$	Impact of energy efficiency savings on annual cooling load per connection for region i in year j.

3.3 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, are then scaled up by the forecast number of connections over the projection period. See Appendix A5 for more detailed discussion on the residential building stock model and associated connections forecast.

Forecasts of annual base load, heating load and cooling load are 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 5 Residential base load, heating load and cooling load model variables and descriptions

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

3.4 Step 4: Calculate the total residential annual consumption forecast

Total residential annual consumption at both underlying and delivered level can be calculated from the previous steps, when adjusting for CER.

3.4.1 Consumer energy resources

AEMO typically obtains CER forecasts – including rooftop PV, EVs and battery storage – from consultants. Details on these forecasts will be available in the consultant reports, referred to in the annual IASR.

Electric vehicles

EV projections are split into business and residential, where the consumption from the residential sector EVs are added to the forecast residential base load, heating load and cooling load to give the total residential underlying annual consumption (see Section 3.4.2). The majority of consumption relates to EV charging, however a small amount relating to Vehicle to Home losses is also modelled. Vehicle to Home losses are assumed to be attributed solely to the residential sector.

Rooftop PV adjustment

Forecast rooftop PV generation from residential customers is subtracted from underlying consumption, as it offsets the need for electricity supplied from the grid, to calculate the delivered consumption (see Section 3.4.3).

Battery storage loss adjustment

As detailed in Section 2.4, battery losses are calculated and incorporated into both business and residential consumption forecasts. This is used to calculate delivered consumption from underlying consumption (see Section 3.4.3) as accounting for battery losses increases electricity that must be supplied from the grid.

Electrification adjustment

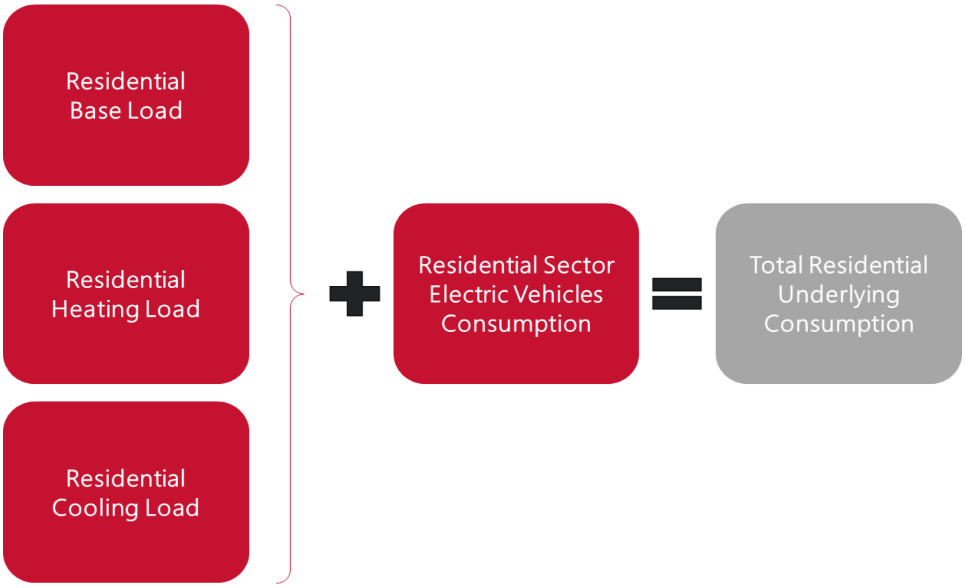
Forecast scenarios targeting net zero carbon emissions may include significant additional electricity consumption from fuel switching in the residential sector. This is a strategy to reduce emissions by replacing fossil fuel use with electricity sourced from renewables.

Annual electricity consumption arising from these electrification activities will be based on consultancy inputs and added to the overall residential forecast.

3.4.2 Total residential underlying annual consumption

The forecast underlying annual consumption is expressed as the sum of base, heating and cooling loads and residential electric vehicles, as shown in Figure 14.

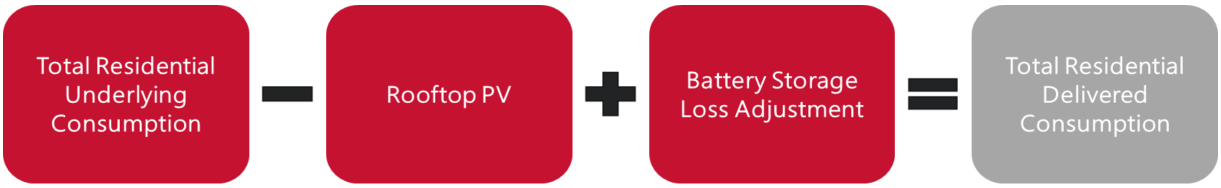
Figure 14 Aggregation process for total residential underlying consumption



3.4.3 Total residential delivered annual consumption

Forecast delivered annual consumption refers to underlying consumption, adjusted for consumption offsets due to solar PV and customer battery storage system losses as explained above. This is illustrated in Figure 15.

Figure 15 Aggregation process for total residential delivered consumption



4 Operational consumption

AEMO uses operational consumption in its medium- to longer-term reliability and planning processes. The following section explains how it is calculated based on the previous sections of this document.

Operational consumption represents consumption from residential and business consumers, as supplied by scheduled, semi-scheduled and significant non-scheduled generating units[30]. The remainder of non-scheduled generators are referred to as small non-scheduled generation (NSG); either PVNSG (for energy generated from small PV sources too large for rooftop PV classification) or ONSG (other non-scheduled generation).

When calculating operational consumption, energy supplied by small NSG is 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.

This is done in two stages, as outlined in Figure 16 and Figure 17. The components are explained in the following sections.

Figure 16 Delivered to the distribution network

Figure 17 Operational consumption (sent-out)

Finally, power station auxiliary load is used to convert from “sent-out” to “as generated” consumption, as shown in Figure 18. The methodology for auxiliary load is explained in Section 4.3.

Figure 18 Converting from operational consumption (sent-out) to operational consumption (as generated)

[30] 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 Small non-scheduled generation

4.1.1 Methodology

The small NSG forecast is split into two components:

- **PVNSG** – PV installations above 100 kW but below 30 MW. These are forecast separately from rooftop PV (up to 100 kW) as the larger projects require special purpose financing and are often ground mounted, sometimes with single-axis tracking.
- **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.

Small NSG can be connected to either the distribution network (most typically) or the transmission network.

PVNSG

The PVNSG annual generation forecast is developed using:

- Forecast PV capacity in the 100 kW to 30 MW range (up to 10 MW for the WEM[31]) unless explicitly included in operational demand definitions[32]. The capacity forecast is typically provided by the same consultant(s) as rooftop PV (see Appendix A3.1)
- A simulated normalised PV generation trace.

Annual PVNSG generation is obtained by multiplying a typical half-hourly normalised generation trace by the capacity forecast to produce a MW generation trace at half-hourly resolution, which is then aggregated to determine annual energy in MWh. A typical half-hourly normalised generation trace is calculated by determining the median normalised generation values from historical values for each half-hour in a year. This typical trace is used as a proxy for future PVNSG generation in each forecast year.

Specifically, the historical normalised generation traces are produced by:

- Using solar insolation and weather data at half-hourly granularity. This data is used in the System Advisor Model (SAM)[33] to simulate PVNSG historical normalised generation from 2001 for each postcode, where PVNSG is present, for fixed plate and single axis tracking technologies.
- Determining regional historical normalised generation traces by capacity weighting postcode normalised generation traces. Each PVNSG installation is classified as fixed plate or single axis tracking. The historical traces are used to update historical underlying demand based on installed capacity in the given years.

ONSG

For technologies other than PV, AEMO maintains a list of existing generators and remove units that may already be captured though net metering of the load it is embedded under. This results in a forecast capacity, for each region of eligible NSG. This is further subdivided into capacity for each technology type, such as small-scale wind, small hydro, landfill gas, and diesel generation.

---

[31] Additionally, PVNSG in the WEM excludes generators that hold Capacity Credits.

[32] Any such exceptions are listed in https://www.aemo.com.au/-/media/files/electricity/nem/security_and_reliability/dispatch/policy_and_process/2020/demand-terms-in-emms-data-model.pdf.

[33] The National Renewable Energy Laboratory's SAM: https://sam.nrel.gov/.

Forecast capacity by region and technology type is based on information such as:

- Information about committed or retiring generators, using the relevant Generation Information release.
- Trend in historical capacity additions.

All new projects are assumed to begin operation at the start of the financial year in which they are due for completion and remain in operation for the entire outlook period.

The forecast capacity is converted into annual energy generation projections, based on historical capacity factors for these technologies in each region. The capacity factors used for the projections are calculated using up to five years of historical data.

Capacity factors for existing projects are 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 estimates capacity factors using the following methods:

- Where similar projects already exist, in terms of NEM region and generator class (fuel source), AEMO uses 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 uses the regional average for all existing generators or applies the capacity factor of similar generators from another region.

AEMO then combines 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

Networks lose energy due to electrical resistance and the heating of conductors as electricity flows through the transmission or distribution network. To support converting delivered demand to operational demand, delivered demand is adjusted to account for these losses.

Distribution losses

AEMO receives historical energy losses and total energy at a transmission level. AEMO forecasts annual distribution losses by using the corresponding regional historical normalised distribution loss factors[34]. AEMO uses the latest available year's loss factor as proxy for future losses, unless a clear historical trend in losses can be identified.

Distribution losses are added to the total delivered annual consumption (both residential and business) minus forecast generation from distribution connected ONSG and PVNSG to give what is delivered to the distribution networks from transmission connected supply (including interconnectors).

Transmission losses forecast methodology

AEMO receives historical energy losses and total energy at a transmission level. AEMO forecasts annual transmission losses by using the corresponding regional historical normalised transmission loss factor in the

[34] The source and values of historical distribution losses are presented in the IASR.

IASR. AEMO uses the latest available year's loss factor as proxy for future losses, unless a clear historical trend in losses can be identified.

Transmission losses are added to the total demand delivered to the distribution networks (as per above) minus any forecast generation from transmission connected ONSG and PVNSG to give operational demand (sent-out).

4.3 Auxiliary loads

Auxiliary loads account for energy used within power stations (the difference between "as generated" energy and "sent-out" energy, as shown earlier in Figure 18). Auxiliary loads are equal to the difference between total generation as measured at generator terminals and the electricity sent to the grid.

Note that auxiliary load is only applied to NEM generators, as the NEM uses as-generated output in its dispatch, while the WEM uses sent-out measured energy.

Auxiliary loads (historical)

The auxiliary load is estimated by multiplying the metered generation for an individual generating unit by using an estimated auxiliary percentage for the generation station such that:

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

The estimated auxiliary percentages are published in the IASR.

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 to all generating units in the NEM to calculate the historical total auxiliary load and operational demand as sent out on a half hourly basis.

Auxiliary loads (forecast)

The future annual auxiliary loads in each region are forecast using the forecast auxiliary load from a future generation forecast that have a mix of generating technologies, such as the ISP, broadly consistent with operation consumption (sent out) for the relevant forecast scenario.

Future auxiliary calculations rely upon the auxiliary factors for existing and new generation technologies published in the IASR.

