Forecasting Approach – Electricity Demand Forecasting Methodology

July 2025

Long-term forecasting for planning purposes, supporting the Electricity Statement of Opportunities and Integrated System Plan

We acknowledge the Traditional Custodians of the land, seas and waters across Australia. We honour the wisdom of Aboriginal and Torres Strait Islander Elders past and present and embrace future generations.

We acknowledge that, wherever we work, we do so on Aboriginal and Torres Strait Islander lands. We pay respect to the world's oldest continuing culture and First Nations peoples' deep and continuing connection to Country; and hope that our work can benefit both people and Country.

'Journey of unity: AEMO's Reconciliation Path' by Lani Balzan

AEMO Group is proud to have launched its first Reconciliation Action Plan in May 2024. 'Journey of unity: AEMO's Reconciliation Path' was created by Wiradjuri artist Lani Balzan to visually narrate our ongoing journey towards reconciliation - a collaborative endeavour that honours First Nations cultures, fosters mutual understanding, and paves the way for a brighter, more inclusive future.

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 contains information which is provided for explanatory purposes and may be subsequently updated or amended. That information does not constitute legal, business, engineering or technical 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.

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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
1.4	29/8/2024	Updates for 2024 ESOO
1.5	29/11/2024	Draft for consultation
2.0	25/7/2025	Published following consultation on AEMO's Forecasting Approach, applied for the 2025 ESOO and 2026 ISP

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1 Introduction

AEMO produces independent customer electricity demand forecasts for use in publications such as the *Electricity Statement of Opportunities* (ESOO) and the *Integrated System Plan* (ISP). These forecasts provide projections of customer connections, customer technology adoption, electricity consumption, 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 either AEMO's *Inputs, Assumptions and Scenarios Report* (IASR)[1] or, in years when the IASR is not formally updated (as it is a biennial publication), in a *Forecasting Assumptions Update*.

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 demand forecasts used across a range of forecasting and planning publications, including the ESOO (for both the NEM and WEM) and the ISP.

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 follows the Australian Energy Regulator's (AER's) Forecasting Best Practice Guidelines which have regard to the principles articulated in the National Electricity Rules (NER) clause 4A.B.5(b). These principles can be described as:

1. Accuracy – to produce unbiased forecasts, based on comprehensive information.

- Adopt best practice techniques (subject to data availability and resourcing requirements).
- Employ robust processes, including Quality Assurance, and use lead indicators to monitor for change.
- Acquire data on the likely drivers of demand and incorporate those drivers into forecasting processes and models.

[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.

- 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, to reduce the risk of forecast bias and garner stakeholder views on areas where forecasts may be improved[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 growth,
  - Economic growth,
  - Electricity price,
  - Technology adoption such as the uptake of consumer energy resources (CER) and potential emerging technologies such as hydrogen production, and
  - Energy efficiency and electrification investments, and other emissions reduction investments.
- 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, and
  - 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.

AEMO recognises that all forecasting models are subject to inaccuracies as no model can predict the future perfectly, and with this in mind develops electricity demand forecasts that provide insights and assist in planning and decision-making. AEMO consults with stakeholders to ensure that inputs and assumptions used in all forecasting models are robust and reasonable.

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:

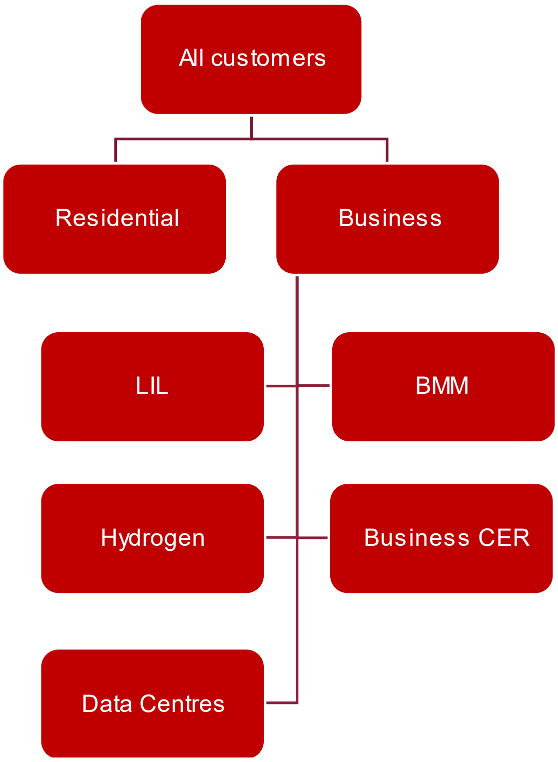
- **Residential** – residential customers only.
- **Business** – includes industrial and commercial users. This sector is subcategorised further (in accordance with Section 2) as follows:
  - Large industrial loads (LIL), including liquified natural gas (LNG) export loads.
  - Hydrogen.
  - Electric vehicles (EVs).
  - Data centres.
  - Business Mass Market (BMM), 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).

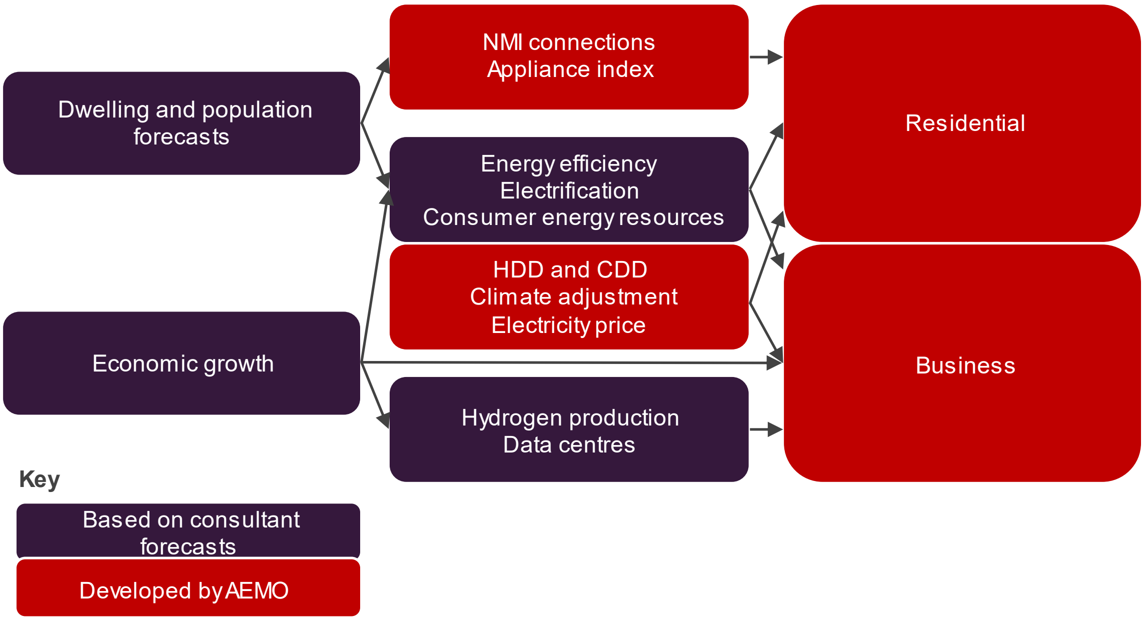
While annual consumption can reasonably be split into residential and business consumption, this cannot be done at the half-hourly level. Therefore, the maximum and minimum demand forecast considers only LIL (where half-hourly data is available) and the remainder of residential and business load into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

Figure 1 Consumption forecasting customer segmentation



Structural drivers identified in Section 1.3 and other forecast components are applied to the electricity customer segments, as shown in Figure 2. Updates to the forecast components are informed by stakeholder consultation and detailed in the IASR. The IASR clearly identifies the source data for each forecast component, including those normally provided by consultants.

Figure 2 Forecast components applied to the residential and business customer segments



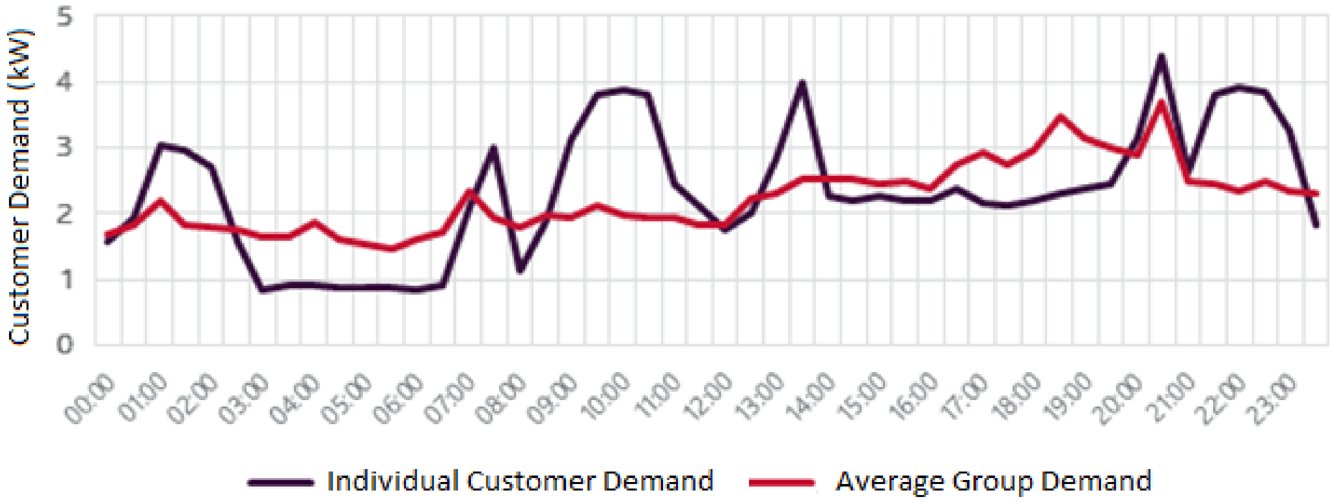
Note: Acronyms in this figure are as follows: NMI: National Metering Identifier; HDD: Heating Degree Day; CDD: Cooling Degree Day.

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 3 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 3 Example individual and group demand shown on one day

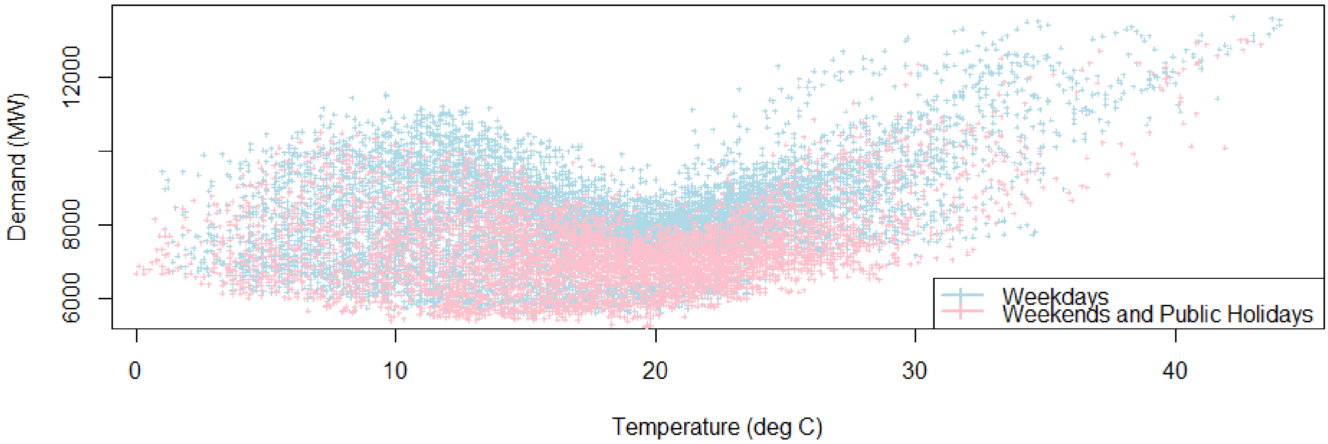


Although demand becomes more predictable when aggregated, it remains a function of individual customer decisions. Periods of high demand exist because individual customers choose to do the same things at the same time. Peak demand is therefore driven by the degree of coincident appliance use across customers, 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 4 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 4 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).

[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.

- **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).
- **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.