For each scenario:

- The forecast auxiliary factor for each financial year j and for each NEM region i is defined as:

$$\text{Auxiliary Load Factor}_{i,j} = \frac{\text{Modelled Auxiliary Load}_{i,j}}{\text{Operational Consumption Forecast (sent out)}_{i,j}}$$

- The annual auxiliary load forecast for financial year j and region i is then determined as:

$$\text{Auxiliary Load}_{i,j} = \text{Operational Demand (sent out)}_{i,j} \times \text{Auxiliary Load Factor}_{i,j}$$

5 Maximum and minimum demand

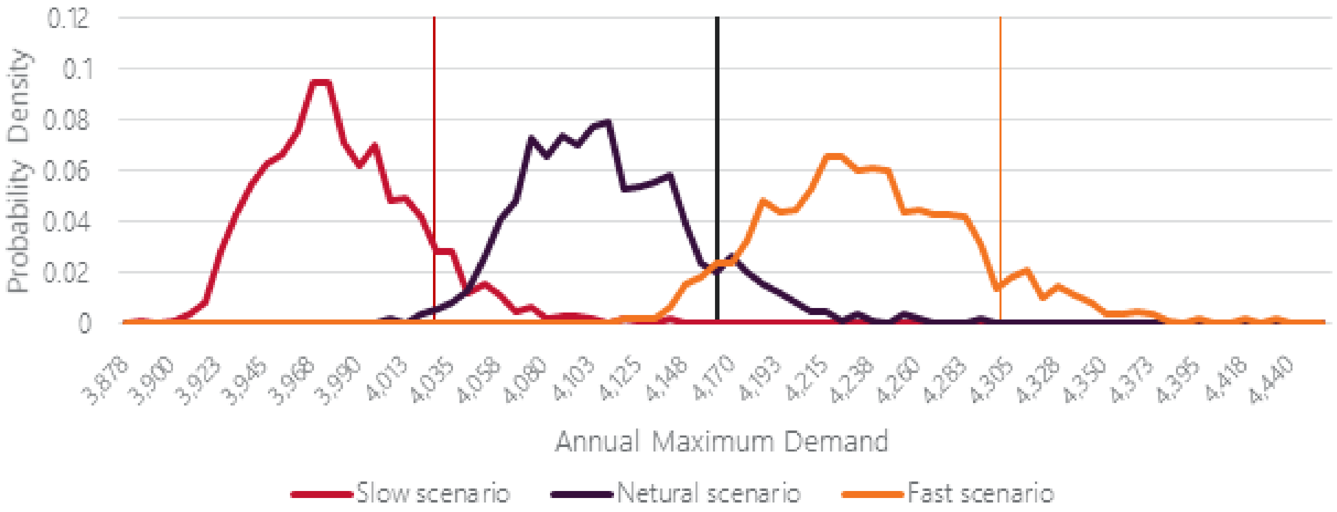
Demand is dependent on both structural drivers as well as random drivers such as weather conditions, seasonal effects and the model residual. To capture the random drivers, AEMO uses a probabilistic methodology to develop regional minimum and maximum demand forecasts.

Several scenarios are developed to capture uncertainty in structural drivers, while uncertainty attributable to random drivers is expressed as an interval, 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 19 shows modelled probability density functions that represent possible maximum demand outcomes for a typical region. Three probability density functions are shown, one for each scenario, collected from sampled simulations, with unique structural drivers. The 10% POE estimates are calculated from the probability distributions and shown by the vertical lines.

Figure 19 Conceptual summer maximum demand probability density functions for three scenarios



AEMO forecasts unconstrained maximum and minimum demand, that is, demand that is unconstrained by subregional network constraints, generation constraints (including constrained rooftop PV generation) or outages, wholesale market dynamics and market levers which are modelled separately (demand side participation, battery VPP and coordinated EV charging).

For battery VPP, a percentage of installed battery capacity is reserved to be captured in the market models as an operational generator. This percentage used is discussed in the IASR. For coordinated EV charging, again, for a given scenario a percentage of EV energy is reserved to be modelled in the demand traces during times of minimum demand. This is discussed in more detail in Section 6.4.

AEMO forecasts operational demand ‘sent out’ as defined in Section 1.6. In the following sections 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, including both summer and winter seasons of the year. If this was not done, and financial years or calendar years were forecast, then the winter season would be spread across 12 months, including July and August at the beginning of the financial year, and June at the end of the financial year. This would likewise occur for summer if calculated on a calendar year basis. The use of season years avoids this problem, and will always place winter chronologically after summer in the season year.

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

The WEM maximum demand is forecast based on Capacity Years which commences in Trading Interval 08:00 on 1 October and ends in Trading Interval 07:30 on 1 October of the following calendar year. While not the exact same season year definition, the Capacity Year benefits from a similar seasonal offset.

5.1 Data preparation

Data preparation for the minimum and maximum demand models is performed similarly to that of annual consumption, however demand requires the use of half-hourly data. The requirement for higher-frequency data drives the need for more thorough data cleaning and consideration of the daily shape of CER technologies and large industrial loads.

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

- Historical and forecast rooftop PV capacity and normalised generation.
- Historical and forecast PVNSG installed capacity and normalised generation.
- Forecast ESS installed capacity and charge/discharge profile.
  - A proportion of ESS may be considered VPP with coordinated charging and discharging to meet a more centralised operational objective, with the proportion varying by scenario.
- Forecast EV numbers and charge profile.
  - A proportion of EVs may feature coordinated charging, with the proportion varying by scenario.
- National Metering Identifier (NMI) data for LIL, that is loads over 10 MW, 10% of the time (see Section 2.1).
- Historical and forecast LILs.
- Historical underlying demand.
- Projected climate change adjusted dry temperature.

AEMO sources half-hourly weather data as outlined in the IASR. The weather data is adjusted for climate change to reflect temperatures expected in the forecast horizon using the method listed in Appendix A2 and based on information available on www.climatechangeinaustralia.gov.au.

The model aims to generate forecasts of *underlying demand less large industrial load*. Large industrial load is subtracted from underlying demand before constructing the model. Large industrial load may be seasonal, and potentially cause structural shifts in demand, but is not considered to be weather-sensitive.

5.2 Exploratory data analysis

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

5.2.1 Outlier detection and removal

Outlier detection procedures are used to detect and remove outliers within the historical datasets caused by data errors and outages. A basic linear model is 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 are used to remove these data points to constrain the dataset. Any data errors detected through this process are tracked to determine cause followed by appropriate data corrections. No data is removed unless there is 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 is performed for missing data.

5.2.2 Selecting an appropriate time span for model training

Time series of demand exhibit trends or variations due to changes in user behaviour. Using data from a decade ago to predict the upcoming year is evidently inadequate, as it fails to reflect current user habits and the current level of end-use technologies, such as air conditioners. Employing the most recent data for future predictions captures the latest end-user tendencies and technologies, yet due to the limited data volume, historical instances of extreme heat or cold might be overlooked, compromising the model's ability to predict such scenarios accurately. Hence, determining the duration of historical data for training the model involves a trade-off between data volume and representativeness.

Data visualisation and statistical analysis are conducted to examine trends and the frequency of extreme hot and cold weather occurrences for each region. This process ensures that the selected data not only captures present user behaviour but also guarantees a sufficient dataset size for the model to learn comprehensively. The selection of this duration is also an integral part of the model retraining process. Different options are explored and tested, with this cycle being repeated multiple times until a favourable balance is achieved.

5.2.3 Exploratory data analysis to identify important short-term demand drivers

EDA is 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 examines variables like:

- Weather data – temperature variables including:
  - Instantaneous cooling degrees (CDs) and heating degrees (HDs).

- Dry bulb or wet bulb temperature, apparent temperature[35] or heat index[36] – both instantaneous and heatwave/coolwave.
  - 'Instantaneous' temperature may be transformed as half-hourly up to three hour rolling average of temperature.
  - 'Heatwaves'[37] and 'coolwaves' as daily or up to three-day rolling average of temperature.
- Higher order terms of the above variables, for example $InstantTemperature^2$ 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 stratify 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 assesses multicollinearity of the explanatory variables by considering the Variance Inflation Factor[38] caused by collinear variables.

5.3 Model development and selection

AEMO develops three models for each region:

- A half-hourly model for forecasting half-hourly demand, and
- A maximum demand Generalized Extreme Value (GEV) model and a minimum demand GEV model that are used to validate the maximum and minimum demand simulated by the half-hourly model.

Models for each region are specified using the variables identified as statistically significant during the EDA process.

The half-hourly models simulate half-hourly demand and perform well in modelling the impact of disruptive technology such as PV, ESS and EVs. These technologies have a half-hourly shape and cause demand to shift over the day. The GEV model approaches demand forecast from a different perspective. It directly forecasts seasonal (or monthly) minimum and maximum demand, instead of predicting half-hourly demand and then selecting the minimum and maximum value.

AEMO uses the half-hourly model to produce the minimum and maximum demand in the first year of the forecast (see Section 5.5), then uses the long-term indices to extrapolate half hourly demand for up to 30 years to produce the minimum and maximum forecast over that horizon, as outlined in Section 5.6.

[35] Measures the temperature perceived by humans. It is a function of dry bulb air temperature, relative humidity and in some cases wind speed.

[36] Measures the perception of temperature above 27°C. It is a function of dry bulb air temperature and humidity.

[37] Heatwaves are collinearly related with temperature variables derived from humidity. To avoid multicollinearity, the heatwave variables are retained, and the temperature variables derived from humidity are dropped.

[38] 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.

Half-hourly model

The half-hourly models aim 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 dry temperature, wet bulb temperature, and heat index.

AEMO uses a selection of Machine Learning algorithms to derive a model with good fit and strong predictive power. Algorithms include:

- LASSO – a special case of Elastic Net, which selects the best model from the range of variables available and all the interactions between the variables. The model is developed trading off the model bias[39] and model variance[40] to derive a parsimonious model with strong explanatory power.
- GBR (Gradient Boosting Regression) – an ensemble learning technique that builds a series of decision trees in a sequential manner, where each tree corrects the errors of its predecessor. GBR can capture complex non-linear relationships in the data and offers mechanisms for regularisation, often resulting in superior predictive performance.
- Decision Trees and Random Forests – decision trees split the data into subsets based on the feature values, making them interpretable and easy to visualise. Random Forests, on the other hand, aggregate the results of multiple decision trees to produce a more robust and accurate model. Both methods provide feature importance rankings, aiding in feature selection.

AEMO then performs additional in-sample and out-of-sample model diagnostic checks on the best model selected. Where the best model fails these checks, AEMO adjusts the algorithm iteratively. In performing this iterative approach, AEMO:

- Performs k-folds out-of-sample cross validation[41] to find the optimal model that trades off between bias and variance.
- Examines the disparity between in-sample and out-of-sample prediction accuracy to ensure that model avoids overfitting or underfitting.
- Inspects the relationship between residuals and individual explanatory variables to verify the appropriateness of the employed variables. If any variable introduces noticeable bias, corresponding variable transformations are applied to eliminate the bias.
- Inspects 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.
- Compares actual data against predictions from the half-hourly model.
- Compares actual detrended historical minima and maxima against simulated minima and maxima from the model.

[39] Under-fitting the model results in a model with high bias.

[40] Over-fitting the model result in a model with high variance.

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

The entire model training and validation process is repeated multiple times, with each iteration involving changes to the variables included in the model and tuning of the hyperparameters. This continues until the accuracy metrics converge to an acceptable and stable range.

Generalised extreme value model

AEMO specifies 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 aims to model the distribution of extreme values (minima and maxima) for operational demand less large industrial load. As such the GEV model is trained on monthly operational minima and maxima less large industrial loads.

The GEV models find the relationship between minimum and maximum demand and PV capacity, PVNSG capacity and monthly weather metrics. AEMO develops 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 GEV model is fitted using monthly operational minima and maxima as a function of PV capacity, PVNSG capacity, customer connections[42] (NMIs), calendar effect variables and average weather. Similar to the half-hourly model, AEMO then assesses 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 are 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 assesses 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.

5.4 Simulate base year (weather and calendar normalisation)

The half-hourly and the two GEV models selected from the above process are used to simulate demand for each region. Specifically:

- The half-hourly model simulates every half-hour and aggregates to the season.
- The GEV models simulate minima and maxima for each month which are aggregated to the season.

This is done such that for each season and region AEMO has minima and maxima from the half-hourly model and minima and maxima from the GEV models (that is, two sets of minima and maxima).

Starting from the 2023 NEM ESOO, because of the improvements in the accuracy of the half-hourly model, there is no longer a need to use GEV model to rebase forecasts[43]. Still, the GEV model provides an alternative approach for predicting minimum and maximum demand, so it serves as a suitable validation tool. AEMO employs the GEV model to forecast the base year result and subsequently compares it against the simulations from the half-hourly model to ensure the accuracy and reliability of its predictions.

[42] See Appendix A5.1.

[43] For the 2023 WEM ESOO, the distribution of the half-hourly model was rebased to align with the outcomes of the GEV models, similar to the approach used in the 2022 ESOO for both NEM and WEM.

Demand is simulated using calendar effects, weather and the model residual[44]. Historical weather events are simulated to develop a weather distribution to normalise demand then the model residual is applied. For the three models, this can be expressed as:

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

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

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

where:

- $f(x_{hh})$ is the relationship between demand and the demand drivers such as weather and calendar effects.
- $f(x_{month})$ is the relationship between monthly minima/maxima demand and the monthly demand drivers such as PV or PVNSG capacity and NMI count.
- $g(x_{month})$ the second moment scale parameter as a function of x variables.
- μ_3 the third moment shape parameter which is found to be a constant.
- ε_{hh} represents random normally distributed[45] changes in demand not explained by the model demand drivers.
- ε_{month} represents random normally distributed[48] changes in demand not explained by the model demand drivers from the GEV models.

Half-hourly model simulation

The weather is 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 is constructed by randomly selecting a full historical year, from 2007 to the latest complete calendar year, and applying a day shift between -3 and 3 days. Building upon the sampled weather year and applied day shift, 25 or more distinct in-sample residual traces are incorporated into the simulation to introduce the historically observed randomness, ε_{hh}.[46]

The weather data includes temperature and transformations of temperature aiming to warm to future climates, rooftop PV normalised generation, PVNSG normalised generation and any other significant variable in the model development process.

The synthetic half-hourly demand traces are simulated at least 2,800 times (16 reference years x 7 day shifts x 25 residuals gives 2,800, though more residuals may be used in some cases). The maximum and minimum demand events for each of the at least 2,800 simulations are used to form the maximum and minimum demand POE results. This can be done annually or by season or month.

[44] While the covariate of demand explains a large amount of the variability of demand the residual is the variance in the consumers response to these covariates. A consumer does not respond consistently to external stimuli such as temperature or day of week due to individual idiosyncrasies. This is a fundamental component of any statistical or machine learning method.

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

[46] This method has been adopted starting from 2023 NEM ESOO to better capture the historical weather's impact on demand. The 2023 WEM ESOO continued to use the approach from the 2022 ESOO, where simulation data was generated through bootstrapping historical weather observations every fortnight.

In summary, the simulation process recognises that there are several drivers of demand including weather, day of week, and hour of day, as well as the natural model residual of a statistical model. The process also preserves the probabilistic relationship between demand and its key drivers.

GEV model simulation

The GEV model is 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 constructs synthetic weather years by sampling monthly weather data from history. The GEV model is then applied to the synthetic weather years to estimate the point forecast component of the GEV.

The GEV distribution is 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 is simulated using the *x* variables from the synthetic weather years.

Finally, the process simulates random normally distribution model residual of demand. The model residual is simulated to account for the demand variability otherwise unexplained by the demand drivers captured in the linear model (ε_{hh}), and which is a feature of all statistical models.

5.5 Forecast probability of exceedance for base year

The base year of the maximum (or minimum) demand forecast is the last year of summer actuals. For instance, if the last summer actual demand was 31 March 2023, the base year for the purpose of the forecast is the financial year ending 2023.

Based on the 2,800 (or more) simulations generated from half-hourly model by varying reference years, day shifts and residuals, the individual seasonal maximum and minimum demand values from each simulation are extracted. By sorting these 2,800 seasonal values, 10%, 50% and 90% POE can be constructed.

5.6 Forecast probability of exceedance for long term

Once the base year is established and validated by the GEV simulation, the half-hourly model then forecasts 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 to derive a periodic growth index. Based on the availability of the input data, the frequency of the growth index may vary from monthly to annual.

The forecast year-on-year change is 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. The process calculates the annual indices and removes the impact of any growth driver explicitly modelled in the half-hourly simulation model to avoid any potential double counting of drivers (these may include, LILs, climate change and EV charging).

Furthermore, the process distinguishes between the heating, cooling, and base (HBC) components and grows them using their respective indices. Segmenting demand into these three HBC portions is achieved through a model-driven approach. Initially, a mild temperature day is selected as a baseline or base component. Its temperature profile is then applied across each forecasting period to reflect the assumption of how demand would behave under mild weather conditions. A comparison is made against the original forecast, with any surplus indicating the heating or cooling component. This component is further determined based on the temperature. Generally, summer demand comprises the base and cooling, while winter demand consists of the base and heating. Shoulder seasons may encompass both base and cooling, or base and heating.

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[47]), and adding LIL[48], distribution and transmission losses back on[49]. The rooftop PV and PVNSG forecast capacities are used with the normalised generation simulated in the simulation step to calculate forecast rooftop PV and PVNSG generation. Further the deterministic (non-coordinated) EV and ESS traces are added to the demand traces within the simulation according to the scenarios discussed in the IASR. Coordinated EV charging is not added until the demand trace process and is discussed in Section 6.4.

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 4 in Section 1.6.

AEMO then extracts 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 2,800 simulations are performed, there will be 2,800 maximum and 2,800 minimum values for each scenario-season-year combination. From the 2,800 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 20:

- The first distribution represents the variability of 17,520 half-hour demands for each simulation. This is obtained for all years needed to produce a forecast year. Data for one half-hour representing the largest predicted maximum demand (indicated by the red box and arrow) is then extracted from the 17,520 half-hours and added to the distribution of annual maxima (represented by the smaller bell curve). This extraction is repeated thousands of times, once for each simulation.
- The second smaller bell curve represents the distribution of maxima[50].

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.

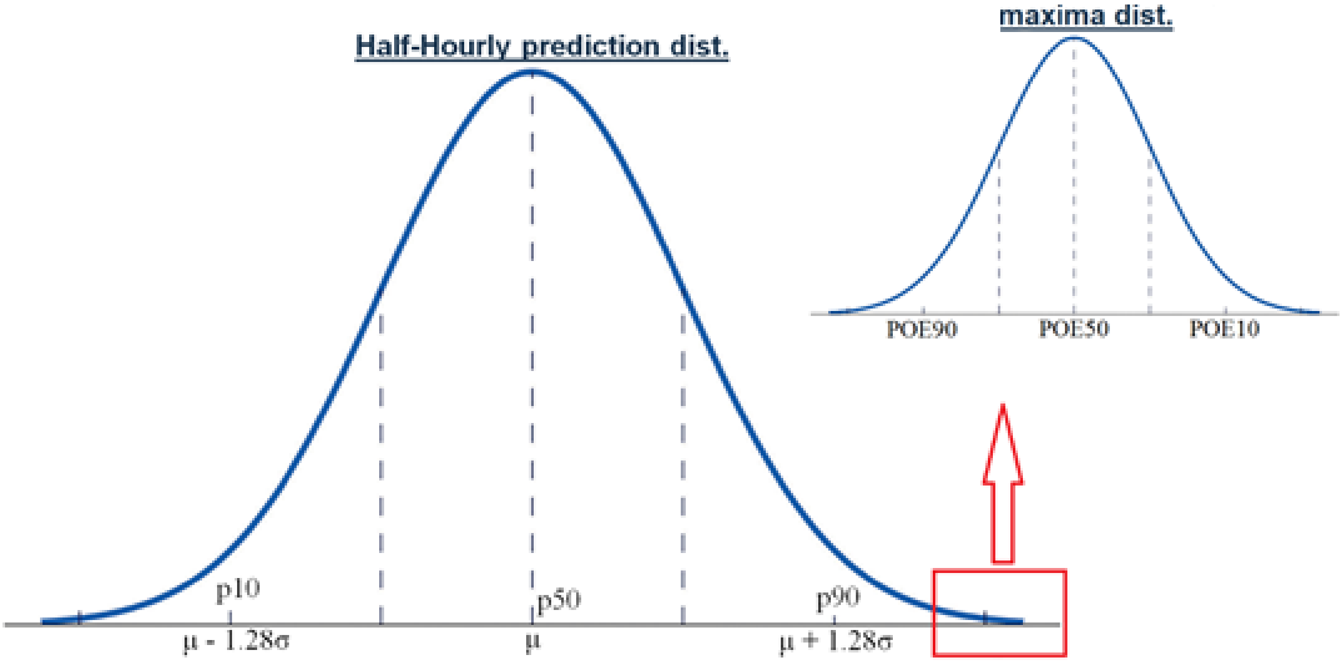
[47] See Section 5.7 more information on the modelling of ONSG.

[48] See Section 5.7 more information on the modelling of LIL within the simulation.

[49] See Section 5.7 more information on the LIL, losses, ONSG and auxiliary (needed for ‘as generated’) forecasts at time of minimum and maximum demand.

[50] It is not necessary for the distributions to follow a normal distribution. Regardless of distribution kurtosis, the percentiles can be found by ranking the demand values and extracting the desired percentile.

Figure 20 Theoretical distribution of annual half-hourly data to derive maxima distribution



Note: Normal distributions are shown as illustrative only, both the main and tail distributions may have other shapes.

AEMO then transitions 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.

5.7 Other forecasting components

The following components are explicitly modelled either in the simulation of demand or added on after the simulation is complete as a component-based point forecast:

- Losses.
- ONSG.
- Large industrial loads.
- Hydrogen sector demand.
- Auxiliary load.
- Electrification.

Transmission and distribution losses

AEMO forecasts transmission and distribution losses using transmission and distribution loss factors as outlined in Section 4.2. These loss factors are applied after the simulation of minimum and maximum demand.

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[51], grown proportionally with any forecast growth in installed capacity.

Generation from peaking-type ONSG is not considered at time of maximum demand. These peaking generators are considered as a form of demand side participation (DSP). As a result, more of the demand at time of maximum demand is modelled as met by operational generators. The ONSG component is forecast separately at time of minimum and at time of maximum demand. The ONSG component is added to the minimum or maximum demand after the simulation of demand.

Large industrial loads

The minimum and maximum demand models are trained and simulated exclusive of large industrial loads. The large industrial load component is explicitly simulated within the simulation engine and added back on.

Based on analysis, AEMO assumes that LILs in all regions except for Tasmania are not correlated with the regional maximum demand. Further, LILs have a load factor of greater than 0.9 in most cases. For all regions except Tasmania, AEMO simulates the average large industrial load demand -/+ the standard deviation in the minimum and maximum regional demand. These LILs are then forecasted using the annual consumption long-term drivers. In the case of Tasmania, however, LILs drive the regional minima and maxima. AEMO applies the large industrial load minimum and maximum to Tasmania’s regional minimum and maximum rather the average.

Hydrogen sector demand

As explained in Section 2.2, the daily dispatch of electricity loads used to produce hydrogen is optimised in AEMO’s market model simulation software to take into account the cost of supply at time of use.

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 market modelling simulation software. The forecast uses the average modelled auxiliary load at time summer/winter minimum and maximum demand.

Operational demand (as generated) is calculated by adding estimated auxiliary load at time of maximum and minimum demand to the operational demand (sent-out) as shown in Figure 21.

Figure 21 Translation from operational demand (sent-out) to operational demand (as generated)

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

Electrification

Electrification is added in the trace growing process, with details provided in Section 6. Impacts of electrification on maximum and minimum demand is extracted from the resulting traces to be able to present these values as forecast components.