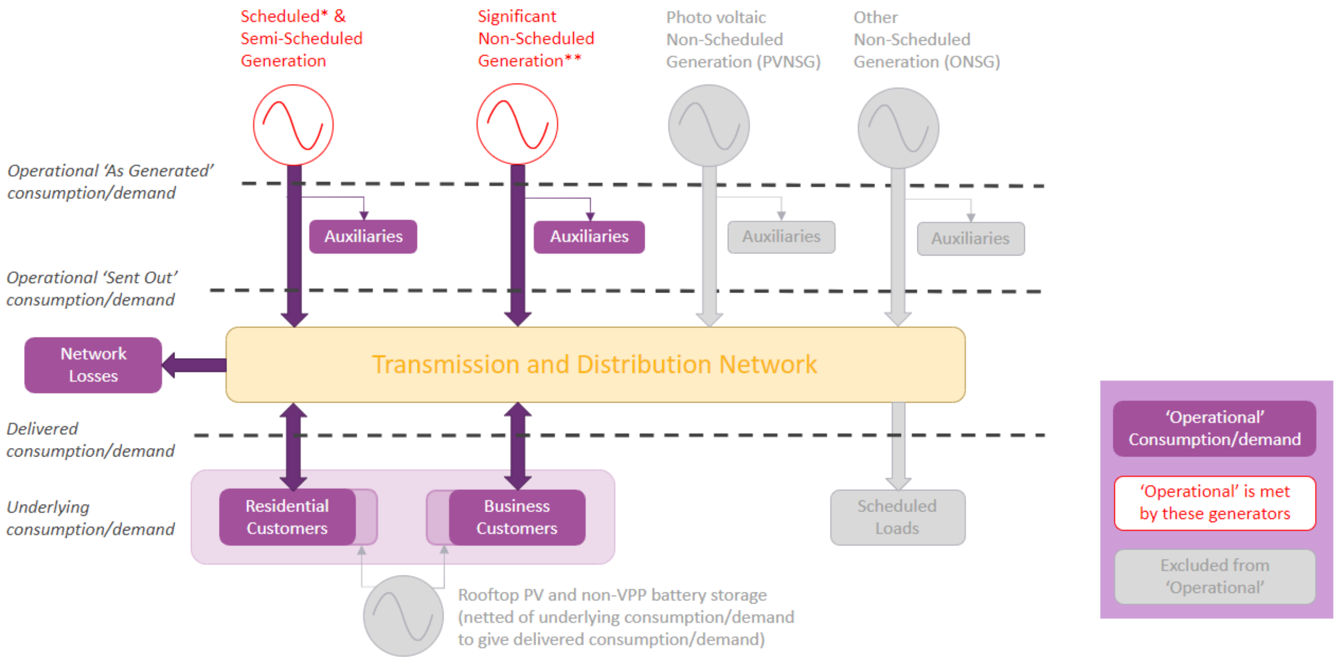
Other key definitions used are:

- **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 non-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 non-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 5 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 5 Operational demand/consumption definition



* Including VPP from aggregated behind-the-meter battery storage, and coordinated charging/discharging from EVs, such as vehicle-to-grid (V2G).
** 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:

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

- 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 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.

This issue of the methodology is an outcome of the 2024 Electricity Demand Forecasting Methodology Consultation, and includes several key updates including:

1. Updates to the large industrial load consumption forecast (Section 2.1) to incorporate prospective projects,
2. A new data centre consumption forecast component (Section 2.2),
3. Updates to the solar rebound estimation method (Section 3.2, Step 2.2),
4. Updates to the half-hourly demand trace method (Section 6) to include a new synthetic trace development method,
5. Updates to the sub-regional demand forecast method (Section 7) to include a new bottom-up sub-regional trace development method and reconciliation method, and
6. A new appendix (Appendix A8) describing the incorporation of demand flexibility.

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

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.
- **Data centres** – any loads associated with serving IT infrastructure that manages data storage, computation and networking.
- **Hydrogen** – any loads associated with the production of hydrogen.
- **Business Mass Market (BMM)** – any business sector loads not included above.
- **Business electric vehicles (EVs)** – covering commercial fleet, trucks and buses (see Section 2.5.1 and Appendix A4).

The LIL sector is further subdivided into subsectors. This allows them to be differentiated between various forecast scenarios. This is summarised in Figure 6 (for the NEM) and Figure 7 (for the WEM) below.

Figure 6 LIL subsectors used in the NEM

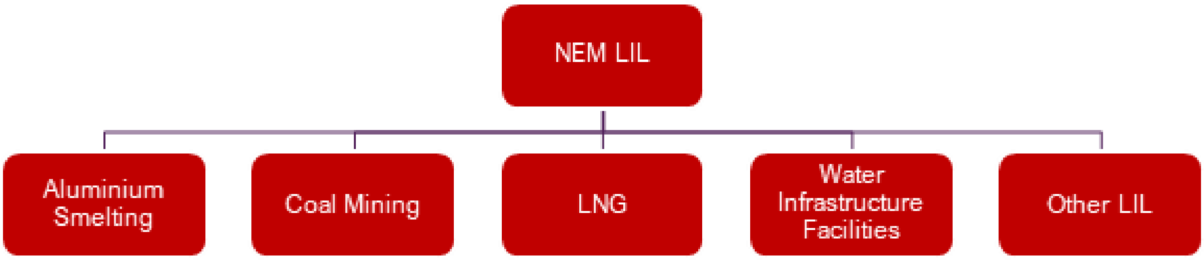
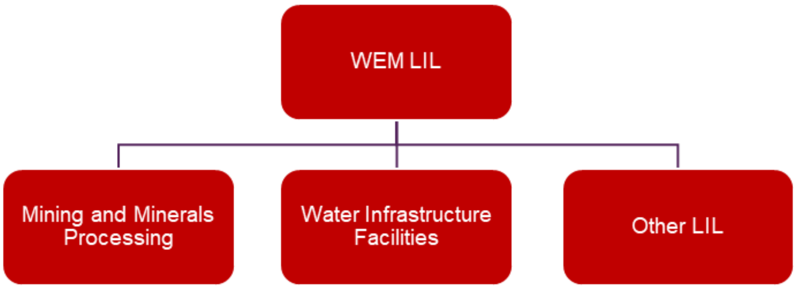


Figure 7 LIL subsectors used in the WEM



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

- **Aluminium smelting** – including all aluminium smelters in the NEM. *Note: This does not apply to the WEM.*

- **Coal mining** – customers mainly engaged in open-cut or underground mining of bituminous thermal and metallurgical coal. *Note: This does not apply to the WEM.*
- **Liquified natural gas (LNG)** – considers the production of LNG via the operation of coal seam gas fields in the NEM. *Note: This does not 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.

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

- **LIL** – scenario-based forecasts supported by survey responses on committed and prospective loads.
- **Data centres** – scenario-based forecasts supported by a combination of econometric modelling (smaller data centres, <10 MW) and survey responses on committed and prospective loads (larger data centres, >10 MW), including consideration for the potential for a load ramp-up over time.
- **Hydrogen** – scenario-based forecasts supported by survey responses describing committed and prospective loads.
- **BMM** – scenario-based forecasts supported by econometric modelling.
- **EVs** – scenario-based forecasts supported by technology adoption modelling.

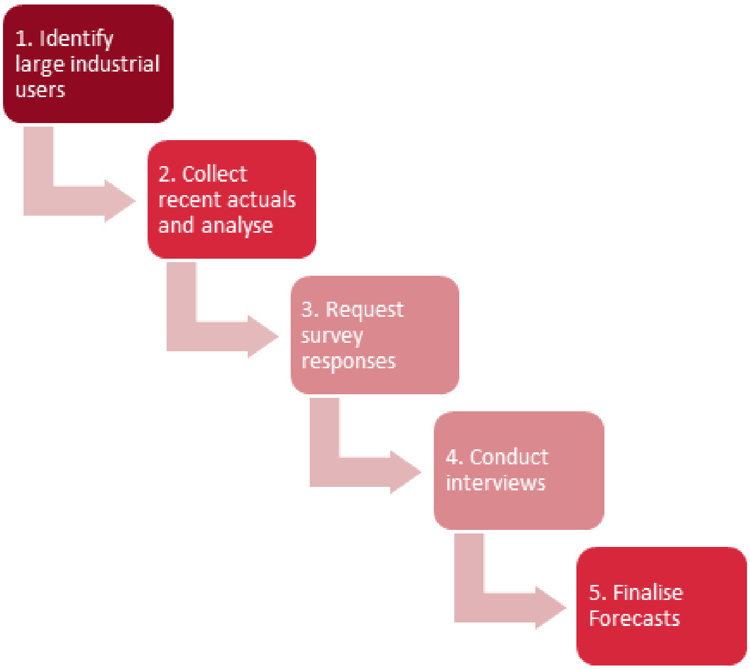
The detailed approaches applied are explained in the following section.

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 8. 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 8 Steps for large industrial load survey process



Step 1: Identify large industrial users

For the NEM, any customers connected or planning to connect 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 (NSP) surveys – requesting information on existing and new loads (also referred to as prospective projects).
- 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 may include 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 (DSP) programs.
- Variations in observed electricity demand relative to previous expectations.
- Assumptions governing the scenarios.

Interviews with large industrial users 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 the Medium Term Projected Assessment of System Adequacy (MT PASA).
- For each subsector, AEMO will review the survey responses[9] and assess the reasonableness of the forecasts (and 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.

LIL evaluation

All scenarios include existing LILs. AEMO may also consider prospective projects identified through information requests, other industry engagement and media searches.

For all prospective projects, AEMO assigns a project status – including committed, anticipated or proposed loads - based on the likelihood of the project being developed.

The project status is informed by a number of commitment criteria that AEMO considers in combination, including:

- The current stage of the connection process for the project, such as pre-feasibility, enquiry, application, contracts, construction and completion
- Environment and planning approvals
- Financial and contract information
- Other information from the LIL survey process, NSP information requests or market research indicating the likelihood of development.

AEMO considers eligible policies (energy or environmental policies which are in the AEMC emissions targets statement or meet at least one criterion in NER clause 5.22.3(b)(2)) across its scenario collection. While an eligible policy will be

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

considered in this way, AEMO's approach to specific prospective loads is to consider those loads in scenarios only if there is a sufficiently explicit connection between the load and an eligible policy, resulting in a clear and modellable dependency between the policy and the load. AEMO relies on information provided via joint planning and regular jurisdictional engagement activities to determine whether a sufficient connection exists, and therefore considers each prospective load on a case-by-case basis.

Reliability obligation thresholds when applying prospective industrial projects

The forecasting approach applies to long-term forecasting activities, which span periods from near-term reliability assessments over the next few years through to long-term planning over decades. When conducting near-term reliability assessments, for example in the NEM or WEM ESOO, it is important for subsequent reliability obligations and reserve requirements to be informed by load developments that are highly likely, to protect consumers from reserve procurement for load growth that is still uncertain. For longer term planning, less conservative assumptions are more appropriate to enable identification of necessary investments to support likely, yet uncertain, load developments, internally consistent with the drivers of the forecast scenario.

To execute this temporal distinction, AEMO applies criteria when evaluating prospective industrial load developments. The temporal boundary applies to the relevant obligation that is developed in response to the relevant reliability assessment:

- In the NEM, this refers to the timeframes associated with the reliability instruments that may be created under the Retailer Reliability Obligation, including up to the T-3 cut-off day, as defined by the National Electricity Law[10]. The T-3 cut-off day refers to the day that is three years away from the current reliability assessment.
- In the WEM, this refers to the Reserve Capacity Mechanism process, and particularly the requirements for the Reserve Capacity Requirement associated with the current reserve capacity cycle (which is associated with the capacity year two years from the WEM ESOO's release).

This threshold is here termed the *reliability obligation threshold*.

Committed projects

Committed projects have a very high likelihood of being developed, based on a combination of information, such as:

- The project is being commissioned or is under construction.
- The project has reached final investment decision (FID), and this has been publicly announced.
- The project is at application or a later stage in the connection process.
- Other information from the LIL survey process or NSP information requests indicate a very high likelihood of being developed.

Anticipated projects

Anticipated projects have a high likelihood of being developed, based on a combination of information such as:

[10] See National Electricity Law, Part 2A (Retailer Reliability Obligation) in https://www.legislation.sa.gov.au/__legislation/lz/c/a/national%20electricity%20(south%20australia)%20act%201996/current/1996.44.auth.pdf.

- The project is at least at enquiry or a later stage in the connection process[11].
- Environmental and planning approvals are progressing.
- Other information from the LIL survey process or NSP information requests indicate a high likelihood of being developed.