5.8 Structural breaks in demand forecasting models

Similar to the discussion in Section 2.4.3, AEMO deals with structural breaks in the maximum/minimum demand forecast models by including a factor variable during model training, if sufficient data history exists to form a training data set. This allows AEMO to develop and train models with good forecast accuracy in the presence of structural breaks.

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

In the event that a structural break is identified, maximum and minimum demand effects are estimated by statistical analysis of time-of-use demand data following the event. This analysis identifies the impact of the event, relating consumption patterns pre- and post-event. The method then applies this adjustment for the estimated timeframe that the event is expected to impact. This may apply the same trend as the consumption forecasts, or a different trend if AEMO considers it more appropriate to do so.

As each structural break can be quite unique, specific methodologies will be developed and applied as necessary to ensure continued forecast accuracy, and consulted with stakeholders through forums such as AEMO's Forecasting Reference Group where time is available to do so.

AEMO allows for structural breaks in the long-term demand drivers of the annual consumption forecast. These drivers flow through to minimum and maximum demand and daily demand profile adjustments. 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.

6 Half-hourly demand traces

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

The traces are 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 are differentiated by:

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

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

The demand traces are developed to target an ‘OPSO-lite’ demand measurement. 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).
- PVNSG.
- ESS.
- EVs.
- Vehicle-to-home discharging (V2H); see Section 6.2 for details on V2H.
- Any material new industry sector, which does not have sufficient history of operation across *all* reference years to be included; for example, in Queensland, the LNG loads.

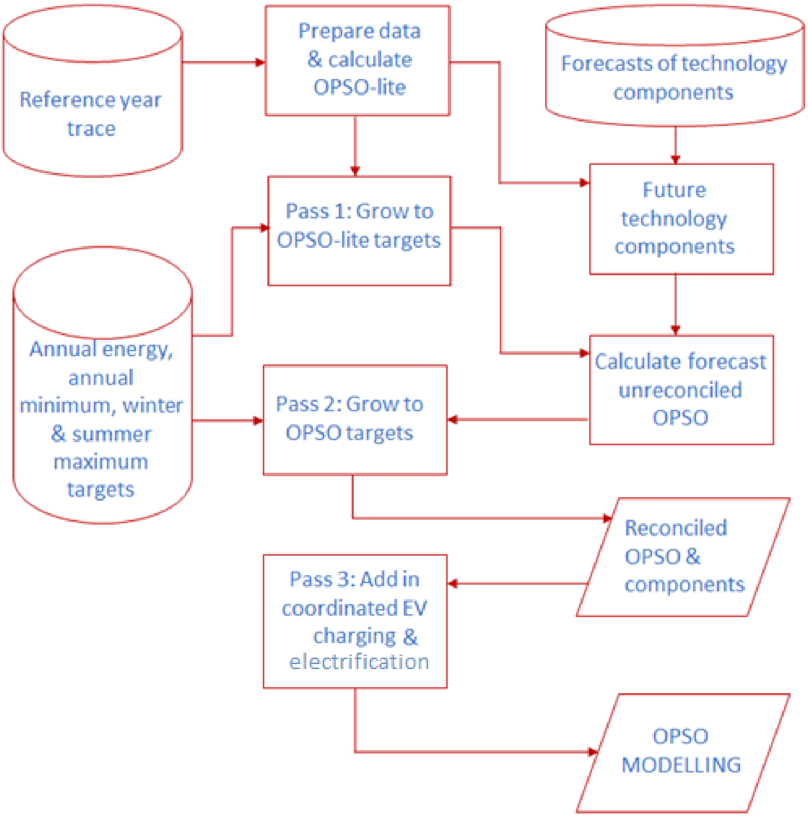
The trace development process is conducted in three passes for each combination of NEM region, historical reference year, forecast year, scenario and POE level:

- Pass 1. Growing the reference year trace on an OPSO-lite 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. Adding electrification and coordinated EV charging to OPSO.

The trace development process is summarised as a flow diagram in Figure 22. A worked example of the growth scaling algorithm (discussed in Section 6.1) is also provided in Appendix A7.

Figure 22 Demand trace development process flow diagram



6.1 Growth (scaling) algorithm

Demand from the particular reference year is scaled to match the targets of the forecast year using a constrained optimisation algorithm. The first two passes of the three-pass approach follow this growth algorithm. The algorithm finds scaling factors for each half-hour which minimises the difference between the adjusted demand and the targets, such that seasonality, weekly and intra-day demand patterns are preserved. The demand trace is adjusted for each period so that the target is met for each pass. The approach:

1. Applies 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. Categorises 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 periods which are used to target the annual consumption target.

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

3. Scales the half-hourly demands across all summer high-demand days such that only the highest demand point exactly matches the summer maximum demand target.
4. Scales the half-hourly demands across all winter high-demand days such that only the highest demand point exactly matches the winter maximum demand target.
5. Scales the minimum demand across all low-demand half-hour periods such that only the minimum demand point exactly matches the annual minimum demand target.
6. Determines the scaling factor for each day-type group such that the energy across the year matches the annual energy target.
7. Calculates 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 has no scaling factor for the purpose of meeting a demand target. As such, the algorithm allocates the remainder of future energy to the ‘other’ day-type category for the purpose of meeting the annual energy target.
9. Checks the grown traces against the targets. If all targets are met, the process is complete. If any of the targets are not fully met, the algorithm re-grows the demand traces for the reference year recursively by repeating steps 1 to 8 until the targets are 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 manages the handling of periods near or below zero by adding a fixed amount to all periods before growing. This is then removed after growing.

6.2 Pass 1 – growing to OPSO-lite targets

As highlighted in Figure 22, the first pass grows the OPSO-lite reference year traces to the forecast year OPSO-lite targets. After growing the traces, the demand components that have been excluded from the OPSO-lite definition (PVROOF, PVNSG, ESS, EV, V2H, LNG) are reinstated. This produces an unreconciled OPSO. The technology components are also prepared to reflect changing installed capacities, vehicle numbers, installation numbers or, in the case of LNG, demand, such that these components are consistent with the forecasts for the forecast year.

V2H represents EVs that act as home batteries (in addition to being EVs). Their battery discharge profile when operating as such is included in this step similar to ESS, but the charging is excluded. Instead, V2H charging is optimised within models that dispatch the generation supply to meet the demand targets in each dispatch interval, 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.

6.3 Pass 2 – reconciling to the OPSO targets

The second pass seeks to ensure that the grown maximum operational demand meets the OPSO targets.

Generally, because the trace is based on historical information, the unreconciled OPSO maximum demand does not always meet the OPSO target once rooftop PV, PVNSG, ESS, EV, V2H and LNG specific to the years are taken into account. This is because the OPSO targets are based on simulating weather, while the reference year is a single actual 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-runs the growth algorithm in Section 6.2 to ensure the OPSO characteristics are met. The technology components are not modified, therefore this process, in effect, ensures OPSO targets are met but can only be done if proximity to OPSO-lite targets is relaxed.

6.4 Pass 3 – adding electrification and coordinated EV charging to OPSO

The third phase adds both electrification and coordinated EV charging to OPSO.

For coordinated EVs, for each day in the demand trace, a daily amount of 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 referred to as an 'OPSO-modelling' trace. 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. Adds a stochastic component to the OPSO-modelling power profile.
6. Reorders the OPSO-modelling power profile according to time.

Electrification is based on the forecasts outlined in the IASR. New electrified loads are assumed to mirror existing electricity temporal consumption patterns, generally with more load in the day than overnight. The business electrification load is dominated by larger sites and is assumed to be flat across the year and across the day as large industrial loads electrify their processes. The residential load profile varies across the day and is much higher in winter compared to summer due to heating load. The electrification component only captures the energy needed to perform the activities previously performed by alternative fuels, with inherent fuel-conversion efficiency gains as appropriate. Changes in the efficiency of the individual appliances over time are captured separately within the Energy Efficiency component.

6.5 Reporting

AEMO prepares the traces with all the components such that they are modular, and the user could apply the components to calculate the desired demand definition. The choice of trace definition depends 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 are discharged.

A1. Electricity retail pricing

AEMO assesses behavioural and structural changes of consumer energy use in response to real or perceived high retail prices. AEMO calculates the retail price forecasts from a combination of AEMO internal modelling and publicly available information. Separate prices are prepared for the residential and commercial/industrial market segments.

The electricity retail price projections are formed from bottom-up forecasts of the various components of retail prices:

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

The retail price structure follows the Australian Energy Market Commission's (AEMC's) most recent Residential Electricity Price Trends[52] report. Of the components:

- The wholesale price forecasts are based on either AEMO's internal market modelling or utilise published prices (such as electricity futures from ASX Energy) or from a reputable, external provider.
- Network components are based on regulated pricing proposals and determinations.
- Additional estimated transmission development costs associated with AEMO's optimal development path, identified in the most recent ISP, may be added to ensure that consumer costs reflect the regulatory assets expected to be actioned by transmission network service providers. Distribution network costs are forecast to move in line with these transmission development costs.
- Environmental charges are based on a combination of regulated pricing proposals, the Victorian Default Offer and the Default Market Offer.
- The retail component of the electricity price is based on the three-year trailing average of the proportion of the price that is driven by retail charges, as per analysis undertaken by the Australian Competition and Consumer Commission (ACCC).[53]

The process of AEMO's pricing modelling is summarised in Table 6Table 6.

With the continued rollout of smart meters, home automation and customer self-supply options (rooftop PV and battery storage), new customer tariff types may evolve, which could affect both electricity use overall and the timing of this usage. AEMO is monitoring tariff offerings along with quantitative assessments of their impacts on consumption and will adjust impacts if warranted.

[52] AEMC, 2021 Residential Electricity Price Trends, at https://www.aemc.gov.au/market-reviews-advice/residential-electricity-price-trends-2021.

[53] ACCC, Inquiry into the National Electricity Market 2018-2025, at https://www.accc.gov.au/about-us/publications/serial-publications/inquiry-into-the-national-electricity-market-2018-2025.

Tariffs that drive short-term responses from consumers to price or reliability signals are captured in AEMO's demand side participation (DSP) forecasts[54], rather than this methodology.

Table 6 Pricing model component summary

Component	Process summary
Wholesale costs*	From internal AEMO modelling or based on published prices (such as ASX Energy electricity futures) or commissioned through an external provider. Combinations of these sources may also be considered.
Network costs	From regulated pricing proposals and regulatory determinations. Extrapolate the trajectories based on AEMO's ISP Central Optimal Development Path Scenario. Benchmark against published network tariffs
Environmental costs	From regulated pricing proposals, the Victorian Default Offer and Default Market Offer. 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	From the three-year trailing average of the proportion of the price that is driven by retail charges according to the ACCC's Inquiry into the National Electricity Market 2018-2025.

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

[54] DSP methodology available at https://aemo.com.au/energy-systems/electricity/national-electricity-market-nem/nem-forecasting-and-planning/forecasting-approach.

A2. Weather and climate

AEMO sources historical weather data for its forecasting models from a number of weather stations[55]. For forward projections, the weather is adjusted to account for climate change. This section outlines key weather data used and how climate adjustments are done.

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

For use in its consumption forecast, AEMO converts historical temperature data into HDD and CDD. These are measures of heating and cooling electricity demand, respectively. They are estimated by differencing air temperature from a critical temperature considered to be a threshold temperature for heating or cooling appliance use.

Table 7 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 calculated for each region using least squares method to identify the temperature at which a demand response is detected that demonstrates the greatest predictive power of the models.

The formula for HDD[56] is:

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

The formula for CDD[57] is:

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

Where $\bar{T}$ is average 30-minute temperature between 9:00 PM of the previous day to 9:00 PM of the 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 region specific.

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

A2.2 Determining HDD and CDD standards

The data used to derive a median weather trend are from 2000 to the reference year. AEMO uses the derived median weather standard for future HDD/CDD projections using a probabilistic methodology for a given region.

[55] These are listed in the IASR.

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

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

This is calculated based on the following formulas:

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

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

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% POE is expected for the given total heating/cooling degree days within that 365-day period.

A2.3 Climate change

AEMO incorporates climate change into its minimum and maximum demand forecast as well as its annual consumption forecast. For the annual consumption forecast, according to ClimateChangeInAustralia (CCiA) data average annual temperatures are increasing by a constant rate. However, half-hourly temperatures have higher variability and may include increasing extremes.

AEMO collaborated with the Bureau of Meteorology (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 adopts a quantile-to-quantile matching algorithm to statistically scale publicly available daily minimum, mean and maximum temperature data out to 20 to 50 years. The approach ensures the historical weather variability is maintained within each climate scenario modelled.

The methodology can be broken into six steps:

- **Step 1.** Collect official climate projection data[58] 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.

[58] The source is presented in the IASR.

Step 1 – Collect daily temperature projection data

- Collect regional daily minimum and maximum temperature projection data from all the recommended climate models (as specified in the IASR).
- 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 (as specified in the IASR).
- Find the daily minimum, median and maximum temperatures.
- To ensure the daily mid-point matches to an actual half-hourly value, the median is used in place of the daily mean. As temperature is typically normally distributed the median should be roughly equal to the mean to within a reasonable accuracy tolerance.

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

- Set up an 11-year rolling window (current year +/- 5 years) to account for variability in weather between different years including a range of different climate models in the same window.
- Rank the daily minimum, mean and maximum temperatures from lowest to highest for the 11-year window across all climate 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 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 year.

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

- T_A is the number of historical actual weather years.
- T_H is the number of projected weather years in the forecast horizon.
- 17,520 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 obtains forecasts for rooftop PV (installations with a capacity < 100 kW) from one or more appropriately skilled consultants each year. The forecast methodologies to forecast PV uptake across the collection of scenarios may vary by consultant, and will be documented by the consultants on each occasion, taking into account key drivers for rooftop PV uptake, such as:

- Financial incentives, such as Small Technology Certificates (STCs) and feed-in tariffs (FiTs).
- Installation costs, including both system/component costs and non-hardware “soft costs”, including marketing and customer acquisition, system design, installation labour, permitting and inspection costs, and installer margins.
- The payback period considering forecast retail electricity prices and feed-in tariffs.
- Population growth in Australia and projected dwelling stock, 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, ESS and EVs).

The mapping of consultant forecasts to individual scenarios is detailed in the IASR. The scenarios may include, where relevant, the impacts on PV uptake from systemic disruption, such as COVID-19 and the GFC.

The forecasts used in the energy and demand models are effective (degraded) panel capacity, which is the direct current (DC) panel capacity adjusted for degradation of panel output over time.

A3.1.2 Rooftop PV generation

AEMO obtains estimates of historical half-hourly normalised generation of installed rooftop PV systems for each NEM region. The dataset, procured from a suitably qualified consultant, 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 obtained in the form of a normalised measure representing (half-hourly) AC power output for a notional 1 kW DC unit of installed capacity. The provided normalised generation includes assumptions about panel tilt and orientation, and AC to DC ratio, determined and validated by the consultant through calibration against a number of actual system installations.

For the energy forecast, a climatological median of normalised generation for each half hour in a year is multiplied by the rooftop PV forecasts above.

A3.2 Energy storage systems forecast

A3.2.1 Installed capacity forecast

AEMO obtains forecasts for uptake of ESS from one or more suitably qualified consultants each year. The forecasts reflect behind-the-meter residential and business batteries, typically integrated with PV systems. These forecasts do not include large-scale, grid-connected batteries.

The ESS uptake forecasts account for key drivers, such as:

- State and federal incentive schemes.
- ESS cost, typical size installed.
- The payback period for ESS systems considering the components above, forecast retail prices and any attached integrated PV system.
- Household growth.
- The uptake of rooftop PV systems (where ESS is forecast as an integrated PV and ESS system).

Further information on the methodology and assumptions, including those specific to each scenario, is detailed in consultant reports and the IASR.

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

The consultant(s) also provides AEMO with daily charge and discharges profile for behind the meter ESS for use in the minimum and maximum demand modelling.

The profiles are based on historical solar irradiance (as ESS is assumed to primarily charge from excess rooftop PV generation) and apply a battery operating strategy to minimise household/commercial business bills without any concern for whether the aggregate outcome is also optimised for the electricity system.

While the number of profiles considered may differ depending on the consultant and the scenario, the demand forecast will typically consider at least two broad types of battery operation:

- **Solar shift**, 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 (TOU)**, where the battery is optimised to take advantage of a time of use tariff, topping up charge at off peak times to maximise avoidance of peak time tariffs. This is most typical for commercial customers.

A third operating type, whereby control of the battery is coordinated by an aggregator, is commonly referred to as a virtual power plant (VPP). In this operation type, battery operation is optimised to reduce overall system costs and operated effectively as a scheduled, controllable form of generation, much like a traditional form of grid-generated electricity supply. The charge/discharge profiles can have the effect of smoothing out demand across the day and reducing maximum demand, however for solar shift and TOU 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, as detailed in the IASR. The electrical losses represent the energy that is lost in the process of charging and then discharging the battery. This lost energy is accounted for in business and residential delivered consumption forecasts (see Sections 2.5.1 and 3.4.1) as an additional form of energy consumption applying to the expected level of battery operation. Battery losses are small compared to the overall NEM demand.

A4. Electric vehicles

AEMO obtains forecasts of EVs from one or more suitably qualified consultants. The EV forecasts cover various vehicle types, including residential, light commercial, and heavy commercial vehicles such as buses and trucks.

The main drivers for the EV uptake forecast are:

- Relative price between EV and alternative vehicle types (including internal combustion engine (ICE) vehicles, and competing EV categories, such as BEV, PHEV and FCEV (defined in Section 1.6).
- Payback period – EVs have higher upfront costs in the initial period of the forecast but lower “fuel” cost as kW per km. The methodology will also capture any per km registration cost component where relevant.
- Level of increased ride sharing – reducing the number of vehicles.
- Vehicle purchasing trends for fleet vehicles and general customers, which considers the minimum vehicle replacement trends.
- Battery and technology improvements.
- Limiting factors such as renters’ access to external household charging points.
- Decarbonisation targets and the role of the transportation sector (scenario-specific).

A4.1 Electric vehicles charge profiles

Consultants also provide AEMO the half-hourly charge and discharge profiles for EVs for use in the minimum and maximum demand modelling and when developing its half-hourly demand traces.

The vehicle charging types used by AEMO include a mix of static and dynamic profiles, described as follows:

- Static profiles do not vary with the availability of supply and are supported by wall socket and dedicated high power chargers (AC level 1 and 2 respectively, with the latter including three phase versions), available at homes, car parks, shopping centres or workplaces:
  - Convenience – driven by user’s lifestyle choices other than cost reduction, and occurs at a residence
    - *An EV owner adopting this charge profile typically would charge their vehicle when returning to the home each evening, with some workplace or carpark charging as well. Charging preference has little regard to electricity costs.*
  - ‘Smart’ daytime – driven by consumer adoption of time of use (TOU) tariffs with charging targeted to reduce peaks, with a focus on daytime charging
    - *An EV owner adopting this charge profile typically would take advantage of charging opportunities at home, or away from home, that are focused during the daytime hours, absorbing solar production at potentially lower costs to the driver.*
  - ‘Smart’ night-time – driven by consumer adoption of TOU tariffs with charging targeted to reduce peaks, with a focus on night-time charging.

    - *An EV owner adopting this charge profile typically would have higher overnight charging than the 'smart daytime' owner, typically at home, but after the household's peak evening loads. Some daytime charging would be used as well, if convenient.*

  - Fast charging – unlike the above static charging profiles, this is enabled by DC fast public charging (Level 3) and ultra-fast public charging (Level 4), and available only at public locations with dedicated infrastructure.

    - *An EV owner adopting this charge profile would typically charge rapidly while stopped at highway facilities, or at carparks, or workplaces with dedicated facilities. Given these activities typically occur during daytime hours, this profile has a daytime bias.*

- Dynamic profiles support the user in managing their household or the broader grid's load, with lower costs compensating the user for use of the vehicle's battery and any potential loss of flexibility. The profiles include a pure load profile, and those that have two-way energy flows:

  - Coordinated charging – vehicle charging is assumed to be optimised by retailer or aggregator to occur when demand otherwise is low (typically associated with high PV generation). This profile does not include energy flows from the EV battery to the home or grid (see Section 6.4),

  - Vehicle to Grid (V2G) – allows use of the vehicle as a battery, storing energy which can be called on by a retailer or aggregator to supply back into the grid.

  - Vehicle to Home (V2H) – allows use of the vehicle as a battery, storing energy which can be called on by the resident's energy management system to supply back into the home.

A4.2 Electric vehicles annual consumption

For the purpose of annual consumption, the consultants calculate this based on their assumptions around the number of kilometres in a year EVs travel and the level of efficiency per charge, per vehicle category. This will be documented in their reporting to AEMO. Based on the forecast number of EVs, the electricity consumption can be calculated. 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), 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 residential connections is driven by demographic and social factors like household projections, which is determined by population projections and changes to household density[59].

AEMO uses 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) latest census and grows the household numbers to the base year (the year before the first forecast year) using the NMI connections growth rate.

For the forecast:

- For the first four forecast years, the building stock model transitions from using the trended NMI connections growth rate to the ABS household projections on a sliding scale of 0% to 100%.
- From the fifth forecast year onwards, the building stock model applies only the ABS Household Projections.

AEMO uses recent data on connections per household to convert the building stock model for each scenario into connections forecasts. Adjustments due to structural breaks may be applied and varied between scenarios. Further spread between the scenarios is drawn from construction sector activity per capita relative to the Central scenario, based on the economic consultant's economic and population forecasts.

A5.2 Uptake and use of electric appliances

AEMO uses appliance data from the former Department of Industry, Science, Energy and Resources[60] to forecast growth in electricity consumption by the residential sector. This includes historical and projected future appliance penetration levels for a range of appliance categories.