Proposed projects

Proposed projects are other projects not classified by AEMO as committed or anticipated, identified explicitly based on the following information:

- The project is at least at application stage of the connection process, or
- The project has not yet reached application stage of the connection process but is assessed as likely, that is, it either:
  - aligns with government policy, or
  - is of state significance (for example, state significant developments in New South Wales), or
  - is otherwise assessed as likely based on the LIL survey process, NSP information requests or market research.

The NSP may assess the probabilities for proposed projects and provide this to AEMO alongside other relevant prospective load information, which AEMO may then include on a probability weighted basis (derating the load by its assessed probability, in energy and demand terms), subject to AEMO's independent review of LIL survey data, NSP information requests and market research.

Figure 9 shows how the evidenced project commitment criteria informs the LIL forecasts for various scenarios, differentiated by the level of economic activity. This is represented by 'Slower economic growth', 'Moderate economic growth' (or the Central scenario) and 'Higher economic growth' scenarios in the figure, although the scenario collection may include other variations to these three examples. In this case, the Central scenario is used as input into AEMO's reliability forecasts.

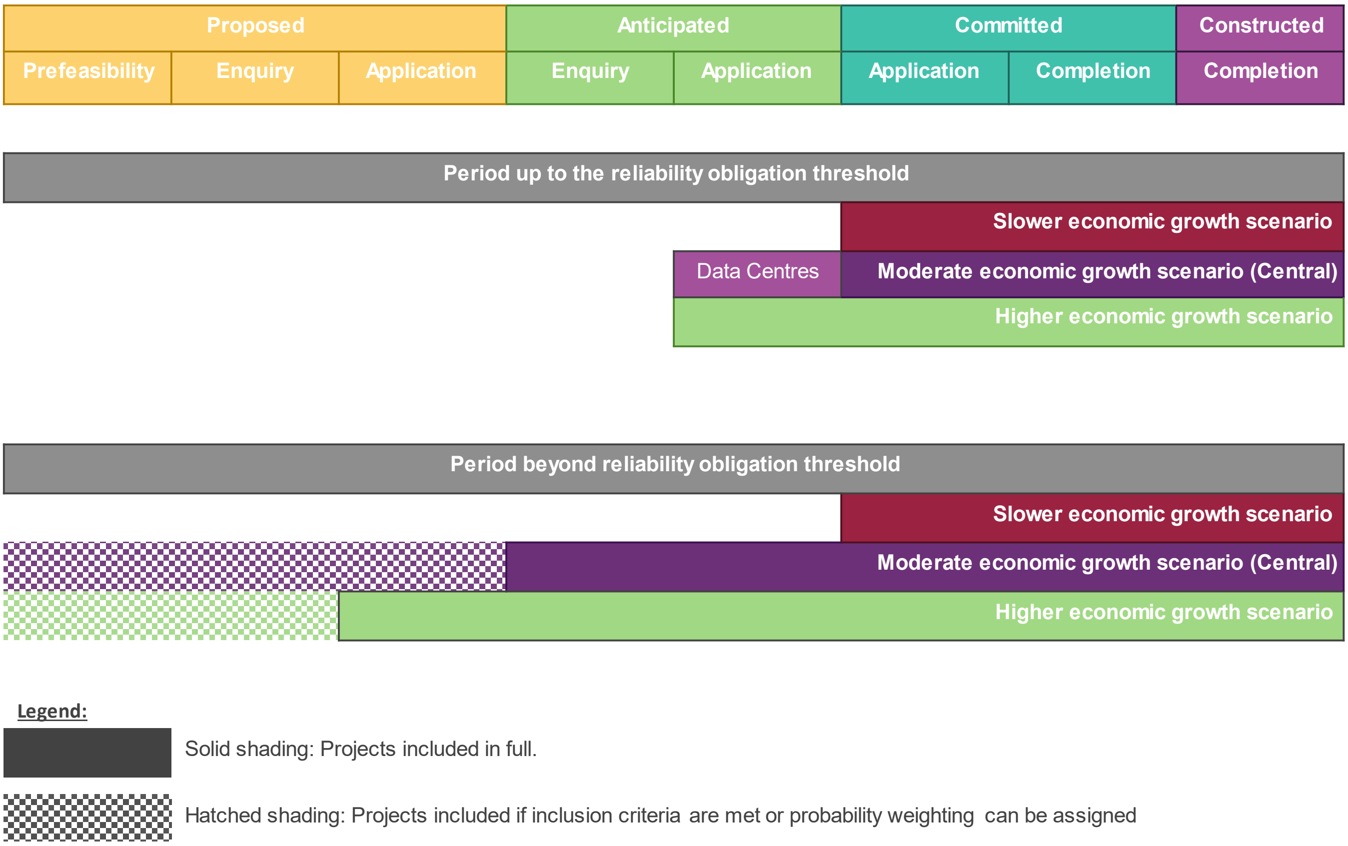
For the period up to and including the reliability obligation threshold, the Central scenario considers all committed projects, while scenarios with higher economic growth will also apply all anticipated projects with a connection application.

Beyond the reliability obligation threshold, the Central scenario also considers all other anticipated LIL projects and a set of proposed projects that meet the proposed project criteria above. The higher economic growth scenario extends to include anticipated projects and proposed projects that meet the proposed project criteria above. Slower economic growth scenarios consider committed projects only across the forecast horizon.

AEMO may apply delays and/or a reduction to the expected annual consumption and rated demand of prospective projects, where this is supported by additional information collected or by scenario-based considerations such as demand-side supply chain factors. This can include in some instances a gradual ramp up of activity for projects that may not immediately reach their full load once operational.

[11] For rapidly growing sectors such as data centres a more stringent criteria is applied: at least application stage in the connection process for the period up to and including the reliability obligation threshold.

Figure 9 Guide to project and grid connection status scenario allocation



Note:

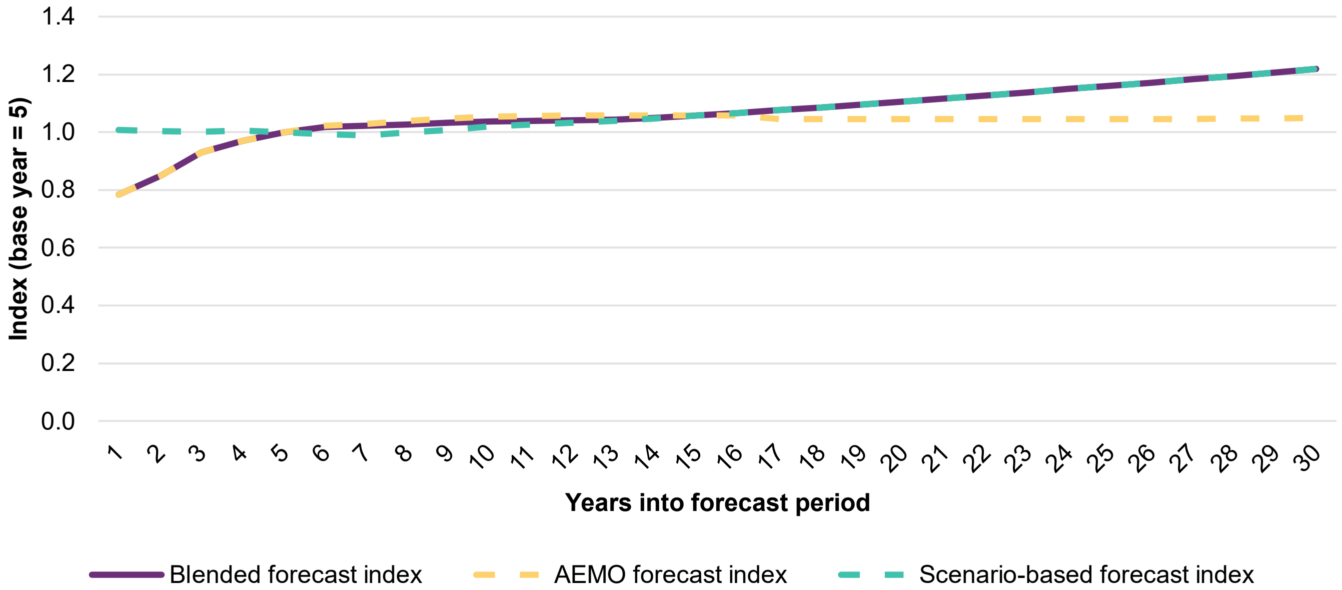
- As symbolised by the lighter shading in the figure, for the data centre forecasts, AEMO considers 'anticipated' projects at the application stage in the connection process, in the period up to and including the reliability obligation threshold in the Central scenario. This recognises the more rapid relative development lead times for data centre projects. Anticipated projects that are not data centre developments are not considered in this period.
- Industrial data centre projects that do not meet the relevant criteria to be considered in full (solid area) are not considered in the subsequent hatched areas in any scenario
- Proposed or anticipated hydrogen projects are only included in the higher economic growth scenario.

Blending survey-based LIL forecasts with scenario-based growth trajectories in the medium to longer term

To account for structural changes in the economy in the medium to longer term, including the potential emergence of new large industrials given expected trends in economic activity in industrial sectors, AEMO may blend aggregated survey-based LIL forecasts with other scenario-based growth trajectories, such as from multi-sectoral modelling. In such cases, the annual growth rate from the causal model(s) is applied to the survey-based LIL forecast, assuming a gradual increase in weight of the growth rate applied over time.

Figure 10 shows an indicative example of how this may be applied, with blending taking place after the fifth year, between the aggregated survey-based LIL forecast and a forecast using a scenario-based growth trajectory. In this example, the weight of the survey-based LIL forecast reduces by 10% each year from the sixth year onwards, until growth in the blended forecast comprises 100% of the scenario-based growth forecast in the fifteenth year.

Figure 10 An indicative blending of the aggregated survey-based LIL forecasts with scenario-based growth trajectories, applying blending weights after the fifth forecast year



Publish forecasts

To comply with confidentiality obligations[12], AEMO may aggregate subsector forecasts before publishing the LIL aggregate forecast. For some sub-sectors, for example the LNG sector, there may be sufficient sites within a region to maintain confidentiality. Further, AEMO may consider publishing LIL forecasts disaggregated by project status (for e.g. committed, anticipated and proposed) if confidentiality can still be maintained.

2.2 Data centre sector consumption forecasting

Data centres are forecast to grow rapidly in the coming years owing to cloud computing and artificial intelligence applications. AEMO applies a mixture of econometric, survey-based and techno-economic modelling approaches to forecast demand, based on whether facilities are either commercial-scale data centres (<10 MW) or industrial-scale data centres (>10 MW).

Two key components drive the techno-economic demand for data centre services:

- The need for data centre services in a modern economy to provide goods and services.
- AI adoption and implementation.

The approach considers the different stages of digital maturity across sectors and models, their AI technology adoption, and consumption of web and data services individually.

The demand for data centre services is then translated into energy consumption using observations and expert judgement on the future energy intensity of data centres.

[12] As required by the National Electricity Law (NEL), the National Electricity Rules and/or other relevant legal obligations.

2.2.1 Commercial-scale data centres (<10 MW)

Commercial-scale data centres are forecast in aggregate, with an econometric regression model of historical consumption data against economic activity applied in the short term and a techno-economic model applied in the medium to long-term, with a blended handover of model outcomes between the two models.

2.2.2 Industrial-scale data centres (>10 MW)

Similar to the methodology for large industrial loads, industrial-scale data centres are driven by information from data centre proponents, large industrial load survey responses, standing information request responses from NSPs, market research and media searches.

Key parameters that may be available through these sources include:

- **Ramp-up period** – designated as the duration in years for the new connection to reach full load.
- **Load realisation factor** – a scaling factor (between 0 and 1) applied to the rated demand, as deemed appropriate by the NSP. For example, a proponent may submit a connection application for 100 MW of rated demand, however, the NSP may deem it appropriate to scale this down to 40 MW, using a load realisation factor of 0.40. AEMO would apply a similar load realisation factor to that project.
- **Load factor** – a ratio between average demand of the data centre and peak demand.

Project-specific data is then combined with techno-economic demand modelling outcomes to produce the forecast total consumption of the sector.

The figures below show the impact of either varying the ramp-up periods or the load realisation factor.