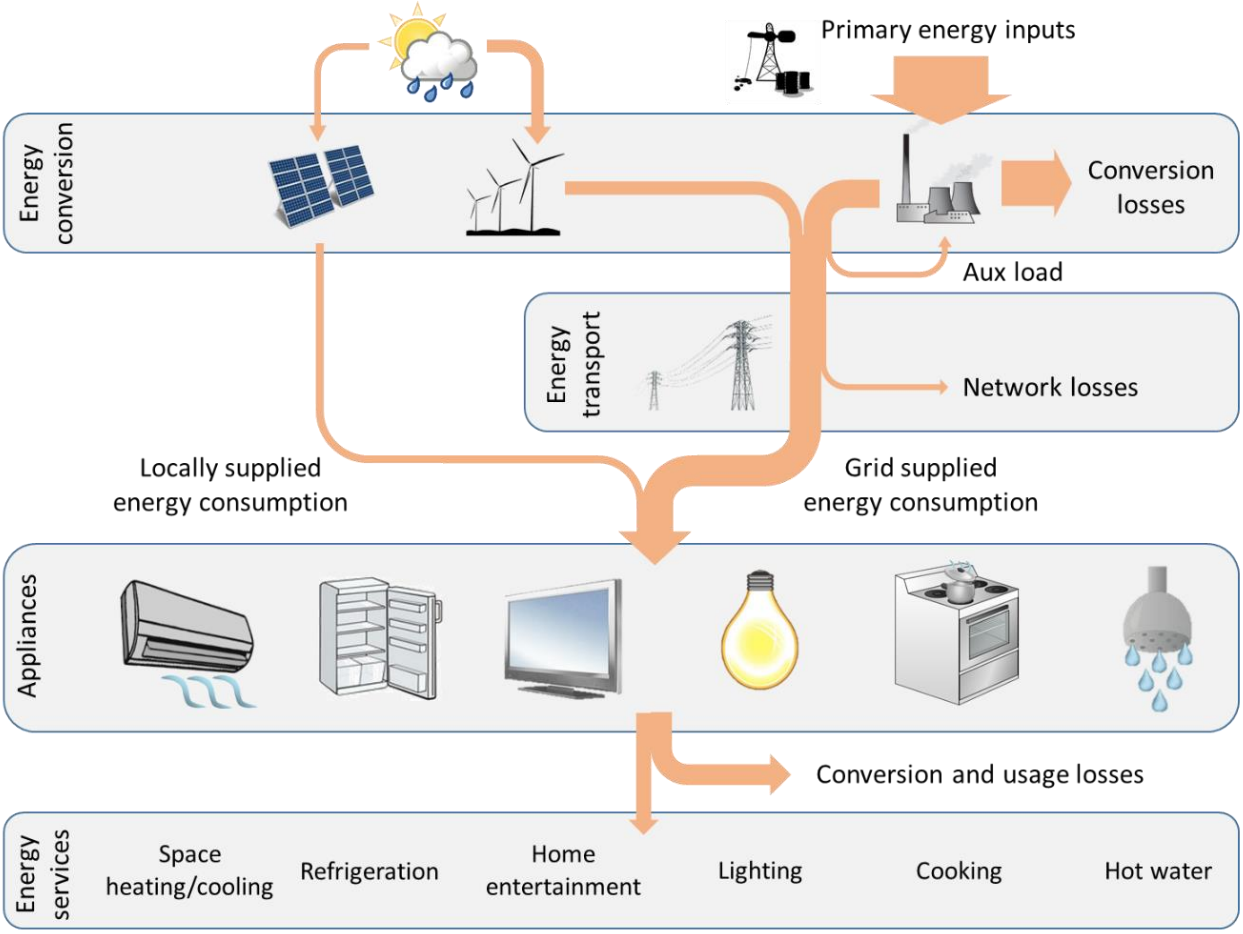
The data allows AEMO to estimate changes to the level of energy services supplied by electricity per household across the NEM. Energy services exclude the impact of energy efficiency, which affects the electricity used by the appliances when delivering the services. Figure 23 illustrates the difference between energy services and energy consumption. Energy services here also excludes the impact of switching from gas to electric devices. The

[59] Commercial/business demand growth is on the other hand determined though economic drivers.

[60] DISER, *2021 Residential Baseline Study for Australia and New Zealand for 2000 – 2040*, at https://www.energyrating.gov.au/industry-information/publications/report-2021-residential-baseline-study-australia-and-new-zealand-2000-2040.

contributions from energy efficiency and electrification are estimated and accounted for separately (see Section 3.2 and Section 3.4).

Figure 23 Electricity consumption from delivering energy services



In AEMO's forecast, the demand for energy services is a measure based on the projected number of appliances per category across the NEM, their usage hours, and their capacity and size. AEMO calculates energy services by appliance group. The following list shows examples of how that can be done (depending on the available appliance data):

- Heating/cooling – number of appliances × output capacity of appliance × hours used per year.
- White goods (freezers/refrigerators) – number of appliances × volume of appliance × number of hours used per year.
- White goods (dishwashers, clothes washers and dryers) – number of appliances x duration of a wash cycle x number of cycles per year.
- Home entertainment – number of appliances × hours used per year × screen size (TVs only).
- Lighting – number of light fittings × hours used per year.
- Cooking – number of appliances × capacity of appliance x hours used per year.
- Hot water – number of appliances × energy output per year.

The demand for energy services by appliance group is calculated for both historical and forecast years. This is then converted into a growth index per household[61] for each heating load, cooling load and base load, with the reference year of the consumption forecast being the base year (index = 100). For base load, the relevant appliance groups are combined into a composite index based on their relative estimated energy consumption in the base year (as referenced in the Residential Baseline Study).

For forecasts post-2040 when the Residential Baseline Study ends, appliance growth trajectories are guided by extrapolation of earlier trends. For heating load and cooling load, the growth indices are further moderated for the likelihood of reaching maximum thermal comfort limits per household. This has been done by calibrating stock growth in regions with extremely high use of energy services, against that in reference regions of similar climate.

Finally, AEMO applies additional adjustments to differentiate between scenarios to account for different assumptions in household disposable income.

[61] AEMO uses household data from the same dataset as the appliance data for consistency.

A6. Residential-business segmentation

AEMO has developed a process for estimating residential and business consumption for the most recent years, of which the latest year (base year) is the starting point for forecasting consumption. The residential-business split process may be summarised as follows:

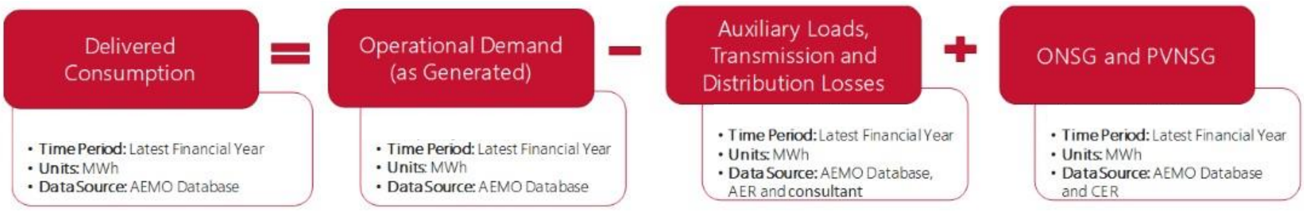
- Calculate distribution-connected delivered consumption.
- Estimate residential consumption per connection based on one of two approaches, depending on the smart meter penetration in a given region.
- Scale residential consumption to a regional level and calculate business consumption

Both delivered and underlying consumption are estimated using this process, which is described in more detail below. For definitions of the consumption types, see Section 1.6.

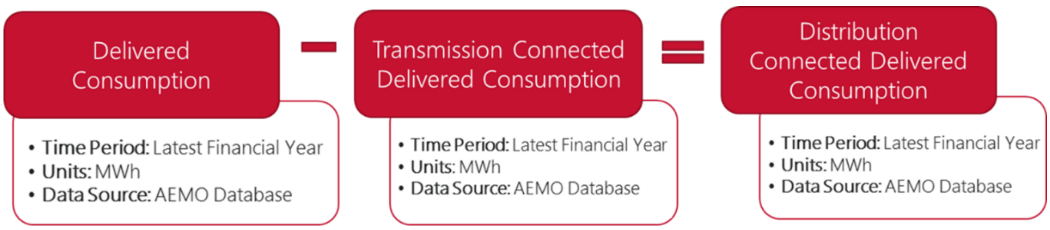
A6.1 Calculate distribution-connected delivered consumption

The calculation of distribution-connected delivered consumption is the starting point for the residential-business split process. Once calculated, AEMO segments this volume into residential and business consumption.

AEMO uses metered operational demand (as generated) data to calculate delivered consumption (to energy users), by netting off auxiliary load and distribution and transmission losses and adding in NSG generation (ONSG and PVNSG):



From delivered consumption, AEMO can determine how much is specifically *distribution*-connected:



Transmission-connected consumption is assumed to be business load, and is separated from the total delivered consumption value.

A6.2 Estimate residential consumption per connection based on one of two approaches

The preferred approach involves sampling of AEMO meter data and is carried out for NEM regions with sufficient interval meter data available. Alternatively, data from the AER Economic Benchmarking Regulatory Information Notice (RIN) is applied in regions with lower penetration of interval meters.

A6.2.1 Approach 1: AEMO sampling-derived estimate

This preferred approach makes use of AEMO's extensive database of smart meter data to calculate the residential delivered energy per connection. Sampling is particularly effective for the residential sector where a representative sample of households is likely to display similar usage patterns to the population. In contrast, this approach can be more challenging for business consumers, which will tend to have industry-specific profiles.

AEMO meter data

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

Smart meters are also known as interval meters, because their reads record delivered consumption at half-hourly intervals, while basic meters are read much less frequently. Typically, most basic meter customers are residential customers while most businesses have transitioned to smart meters.

With the above in mind, AEMO preserves the consumption profile of business data and then calculates the residential data as the residual, taking the difference between the total grid consumption and the business profile.

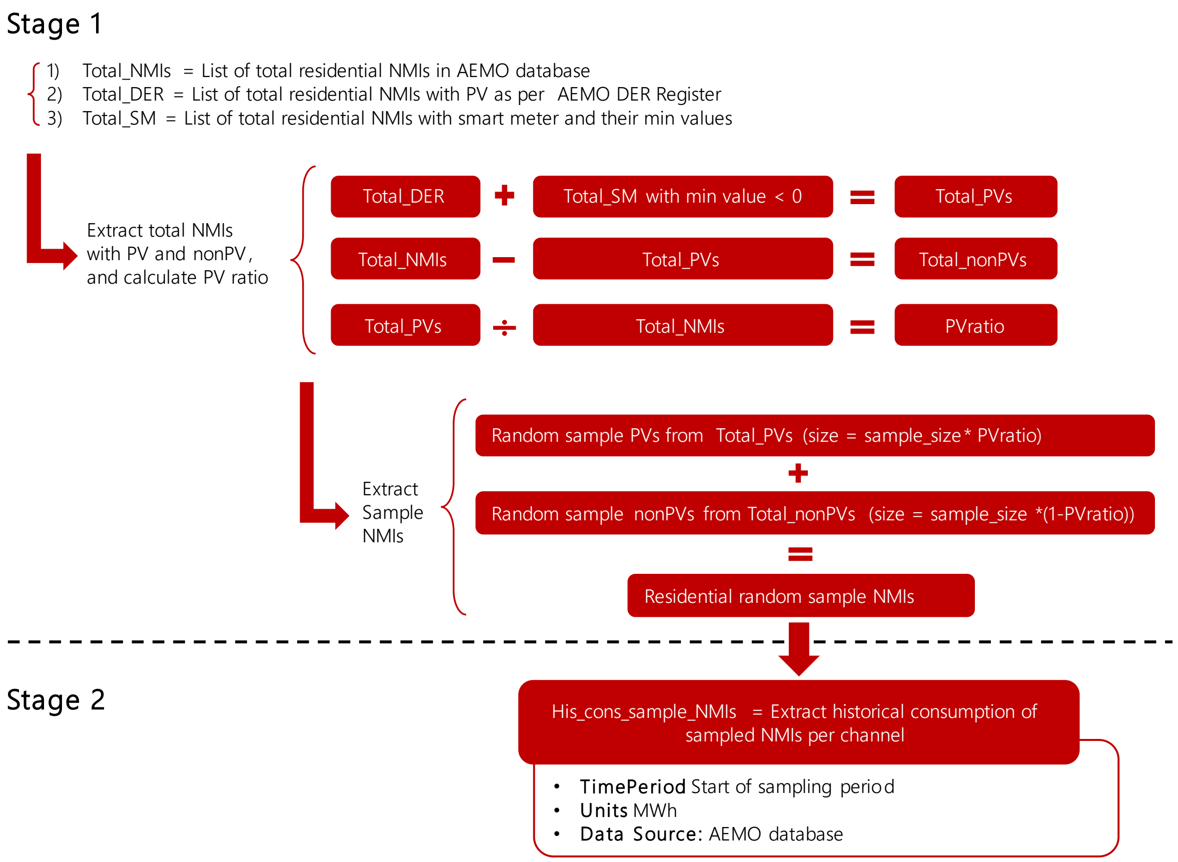
AEMO sampling methodology

The methodology is depicted below and involves three stages for calculating the delivered residential consumption per connection.

Stage 1: Sample NMIs

This stage involves extracting a representative sample (approximately 30,000 NMIs) that represents the whole region. A stratified sampling process ensures a representative sample by maintaining the correct proportion of NMIs with and without PV. AEMO has implemented further improvements to ensure that the consumption of the sample represents the broader fleet of meters, including households with basic meters.

Customers with PV are identified using AEMO's DER Register[62] data, validated by analysing meter data, and identifying periods of energy export back to the grid. The PV ratio is calculated by dividing the number of residential PV systems by the total number of residential NMIs.



Stage 2: Extract 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: Calculate average residential delivered energy

Finally, the average consumption per household is calculated across the cohort of sampled NMIs. This typically involves averaging the delivered energy of approximately 30,000 meters.

A6.2.2 Approach 2: AER data derived residential estimate

The AER annually surveys DNSPs via the Economic Benchmarking RIN. This provides AEMO with an important data source to estimate residential delivered energy per connection, however, a time lag may exist between the data reported and the publication date, which means more recent trends may not be captured. For this reason, the approach is considered an alternative for regions with insufficient interval data to adopt the preferred AEMO sampling approach. AEMO must perform some calibration of the RIN data to bring it into alignment with AEMO's definition of delivered energy, as described below.

[62] At https://aemo.com.au/en/energy-systems/electricity/der-register.

AER residential estimate methodology

The RIN data provides DNSP reported figures at a sub-regional level, based on the coverage of their distribution zone. AEMO aggregates the figures to a monthly level, for both DNSP residential billed energy[63] and DNSP residential customer numbers, to calculate billed energy per household:

$$\text{Billed energy per household} = \frac{\text{Total billed energy}}{\text{Number of residential customers}}$$

The next step is to estimate the NEM regional residential PV generation, which is calculated based on the Clean Energy Regulator's installed residential PV capacity multiplied by the annual PV capacity factor (see Appendix A3):

$$\text{Residential PV generation estimate} = \text{Residential Installed PV capacity x Annual capacity factor}$$

Then AEMO calculates a normalised value for PV generation, noting that this will be less than a typical residential installation, as no NEM region has 100% penetration of rooftop PV.

$$\text{PV generation per connection} = \frac{\text{Residential PV generation estimate}}{\text{Number of residential customers}}$$

To calibrate the AER RIN data to align with AEMO's definition of delivered energy, it is necessary to quantify the self-consumption of PV for a typical household. This may be calculated using AEMO metering data for PV exports, or a suitable alternative source may be adopted.

$$\text{PV self consumption} = 100\% - \left(\frac{\text{Average PV exports per household}}{\text{Total expected household PV generation}}\right)$$

Finally, AEMO delivered energy may be calculated as follows:

$$\text{AEMO residential delivered per connection} =$$
$$\text{Billed energy per household} + \text{PV generation per connection} \times (\text{PV self consumption} - 1)$$

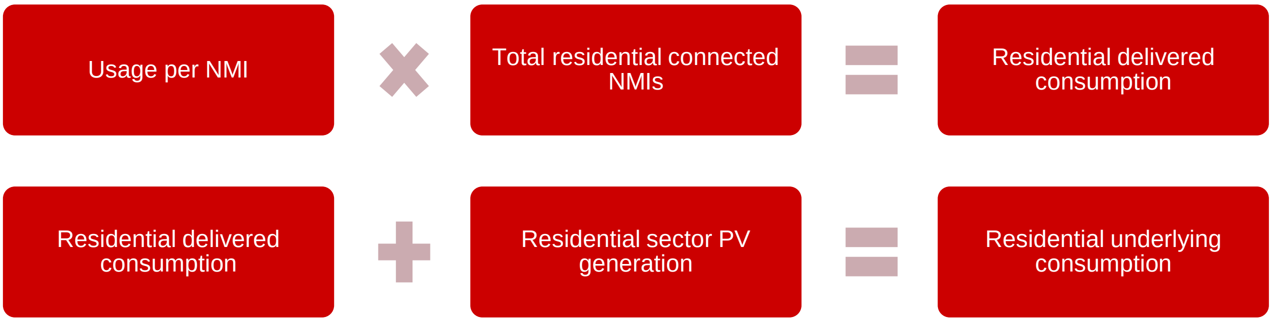
A6.3 Scale to a regional residential-business split

Calculate residential delivered and underlying consumption

Once residential delivered consumption per connection is calculated using one of the two approaches defined above, AEMO scales consumption to a regional level using the total number of residential-connected NMIs.

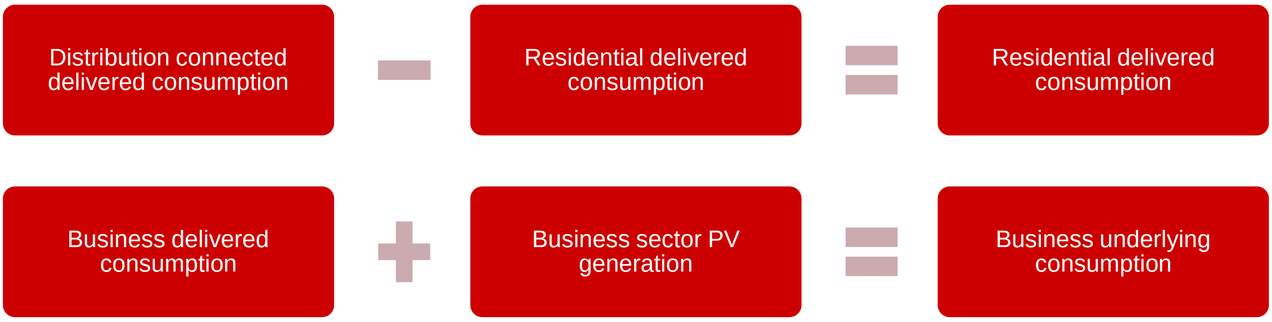
Residential underlying consumption is then calculated by adding residential PV generation (and other CER devices, if material) as estimated for each region (refer to Appendix A3) to the residential delivered consumption:

[63] To distinguish from AEMO's definition of delivered energy, DNSP delivered energy is referred to as *billed energy* above. This refers to tariffed electricity that doesn't net-off exports.



Calculate business delivered and underlying consumption

In this final stage, the business delivered consumption is calculated by first taking the distribution-connected delivered consumption (as described in Section A6.1) then deducting the regional residential delivered consumption. Similarly, using the same method as for residential consumers, the business PV generation is added on, to derive business underlying consumption.

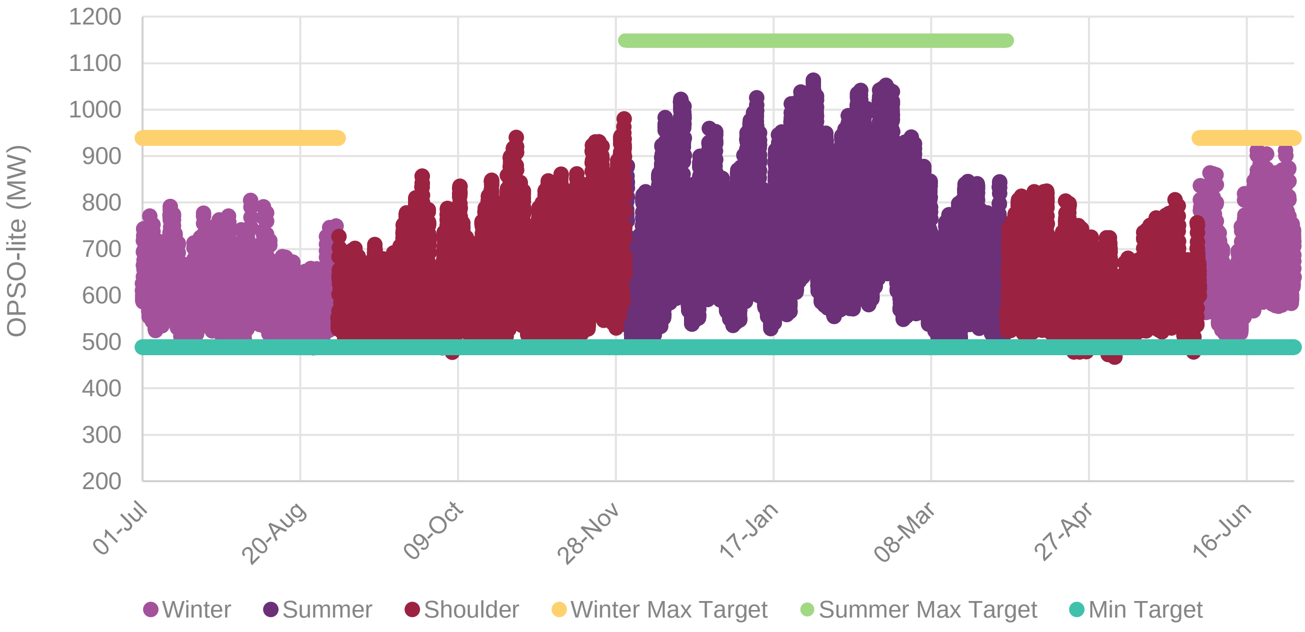


A7. Demand trace scaling algorithm

This appendix provides a worked example of how half-hourly demand traces are scaled for the outlook period. This covers the three 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, ONSG, LNG, ESS and EVs). The example trace is shown in Figure 24.

Figure 24 Prepared demand trace



Day swapping is performed to exchange weekend and holiday dates between the reference year and the forecast year.

After day swapping is complete, the trace scaling algorithm uses demand targets to grow the historical reference demand profile. The targets are summarised in Table 8. All targets represent an increase to the reference trace in this example, but negative growth (particularly of minimum demand) may occur.

Table 8 Prepared demand trace and targets

	Prepared trace	Target	Unit
Summer Max	1,063.231	1,148.29	MW
Winter Max	911.79	938.33	MW
Minimum	466.695	488.695	MW
Energy	5,733.727	6,364.407	GWh

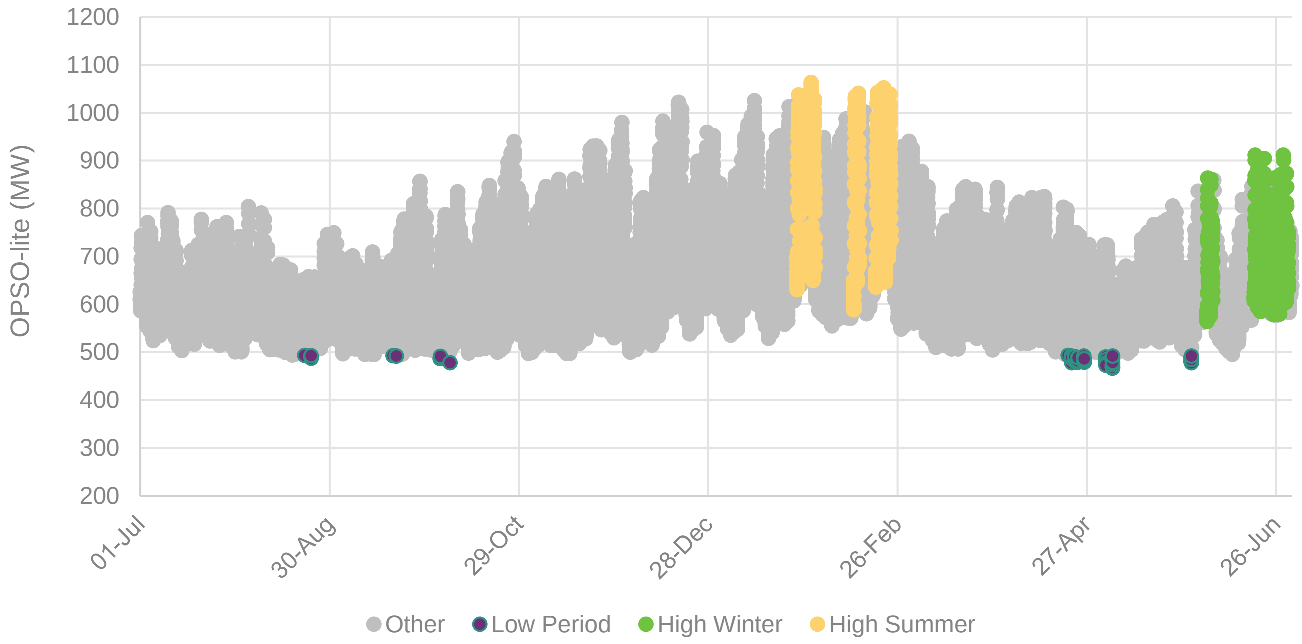
The series is categorised into *n* highest-demand days in summer (using daily maximum as the reference), *n* highest demand days in winter, *p* lowest demand half-hour periods. In this example,

n = 10 days

p = 70 half-hour periods

The day-type categorisation (High Summer, High Winter, Low Period and Other) is displayed in Figure 25.