Figure 11 The impact of various ramp-up periods on industrial-scale data centre forecast, with 20 MW rated demand, 100% load realisation and 80% load factor

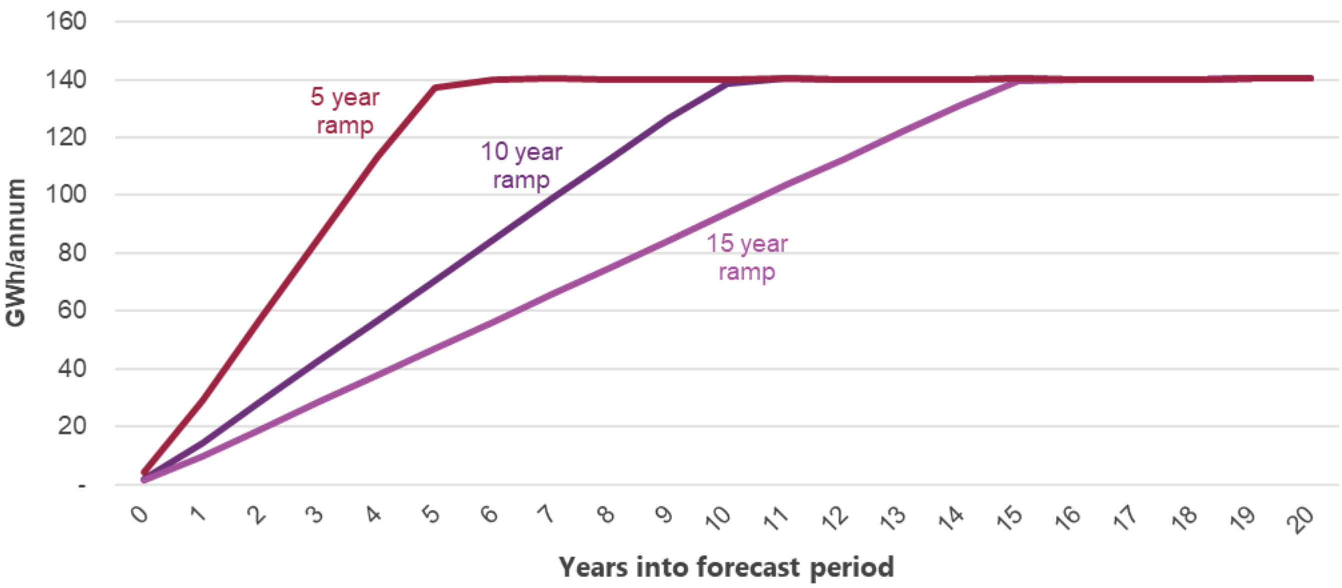
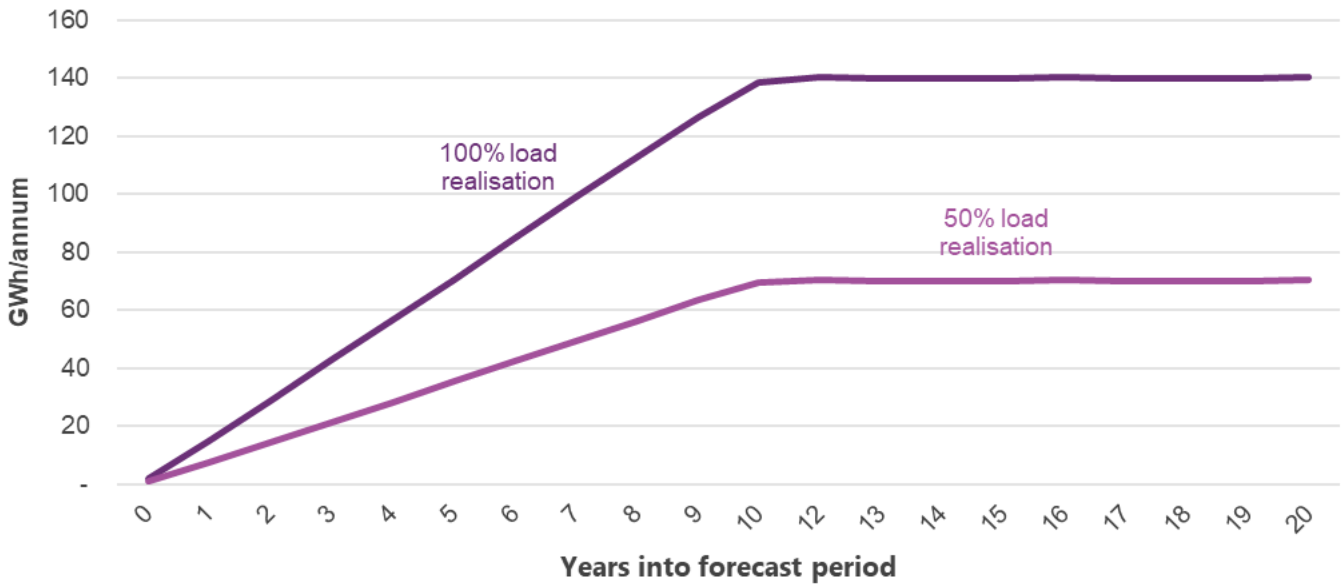


Figure 12 The impact of various load realisation factors on industrial-scale data centre forecast, with 20 MW rated demand, 10-year ramp-up period and 80% load factor



Similar to other prospective LIL projects, AEMO assigns a committed, anticipated or proposed status to a prospective data centre project, based on the likelihood of the project being developed (see Section 2.1 for further details).

Up to and including the reliability obligation threshold, AEMO considers anticipated data centre projects with a grid connection application in the Central and High scenarios (see Figure 9). Beyond the reliability obligation threshold all anticipated projects are included in the Central and High scenarios, while proposed projects with a connection application are only included in the High scenario. This refined inclusion criteria reflects both the fast pace and high uncertainty of data centre developments relative to more traditional industrial loads.

2.3 Hydrogen sector consumption forecasting

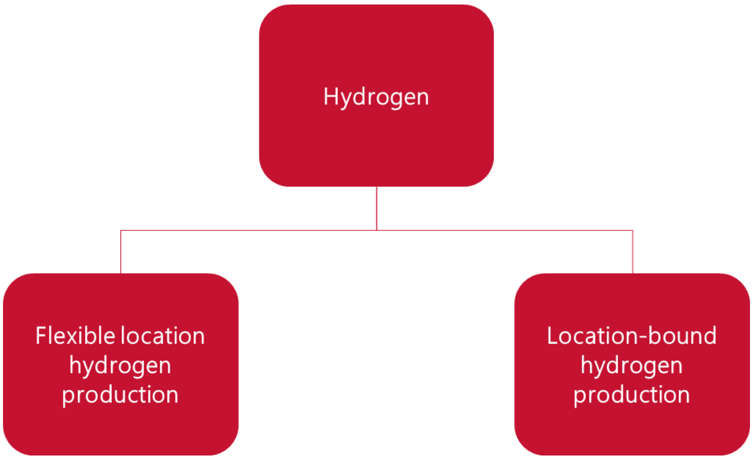
An emerging sector within Australia's economy is the development of a renewable hydrogen industry to support the transformation of existing and new industrial processes, and potential export to international consumers and support carbon emission reduction objectives. If established, hydrogen production has the potential to 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 REZ-located electricity consumption used to produce hydrogen within the Australian economy.

As illustrated in Figure 13, the hydrogen sector covers two components:

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

Figure 13 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 vary the scale and type of hydrogen production across scenarios. The level of hydrogen production for export and green commodities 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[13].

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

2.3.1 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, and government policy (where relevant). With no locational requirement, the location of electrolyser loads is optimised within the modelling as per AEMO's ISP Methodology[14].

By treating these facilities as flexible loads coordinated with available supply within AEMO's market models and operating within technical envelopes defined in the IASR, 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 somewhat flexible. The ISP methodology provides greater detail on the optimisation approach, including any constraints that apply to the operation of these assets and assumed interactions with transport and storage infrastructure.

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.

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

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

2.3.2 Location-bound hydrogen production

Location-bound hydrogen production refers to hydrogen produced for existing and emerging industrial processes with known locations. To service these customers, hydrogen facilities will require access to existing gas distribution networks for gas-blending, transmission pipelines for transport to hubs or ports, or proximity to the specific loads that may directly consume hydrogen. This sector includes, for example, units producing hydrogen for transport refuelling.

Emerging hydrogen production projects are identified using a combination of NSP and customer surveyed information, and publicly available data[15]. The projects are allocated a status using a process largely aligned to that used for other LILs (see Figure 9). Note that proposed hydrogen projects are only included if sufficient information is provided by NSPs to assess their likelihood, and with sufficient detail to allow AEMO to assess and include each project in the appropriate forecast. AEMO also assumes a five-year lead time is required for any project that has not yet reached FID at the forecast date.

Similar to the flexible location production, operation of this component is optimised within AEMO's market models.

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, EV, data centre 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[16] 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[17] 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.

[15] This can include the CSIRO HyResource dataset. See: https://research.csiro.au/hyresource/projects/facilities/.

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

[17] 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:

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

where $m = 1,2, \dots, 60$ is a month counter. The coefficients to be estimated are the intercept (β_i), trend ($\beta_{\text{Trend},i}$), 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 variables are described in Table 1Table 1. More detail on critical temperatures applied in the calculation of HDD and CDD is provided in Appendix A2.

Table 1 Short-term base model variable description

Variable	Abbreviation	Units	Description
Business consumption	BMM_cons	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 economic model

The long-term BMM forecast reflects the strong relationship between electricity consumption and economic growth. The following equation describes the model used. The subscripts i and t represent regions and years, respectively[18].

$$BMM\_cons_{i,t} = BMM\_cons_{i,t-1} + economic\_impact$$

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

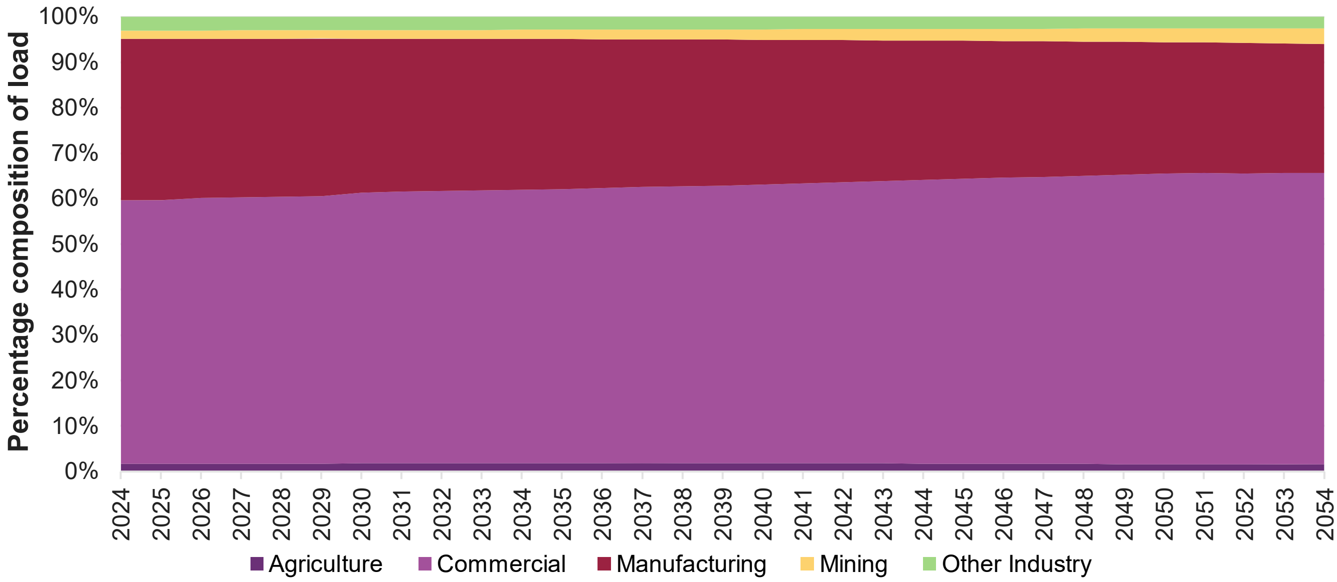
1. Modelling the scenario-based forecasts as energy intensity forecasts (for example from multi-sectoral modelling).
2. Applying economic forecasts to the energy intensity forecasts.

In the first step, for each scenario, the scenario-based modelling outputs from relevant consultants commissioned by AEMO, describe the long-term dynamics of energy consumption, driven from causal factors such as industry activity changes, trade, import substitution and sectoral changes in a decarbonising economy.

Figure 14 shows an example of different sectors' forecast in proportion to the total sectoral forecast.

[18] 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.

Figure 14 Example of multi-sectoral electricity forecast used for calculating sectoral 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[19]. AEMO combines energy intensities calculated using scenario-based consumption forecasts and economic forecasts, and an extrapolation of energy intensities calculated from historical consumption and economic indicators, outlined below, to produce BMM consumption forecasts in the long-term model. In the short term, extrapolations of historical energy intensities are used. The growth trajectory of scenario-based energy intensities is then applied to energy intensities with gradually-increasing weight over time.

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:

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

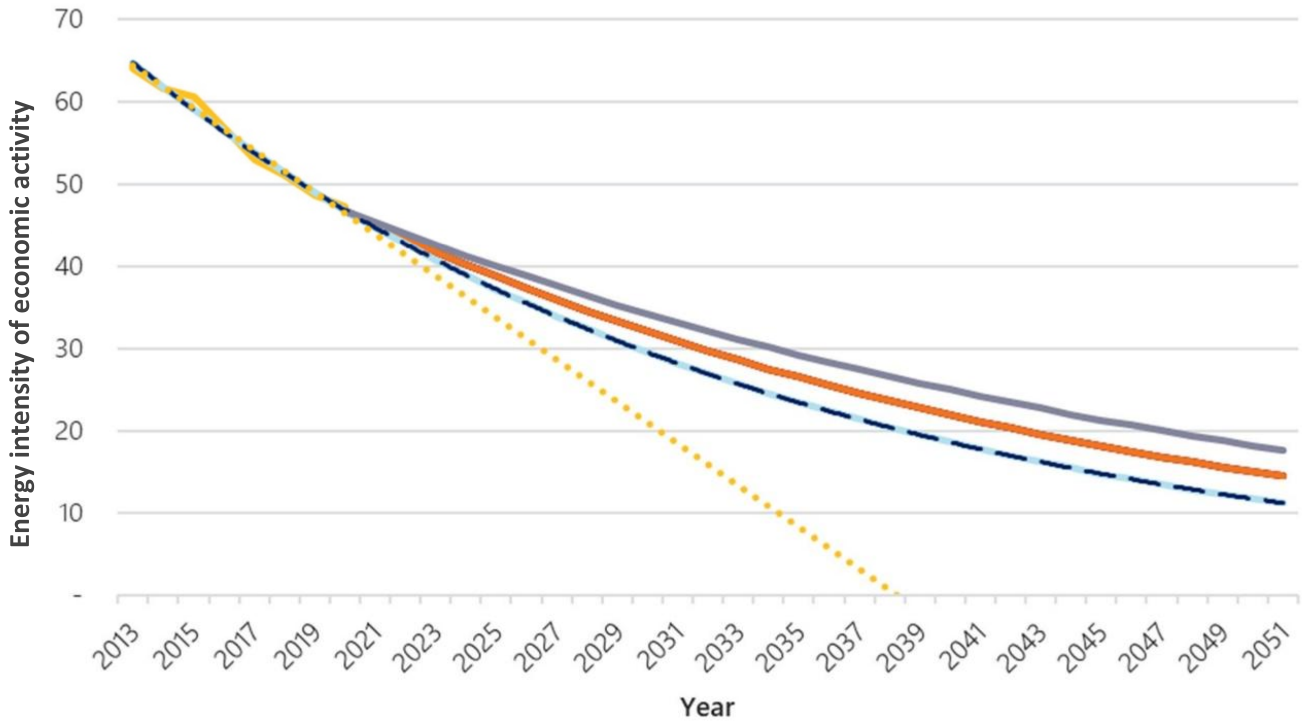
where A and B are the parameters fitted to historical energy intensities with ordinary least squares and t is time in financial years.

Figure 15 is an example of energy intensity forecasts based on the multi-sectoral 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.

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

Figure 15 Estimation of the energy intensity trends over time



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 on the BMM sector following the GFC and the COVID-19 pandemic.

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[20].

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

Time-series models are generally more accurate in the short term, so generally AEMO adopts a declining short-term weighting, with the remainder coming from the long-term economic model:

- 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,

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.

When combining the short-term (econometric) and long-term (economic) forecasts, AEMO includes components understood to have a material impact on electricity consumption. These components include retail price impact, energy efficiency, and climate change impact, and are introduced such that their impacts influence consumption forecasts in subsequent periods. These are applied after the blending of short- and long-term forecasts so that shocks such as price impacts and energy efficiency savings are not muted in the short-term because of the blending.

Reflect price impact

Even though electricity use is an essential service, 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 blended model using the concept of price elasticity of demand[21].

Adjust for energy efficiency

AEMO obtains forecast energy efficiency savings either through consultants which AEMO engages, 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[22]. This may include schemes that 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[23].

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

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

[23] 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 remove LIL savings from the consultant's forecasts.

- 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[24] 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[25]) and the potential non-realisation of expected savings from policy measures.

Adjust for climate change

AEMO adjusts consumption forecasts in the BMM sector to account for the impact of increasing temperatures. Forecasts are produced using normalised weather standards which change over the forecast period, reflecting historical observed weather data and projected future climate scenarios (see Appendix A2).

These adjustments are anticipated to reduce heating load while increasing cooling load[26] forecasts for the BMM sector. The annual net impact of climate change can take a positive or negative value depending on which effect, on average, is larger.

Adjust for electrification

Forecast scenarios consider the role of emissions reduction in the short and long-term evolution of customer's electricity consumption, and therefore 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, it will generally be captured though the adjustment for energy efficiency, to ensure these are not double counted.

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] 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.

[25] 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.

[26] 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.

2.5.1 Consumer energy resources

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

Electric vehicles

EV projections are split into 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 include those not physically on rooftops). Larger systems (up to 30 MW) are accounted for in Section 4.1.

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 utilised capacity of each of the storage systems. It is assumed that each battery performs a full cycle each day.

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

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

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 16 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 17.

Figure 17 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

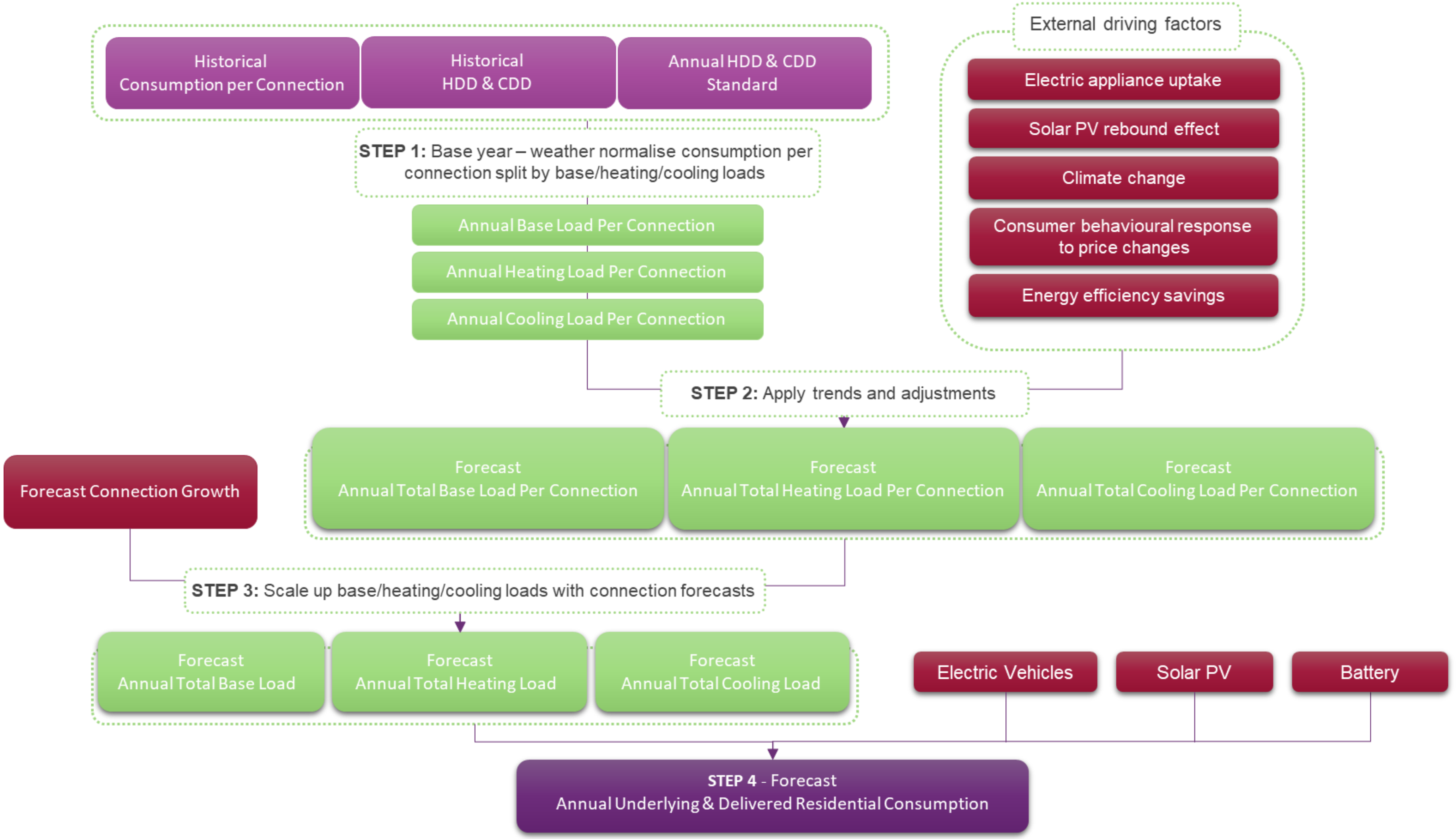
AEMO applies a "growth" model to generate 30-year annual residential electricity consumption forecasts. The key four steps are summarised below and detailed further in the rest of the chapter:

- **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[27].
- **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 18 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.

[27] 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 18 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 a four-year time series leading up to the reference year as training data.

A 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 2.

Table 2 Weather normalisation model variable description

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

Step 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 2 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[28] is assessed and allocated individually to base load, heating load, and cooling load per connection.

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).

[28] AEMO assumes a rebound of energy consumption as a proportion of consumption, 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.

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[29] 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[30] 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[31]) and the potential non-realisation of expected savings from policy measures. This is applied equally to heating load, cooling load and base load savings.

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.

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

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

[31] 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.

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

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

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

Variables and their descriptions are detailed in Table 3.

Table 3 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 4 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

Details on the CER forecasting methodology for rooftop PV, EVs and battery storage are described in Appendix A3 and Appendix A4.

Electric vehicles

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 losses is also modelled (for vehicles that may provide discharge capabilities via vehicle-to-grid or vehicle-to-home coordination services). Losses associated with these coordinated discharge and charge activities 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 tends to increase electricity that is supplied from the grid.

Electrification adjustment

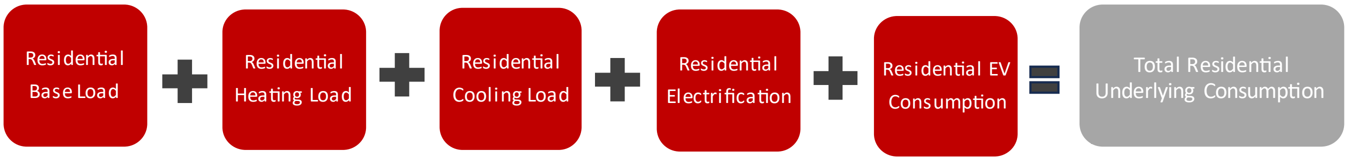
Forecast scenarios that consider decarbonisation pathways to reduce carbon emissions may include significant additional electricity consumption from fuel switching in the residential sector. This is a strategy to reduce emissions by replacing fossil fuel use with electricity sourced from renewables.

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, residential electrification and residential EVs, as shown in Figure 19.

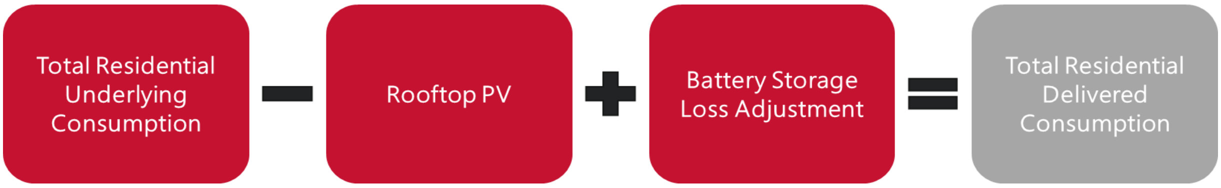
Figure 19 Aggregation process for total residential underlying consumption



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 20.