Figure 25 Day-type categories



Scaling then commences. The demand, categorised into day-types, is scaled according to the ratios in Table 9. The ratios are calculated as *target/prepared trace* using the information from Table 8.

Table 9 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 the energy target still needs to be addressed.

Application of the scaling factors results in the energy presented in Table 10 and the remaining energy difference is calculated as the *target minus the current grown total*.

Table 10 Resulting energy

	Resulting Value	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 10 equates to an 11.38% increase on the ‘other’ category’s energy, which is applied, and all targets are then checked. The check is summarised in Table 11 and the grown trace is plotted in Figure 26.

Figure 26 Grown trace and targets

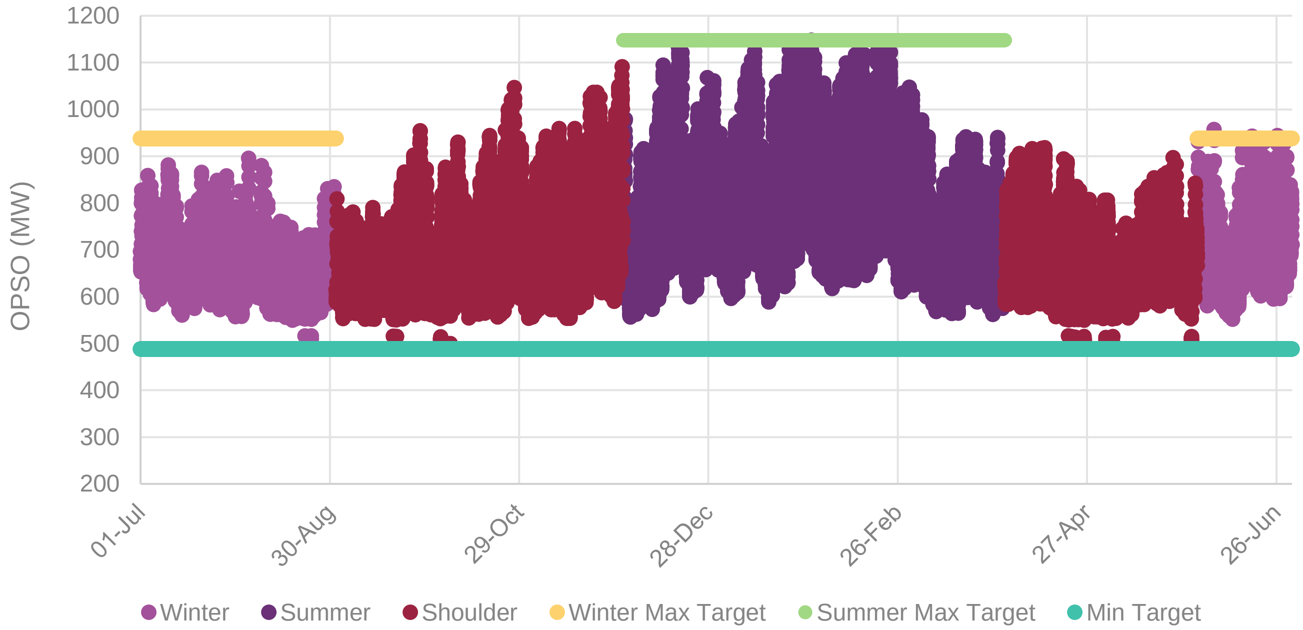


Table 11 Check of grown trace against targets

	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 11 uncovers an inconsistency between the grown winter maximum and the target (bold highlight). This is caused by the allocation of energy in the ‘other’ category which increased some winter values (that initially fell outside of the reserved 10 days of maximum winter demand) above the initial peak.

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

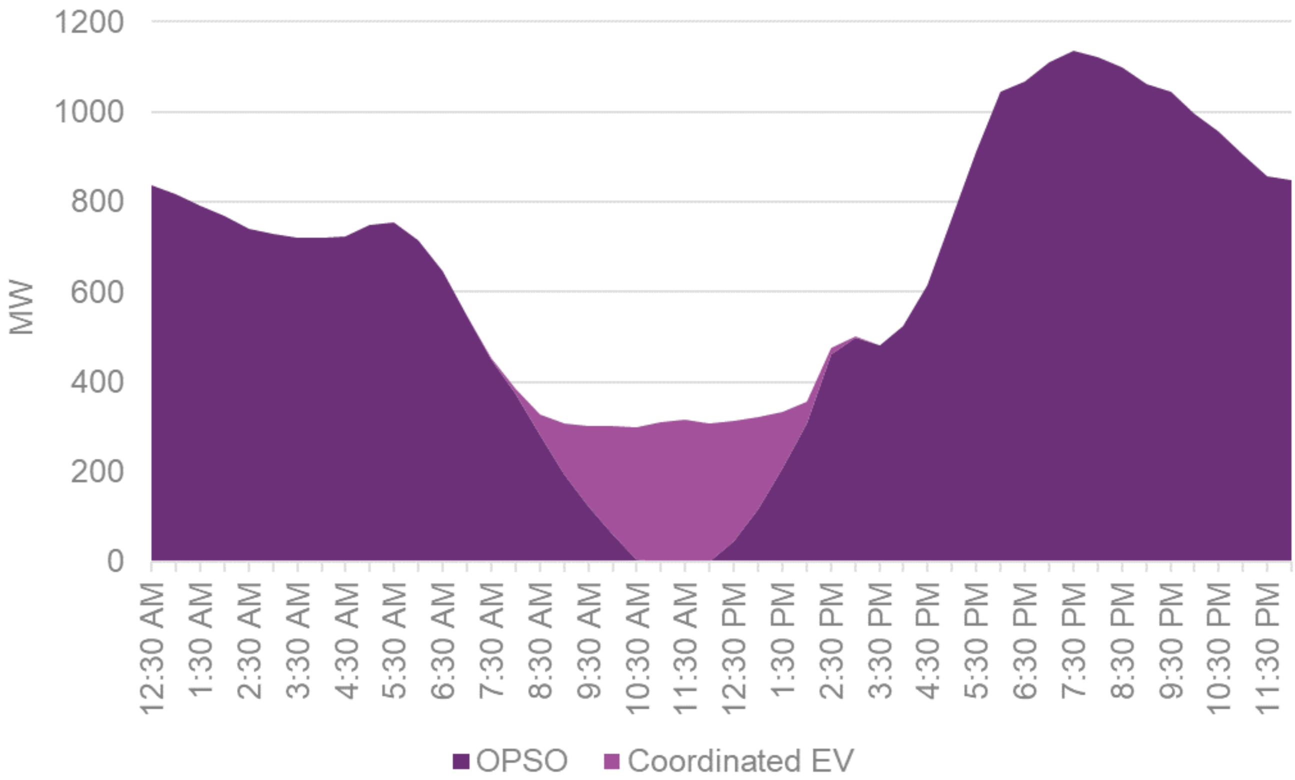
Following completion of this first-pass growing process, and in accordance with the methodology, the forecast technology components are added back to the trace to derive the unreconciled OPSO trace. Each component-trace is prepared to reflect the forecast capacities or numbers in the target year and the nominal or normalised power trace (from the reference year). In this way, the influence of PV, NSG, LNG, 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.

The third pass adds any electrification and coordinated EV charging to OPSO to generate the 'OPSO-modelling'.

Figure 27 shows an example day of adding coordinated EV charging (1,240 GWh) to OPSO, the sum of which is OPSO-modelling.

Figure 27 Adding coordinated EV charging

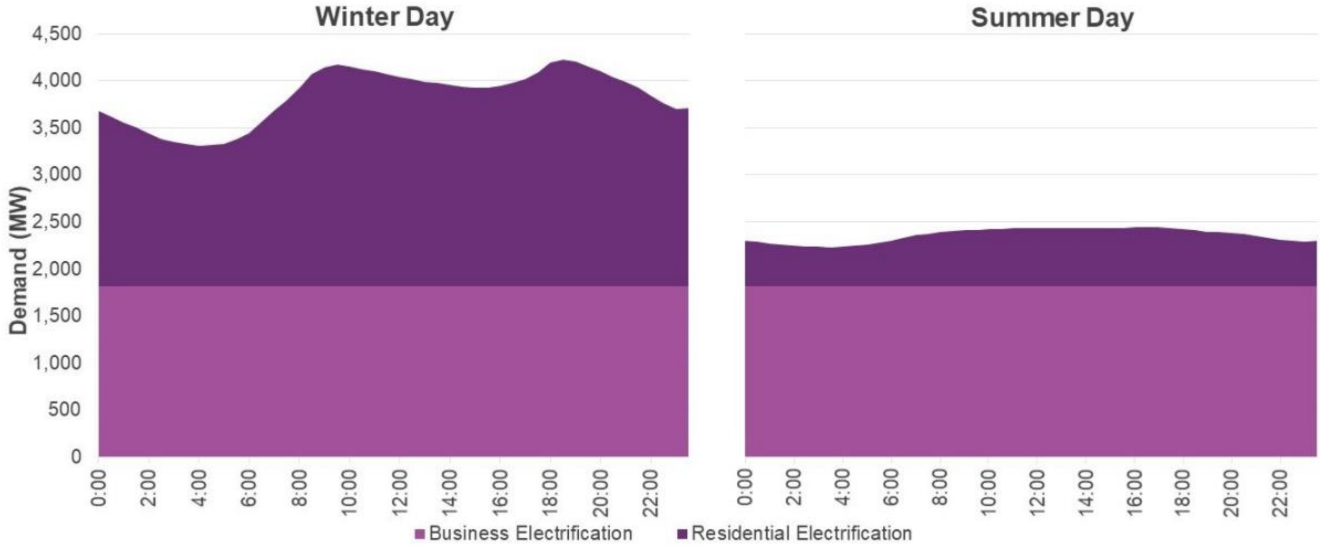


The impact of electrification is also calculated at this stage. As explained in the IASR, new electrified loads are assumed to mirror existing electricity temporal consumption patterns, and are added as follows:

- Business electrification load is dominated by larger sites and is assumed to be flat across the year and across the day as large industrial loads electrify their processes.
- Residential load varies across the day and is much higher in winter compared to summer due to heating load.

The resulting electrification impact is shown in Figure 28.

Figure 28 Example electrification daily load shape contrasting winter and summer



Abbreviations

Abbreviation	Full name
ABS	Australian Bureau of Statistics
AER	Australian Energy Regulator
BMM	Business Mass Market
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
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
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

Abbreviation	Full name
STCs	Small-scale technology certificates
V2H	Vehicle-to-home discharging
VPP	Virtual power plant
WBT	Wet-bulb temperature
WEM	Wholesale Energy Market