Figure 20 Aggregation process for total residential delivered consumption



4 Operational consumption

AEMO uses operational consumption in its 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[32]. 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 21 and Figure 22. The components are explained in the following sections.

Figure 21 Delivered to the distribution network

Figure 22 Operational consumption (sent-out)

Finally, power station auxiliary load is used to convert from “sent-out” to “as generated” consumption, as shown in Figure 23. The methodology for auxiliary load is explained in Section 4.3.

Figure 23 Converting from operational consumption (sent-out) to operational consumption (as generated)

[32] 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

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[33]) unless explicitly included in operational demand definitions[34] .
- A simulated normalised PV generation trace.

See Appendix A3 for further detail on the methodology for developing capacity and normalised PV generation traces.

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)[35] to simulate PVNSG historical normalised generation from 2001 for each spatial unit, where PVNSG is present, for fixed plate and single axis tracking technologies.
- Determining historical normalised generation traces at the required spatial grain by capacity weighting relevant spatial unit (such as 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.
- Historical normalised generation traces derived from weather data are also calibrated based on metered PVNSG output data, where such data is available and considered suitable for calibration purposes.

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

[34] 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.

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

ONSG

For technologies other than PV, AEMO maintains a list of existing generators and remove units that may already be captured through 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.

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.

ONSG’s influence on maximum and minimum demand forecasts is outlined in Section 5.7.

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[36]. 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 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 23). 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 that 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.

36 The source and values of historical distribution losses are presented in the IASR.

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 operational 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

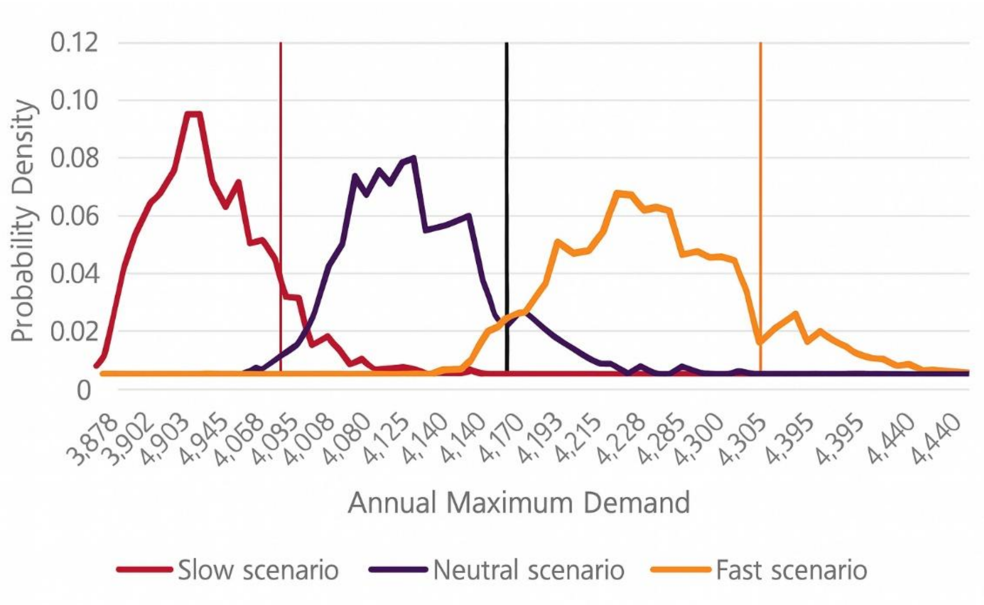
Demand is dependent on both structural drivers as well as random drivers such as weather conditions, seasonal effects and the model residual. To capture the random drivers, AEMO uses a probabilistic methodology to develop regional minimum and maximum demand forecasts.

While forecasting scenarios are developed to capture uncertainty in structural drivers, uncertainty attributable to random drivers is expressed as a POE forecast, targeting specific intervals in the 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 24 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 24 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).

AEMO incorporates specific assumptions regarding the participation and availability of embedded energy storage and electric vehicles.

- AEMO forecasts the relative share of passive and coordinated CER, with the total available VPP storage calculated by multiplying the total battery storage uptake by the proportion of consumers that opt into a VPP coordination arrangement. The resulting capacity is published in the IASR. This storage capacity has its charging and discharging behaviours coordinated within the market modelling, providing dynamic charging and discharging operation depending on prevailing model conditions, similar to an operational generator and/or scheduled load.
- The same approach applies to vehicle-to-grid (V2G) electric vehicles, with the relative share of these vehicles forecast within the CER forecasts.
- Additionally, AEMO forecasts that a proportion of EV users will adopt existing and/or emerging time-of-use (TOU) tariffs. These tariffs are purposefully priced to reflect typical solar energy availability, providing a financial incentive to shift vehicle charging to off-peak periods during times of high solar availability and/or low price. This is captured in the demand traces and discussed in more detail in Section A4.1.

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 in the NEM is forecast as Season Year to prevent any of the seasons (summer/winter) being arbitrarily split by the year definition. Season Year is defined as 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.

- Historical and forecast half-hourly ONSG generation.
- Forecast ESS installed capacity and charge/discharge profile.
  - A proportion of ESS may be considered VPP with coordinated charging and discharging to optimise operation given modelled supply and demand conditions, with the VPP 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 LILs.
- 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 to reflect temperatures expected in the forecast horizon using the method listed in Appendix A2, based on information included in the IASR.

The model aims to generate forecasts of *underlying demand excluding large industrial load*. Large industrial load is deducted from underlying demand prior to the model's development, as the drivers influencing industrial load consumption patterns significantly diverge from those of other electricity consumers. To preserve the load shape integrity of LILs, half-hourly demand for LIL is forecasted separately using the method outlined in Section 5.4. Subsequently, these LIL projections are aggregated with the underlying demand forecast, excluding LIL, to yield the ultimate underlying demand forecast.

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[37] or heat index[38] – both instantaneous and heatwave/coolwave.
    - ‘Instantaneous’ temperature may be transformed as half-hourly up to three hour rolling average of temperature.
    - ‘Heatwaves’[39] 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[40] caused by collinear variables.

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

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

[39] 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.

[40] 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.

5.3 Model development and selection

AEMO develops a half-hourly model for forecasting minimum and maximum demand. The half-hourly model for each region is specified using 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 technologies such as PV, ESS and EVs. These technologies have a half-hourly shape and may cause consumers to shift their demand over the day.

AEMO uses the half-hourly model[41] to produce the minimum and maximum demand forecast for the first year (see Section 5.5). To project year-on-year demand changes over the long-term forecast horizon, as outlined in Section 5.6, AEMO applies long-term growth indices based on economic conditions such as price and GSP, demographic conditions such as connections growth, and technological conditions such as appliance uptake and energy efficiency improvements. These indices are applied on either an annual or seasonal basis, depending on data availability. The model segments demand into heating, base and cooling components, with each component grown using its respective indices. This segmentation relies on a model-driven approach, where a mild temperature day is selected as a baseline, and its temperature profile is applied consistently across the forecast period to distinguish base demand from heating and cooling components.

The half-hourly model aims 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. The model generates forecasts of underlying demand excluding LIL, which is forecasted separately and is outlined in Section 5.7. The half-hourly LIL demand forecast is then added back to the underlying demand forecast to produce the final underlying demand forecast.

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[42] and model variance[43] 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:

[41] Previously, AEMO employed a Generalised Extreme Value (GEV) model to validate the outputs of the half-hourly simulations for minimum and maximum demand. However, due to advancements in the half-hourly model's accuracy, the GEV model is no longer required for these validations.

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

[43] Over-fitting the model results in a model with high variance.

- Performs k-folds out-of-sample cross validation[44] 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.

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.

5.4 Simulate base year (weather and calendar normalisation)

The half-hourly model developed during the above process is used to simulate demand for each region. Specifically, the half-hourly model simulates every half-hour and aggregates demand to the season such that for each season and region AEMO has minima and maxima from the half-hourly model.

Half-hourly model simulation

The weather is simulated for the base year by block bootstrapping historical weather observations 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 2001 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.

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 half-hourly demand simulations are generated at least 4,200 times (based on various weather assumptions including, 24 reference years[45] x 7 day shifts x 25 residuals, yielding 4,200, however, more residuals may be utilised in some cases). The half-hourly forecast of LILs is added back to these simulations, after which the maximum and minimum demand events for each simulation are identified to form the maximum and minimum demand POE results. This can be done on an annual, seasonal, or monthly basis.

[44] 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.

[45] For the 24 complete calendar weather reference years available between 2001 to 2024 inclusive (and potentially increasing each year that provides an additional historical reference year).

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.

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 2024, the base year for the purpose of the forecast is the financial year ending 2024.

Based on the 4,200 (or more) simulations generated from the half-hourly model by varying reference years, day shifts and residuals, and adding the half-hourly LIL forecasts, the individual seasonal maximum and minimum demand values from each simulation are extracted. By sorting these 4,200 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, 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 such as appliance uptake and energy efficiency, 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 climate change and EV charging).

Furthermore, the process distinguishes between the heating, base and cooling components and grows them using their respective indices. Segmenting demand into these three heating, base and cooling 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. As previously explained, these prediction values represent underlying demand excluding LIL. At this stage, the half-hourly demand forecast for LIL is added to the simulation to complete the representation of underlying demand.

At this point, the process converts this to operational demand 'sent out'. This is done by subtracting other forms of generation (rooftop PV, PVNSG and ONSG[46]), distribution and transmission losses back on[47]. 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 5 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 4,200 simulations are performed, there will be 4,200 maximum and 4,200 minimum values for each scenario-season-year combination. From the 4,200 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 25:

- 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[48].

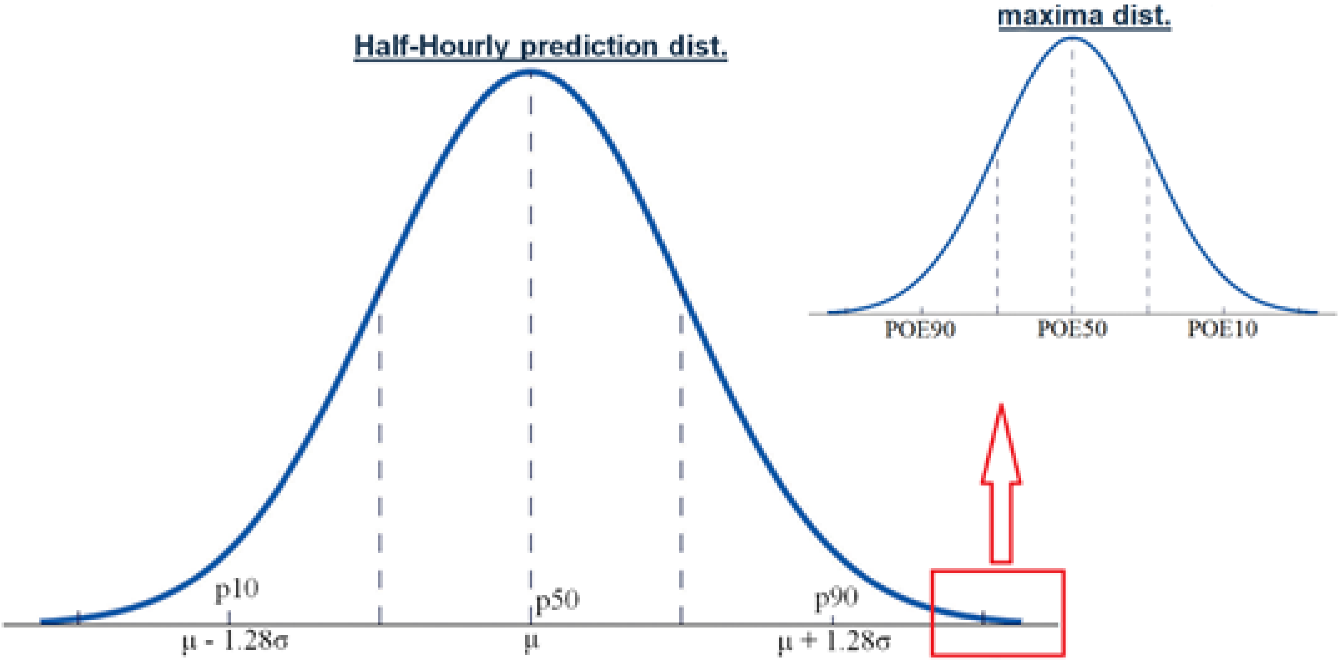
AEMO extracts minimum/maximum values by region from this minima/maxima distribution by selecting the 10th, 50th and 90th percentile as 90%, 50% POE and 10% POE values, respectively.

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

[47] 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.

[48] 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 25 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.

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 explained in Section 4.1, the half-hourly ONSG generation forecast is done by technology categories, such as small-scale wind farms. To develop the half-hourly ONSG generation forecasts, AEMO uses the following data inputs at the regional level:

- Historical ONSG generation at the half-hourly level for each technology categories by region.
- Historical capacity data.
- Forecast installed capacity, as detailed in Section 4.1.

To generate forecasts, AEMO first normalises the historical generation data against installed capacities. This process involves calculating values for each half-hour interval by dividing the actual historical generation by the corresponding installed capacity. With these normalised values in hand, AEMO proceeds to create a synthetic trace of future generation for each half-hour interval for each technology category by multiplying the normalised generation values by the forecast installed capacities for the corresponding future periods. Through this methodology, AEMO projects future energy generation based on past performance adjusted for expected changes in capacity.

Generation from peaking-type ONSG are not considered to contribute to maximum demand to preserve the likely contribution that these generators may be providing under the DSP framework. AEMO may revert this assumption if the DSP forecasts, informed by registered participant submissions to the DSP information portal, cannot corroborate this approach.

Large industrial loads

As LIL consumption drivers differ significantly from those of other consumer segments, the half-hourly model in Section 5.3 generates demand forecasts exclusive of LIL. A separate component explicitly models the half-hourly demand for LIL, which is then integrated with the half-hourly model outputs to produce a complete underlying demand forecast as explained in more details in Section 5.4.

The LIL model leverages actual demand data for each region in its computations. To establish the LIL demand forecast for the base year, the model first selects demand data from a single year within the last five years of historical LIL demand for each region, focusing on a year with minimal extreme values and outliers to ensure stability and representativeness. To introduce variability, the LIL data is shuffled by day: unique dates are randomly permuted, and half-hourly intervals (48 points per day) are reassigned across these shuffled dates, maintaining overall demand characteristics while introducing natural variability. To ensure consistency with the half-hourly demand model outlined in Section 5.3, this process is repeated for every combination of reference year and day shift (that is, 24 reference years x 7 day shifts). Once the simulations of base year are established, the model applies long-term annual consumption drivers to project year-on-year changes in LIL demand.

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 influence that price and/or renewable energy supply has on the operation of electrolysers. The operation from the market models of electrolysers is added to the half hourly forecast.

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 of 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 26.

Figure 26 Translation from operational demand (sent-out) to operational demand (as generated)

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 add these values as forecast components to the aggregate maximum and minimum demand forecasts.

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, such as 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 annual consumption and the 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 an 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 (in general terms, this refers to a half-hourly resolution time series of forecast load) are prepared by deriving a synthetic load trace from the half-hourly model (described in the previous section) 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:

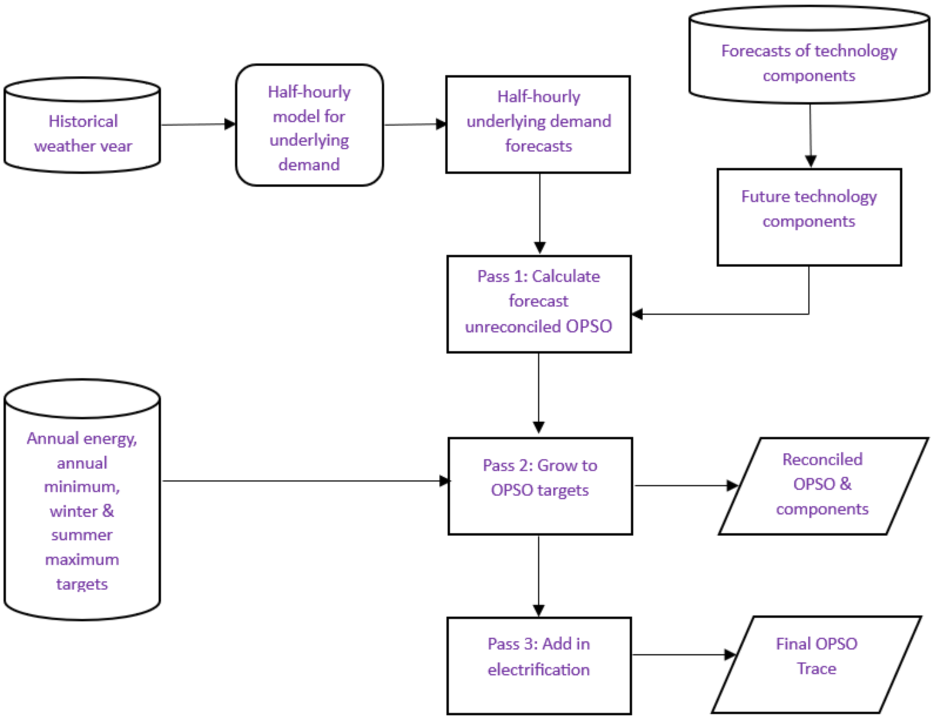
- Region (or sub-region).
- Historical reference year.
- Forecast year.
- Scenario.
- POE level.

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

- Pass 1. Prepare unreconciled OPSO trace from a synthetic trace for underlying demand obtained from the half-hourly model described in Section 5.3
- Pass 2. Growing the unreconciled OPSO trace to reconcile with OPSO targets
- Pass 3. Adding electrification to OPSO.

The trace development process is summarised as a flow diagram in Figure 27. A worked example of the growth scaling algorithm (discussed in Section 6.1) is also provided in Appendix A7.

Figure 27 Demand trace development process flow diagram



6.1 Growth (scaling) algorithm

Unreconciled OPSO time series forecasts are scaled to match the annual consumption, and maximum and minimum demand targets of the forecast year using a constrained optimisation algorithm. The second pass of the three-pass approach applies 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, as well as any weekly and intra-day demand patterns are preserved. The demand trace is adjusted for each period so that the OPSO targets are met.

6.2 Growth Pass1 – Prepare unreconciled OPSO forecasts from a synthetic trace for underlying demand

The first step in computing demand traces is to obtain a half-hourly demand forecast trace for underlying demand. For any historical weather year, the half-hourly model described in Section 5.3 is used to generate a 'synthetic' time series for underlying demand for each combination of region (or sub-region), forecast year, and scenario. The financial year dates from the historical weather year are mapped to the financial year dates of the forecast year. LIL and non-LIL demand are modelled and forecasted separately in the half-hourly model. Therefore, the underlying demand forecast trace from this model will capture increases in industrial loads appropriately, applying these potential increase in LIL consumption in a future year.

After preparing the underlying demand forecast trace, the impacts of CER technologies — such as rooftop PV (PVROOF), non-scheduled solar (PVNSG), energy storage systems (ESS), electric vehicles (EV), vehicle-to-home (V2H), and customer-embedded generation (ONSG) — are added back in to produce the final OPSO demand trace. The CER component traces reflect the latest assumptions and projections, such as installed capacities, vehicle numbers, and installation rates for the relevant 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. 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 ensures that the forecast operational demand meets the OPSO targets. The synthetic unreconciled OPSO demand trace from Pass 1 will not necessarily meet the OPSO targets at a specific POE level. Any potential mismatch is because the maximum OPSO target is obtained by simulating the distribution of maximum demand based on possible weather outcomes for the future year, whereas the maximum demand in the unreconciled OPSO trace will be representative of the maximum demand distribution of the actual weather from a historical year.

Thus, the second pass of the process involves applying the growth algorithm described in Section 6.1 to ensure that the OPSO characteristics at a specific POE level are met, while keeping the CER technology components unchanged.

6.4 Pass 3 – adding electrification to OPSO

The third phase adds electrification to OPSO. Electrification forecasts are based on the assumptions outlined in the IASR. Newly electrified loads are assumed to follow existing gas consumption patterns. The annual electrification components for both business and residential sectors must be scaled and allocated to each half-hour of a given forecast year.

- *Business electrification loads* are primarily driven by larger sites, which are assumed to maintain consistent energy usage throughout the year and across the day. To determine the business electrification load for each half-hour, the annual business electrification forecast is divided evenly by the total number of half-hours in the year.
- *Residential electrification loads*, on the other hand, vary by time of day and season, with higher demand observed in winter compared to summer. The process involves two steps:
  1. The annual residential electrification forecast is first scaled to estimate daily residential electrification, assuming it is proportional to daily residential gas usage.
  2. The daily residential electrification estimate is further scaled to allocate demand to each half-hour of the day, based on the assumption that diurnal electrification patterns align with the hourly residential gas usage. Further details about disaggregating annual to half hourly residential electrification are provided in Appendix A7.

Once the electrification components for residential and business sectors are determined for each half-hour, these are added to the OPSO synthetic trace to obtain the OPSO trace with electrification.

The electrification component only reflects the energy required for activities previously performed by alternative fuels, accounting for inherent fuel-conversion efficiency gains where appropriate. Changes in individual appliance efficiency over time are addressed separately within the Energy Efficiency component.

The electrification component for each half-hour, estimated using this method, is used to adjust the POEs outlined in Section 6. This adjustment involves determining the electrification component at the time of the maximum or minimum OPSO trace for each forecast year, averaging this value across the reference years, and adding it back to the OPSO POEs. This ensures the POE forecasts account for the impact of electrification.

6.5 Output traces

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 could choose to model PV separately or treat ESS as a virtual power plant, requiring coordinated control over the discharge and charge of these resources.

- OPSO: Contains half-hourly regional/ sub regional demand traces for operational demand (demand after the impact of rooftop PV and PVNSG).
- ICL: Estimated interconnector losses (to allow netting off those if you are modelling interconnector losses in the market modelling).
- OPSO_MODELLING: Version of demand used in AEMO's market modelling, OPSO_MODELLING = OPSO – ICL+ EVVPP.
- OPSO___PVLITE: Contains half-hourly regional demand traces for operational demand (demand before the impact of rooftop PV and PVNSG).
- PV: Contains half hourly regional generation traces for rooftop PV.
- PV_TOT: Contains half hourly regional generation traces for all embedded PV, including rooftop PV and PVNSG. Generation from PVNSG can be found as PV_NSG = PV_TOT – PV.
- EV: Contains half-hourly regional aggregate EV charging.
- ESS: Contains half-hourly regional aggregate customer installed battery charging/discharging. ESS is capturing the net impact of battery storages (charge – discharge). To remove ESS from OPSO you would subtract it: OPSO – ESS.
- VTOH: Contains half-hourly regional aggregate discharging from EVs to homes (only used in the *Step Change* scenario).
- ELECTRIFICATION_BUS: Electrification impact on the business sector.
- ELECTRIFICATION_RES: Electrification impact on the residential sector.
- EVVPP: Coordinated EV charging (targeting low demand periods, helping to lift minimum demand). Not reflected in demand traces.

7 Spatial forecasts

AEMO primarily forecasts energy (consumption per annum) and demand (minimum and maximums of instantaneous consumption in a half-hourly period per season) at the regional level as outlined in Sections 2-4 and Sections 5-6, respectively. However, to capture local variations in demand patterns, AEMO also develops sub-regional demand forecasts.

A number of sub-regions may be defined for each region, outlined in the IASR. These sub-regions are represented by regular geographical boundary definitions, such as postcodes, Australian Bureau of Statistics (ABS) statistical geographies, or local government areas, facilitating the integration of demographic and economic data where available, and allowing greater consideration of spatial load diversity, including variations in CER investments.

In the case of electricity consumption forecasting, AEMO uses equivalent methodologies when developing sub-regional and regional values, effectively translating regional forecasts to sub-regional forecasts with a top-down approach unless more spatial information is available. Where forecast components are not available at the sub-regional level (for example, energy efficiency savings per residential connection), regional values are adopted instead and scaled appropriately. AEMO may also reconcile aggregated sub-regional and regional forecasts for forecast components where necessary, to verify there is alignment across both spatial definitions.

In the case of electricity demand forecasting, the availability of local weather information may enable improved insights by developing non-coincident maximum and minimum demand forecasts and load traces at the sub-regional level. This additional layer may provide deeper insights into local demand patterns while the core methodology is preserved at the regional level.

To maintain consistency, sub-regional forecasts are reconciled with regional forecasts, produced using the methodology discussed in Sections 5 and 6, using an adjustment factor. This ensures that the sum of sub-regional forecasts and traces aligns with the corresponding regional forecasts and traces at each half-hour interval. As a result, the aggregated sub-regional forecasts remain coherent with regional forecasts and their associated POE values.

7.1 Overview of sub-regional demand forecast approach

The forecasting steps follow the same process as the established regional forecasting methodology outlined in Sections 5 and 6, with the only enhancement being the use of sub-regional data for more detailed insights. The sub-regional forecasts are then reconciled with regional forecasts to ensure alignment. Below is a summary of the key steps involved in generating non-coincident sub-regional maximum and minimum values and reconciled sub-regional traces:

7.1.1 Sub-Regional Non-Coincident Forecast Development

The existing methodology for maximum and minimum demand forecasting (outlined in Section 5) is applied at the sub-regional level to generate non-coincident forecasts for each sub-region. The same data inputs prepared for the regional forecast are firstly mapped for each sub-region (for the list of inputs see Section 5.1).

Using the same methodology described in Section 6, non-coincident load traces are developed at half-hourly resolution for each sub-region, capturing the unique demand patterns specific to those areas.

7.1.2 Reconciliation with regional forecasts:

For each half-hour, POE, and reference year, the sum of the sub-regional unreconciled forecasts/traces is calculated to produce unadjusted half-hourly regional demand traces.

A reconciliation adjustment factor is calculated for each half-hour, POE, and reference year to ensure that the aggregated sub-regional forecasts align with the regional forecasts at each half-hour interval using the following formula:

$$Adjusted\ Factor_{hh,poe,refyear} = \frac{regional\ forecast_{hh,poe,refyear} - \sum sub\ regional\ forecast_{hh,poe,refyear}}{\sum absolute\ value\ of\ sub\ regional\ forecast_{hh,poe,refyear}}$$

The reconciliation adjusted factor is applied on the unreconciled sub-regional traces using the following formula:

$$\begin{aligned} &Adjusted\ subregional\ demand \\ &\quad = Unadjusted\ subregional\ demand \\ &\quad + Adjusted\ Factor_{hh,poe,refyear} \times |unadjusted\ demand| \end{aligned}$$

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[49] 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, the Default Market Offer and the AEMC Residential Electricity Price Trends – environmental costs.
- 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).[50]

The process of AEMO's pricing modelling is summarised in Table 5.

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. Scenarios may assume that new tariff structures are deployed consistent with the general themes of each scenario, where appropriate.

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

[50] 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[51], rather than this methodology.

Table 5 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, Default Market Offer and AEMC reporting on residential electricity price trends. 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.

[51] 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[52]. 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 6 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[53] is:

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

The formula for CDD[54] is:

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

Where $\overline{T}$ 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.

[52] These are listed in the IASR.

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

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

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.

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[55] 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.

[55] The source is presented in the IASR.

- **Step 5.** Match the temperature quantiles of the projected temperature distribution with the quantiles of the historical temperature distribution. Assign a scaling factor for each quantile for daily minimum, mean/median and maximum temperature to transform the historical temperatures to the distribution of projected temperatures.
- **Step 6.** Interpolate the daily minimum, mean/median and maximum scaling factor for each quantile down to the half-hourly level.

Step 1 – Collect daily temperature projection data

- Collect 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 develops forecasts for rooftop PV with one or more suitably qualified consultants, using a diffusion product adoption model that takes into account key drivers for rooftop PV uptake, such as:

- 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.
- Financial incentives, such as Small Technology Certificates (STCs) and feed-in tariffs (FiTs).
- 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 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.

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

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 develops forecasts for the uptake of behind-the-meter residential and business batteries, typically integrated with PV systems. The ESS uptake forecasts are developed with one or more suitably qualified consultants using a diffusion product adoption model, accounting for key drivers of ESS uptake, such as:

- ESS cost, typical size installed.
- State and federal incentive schemes.
- 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).

Note these forecasts do not include large-scale, grid-connected batteries.

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

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

AEMO develops daily charge and discharges profiles 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 vary, 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. VPP charge/discharge profiles can have the effect of smoothing out demand across the day and reducing maximum demand, whereas non-VPP solar shift and TOU battery operating types target residential load reductions rather than whole-of-grid reductions, so provide a relatively small operational demand reduction at peak times in summer.

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

A4.1 Electric vehicle fleet forecast

AEMO develops forecasts for a range of vehicle types, including residential, light commercial, and heavy commercial vehicles such as buses and trucks.

The EV fleet forecasts are developed with one or more suitably qualified consultants using a diffusion product adoption model, accounting for key drivers for the EV uptake forecast including:

- 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).

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

A4.2 Electric vehicles charge profiles

AEMO develops 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 range of EV charging profiles developed is described in Table 7.

Table 7 EV charging profiles

Charging Profile Name	Previous name	Description
Unscheduled	Convenience	Unscheduled home charging that occurs on a flat tariff
TOU Grid solar	Day	The use of a Time of Use (TOU) tariff which includes day charging incentives. Even customers without solar will be incentivised to use abundant low cost solar energy
Off-peak and solar	Night	Traditional TOU tariff without day incentives, other than use of home solar
Public	Fast/Highway (FHWY)	Public L2 and fast charge
TOU Dynamic	Coordinated	TOU tariff, but dynamically priced to reflect solar energy availability. Used for charging only – does not include V2H and V2G power flows
V2G/V2H	V2G/V2H	Vehicle to home/grid (dynamic system-controlled charging)

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:
  - Unscheduled – 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.*
  - TOU Grid solar– 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.*
  - Off-peak and solar – 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.*
  - Public – 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:
  - TOU Dynamic – 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)

A4.3 Electric vehicles annual consumption

AEMO calculates the annual consumption of electric vehicles based on assumptions around the number of vehicles, the number of kilometres in a year EVs travel and the level of efficiency per charge, per vehicle category. This is documented in the IASR, and accompanying reports.

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[56].

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 dwelling completion data supplied by the economic consultant. For the forecast:

- For the first four forecast years, the building stock model transitions from using the trended NMI connections growth rate to the economic consultant dwelling completions on a graduated scale from 0% to 100%.
- From the fifth forecast year onwards, the building stock model applies only the economic consultant dwelling completions.

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[57] 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.

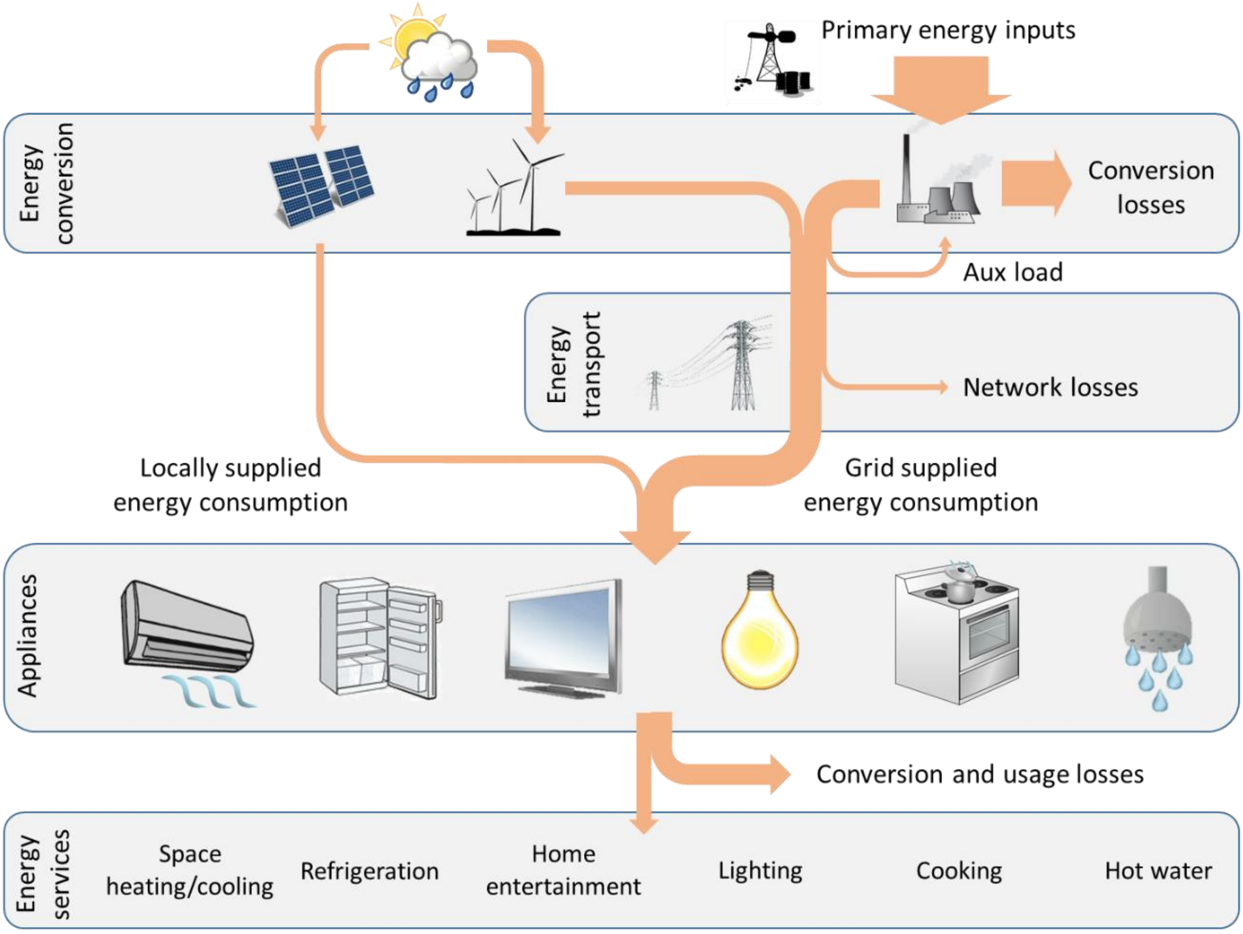
The data allows AEMO to estimate changes to the level of energy services supplied by electricity per household across the NEM. Energy services exclude the impact of energy efficiency, which affects the electricity used by the appliances when delivering the services. Figure 28 illustrates the difference between energy services and energy consumption. Energy

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

[57] 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.

services here also excludes the impact of switching from gas to electric devices. The contributions from energy efficiency and electrification are estimated and accounted for separately (see Section 3.2 and Section 3.4).

Figure 28 Electricity consumption by appliances 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[58] 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.

[58] 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 process for segmenting residential and business actuals may be performed at either a regional level or a sub-regional level and follows the same steps. The residential-business split process may be summarised as follows:

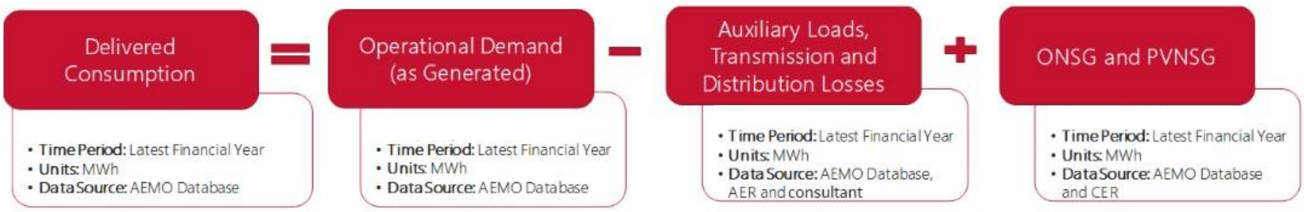
- Calculate distribution-connected delivered consumption.
- Estimate residential consumption per connection based on one of two approaches, depending on the smart meter penetration in a given region or sub-region.
- Scale residential consumption to a regional or sub-regional level and calculate business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

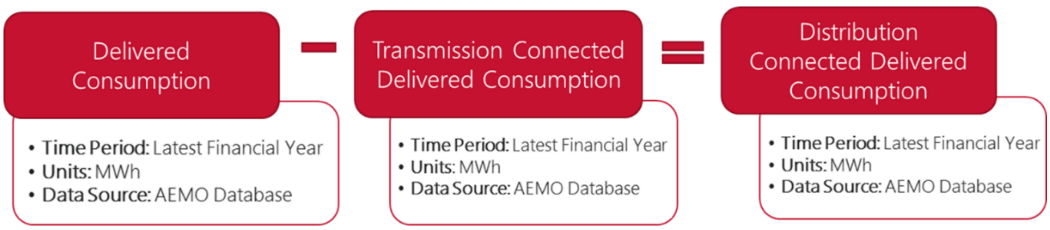
A6.1 Calculate distribution-connected delivered consumption

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 or sub-regions with sufficient interval meter data available. Alternatively, data from the AER Economic Benchmarking Regulatory Information Notice (RIN) is applied in regions or sub-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.

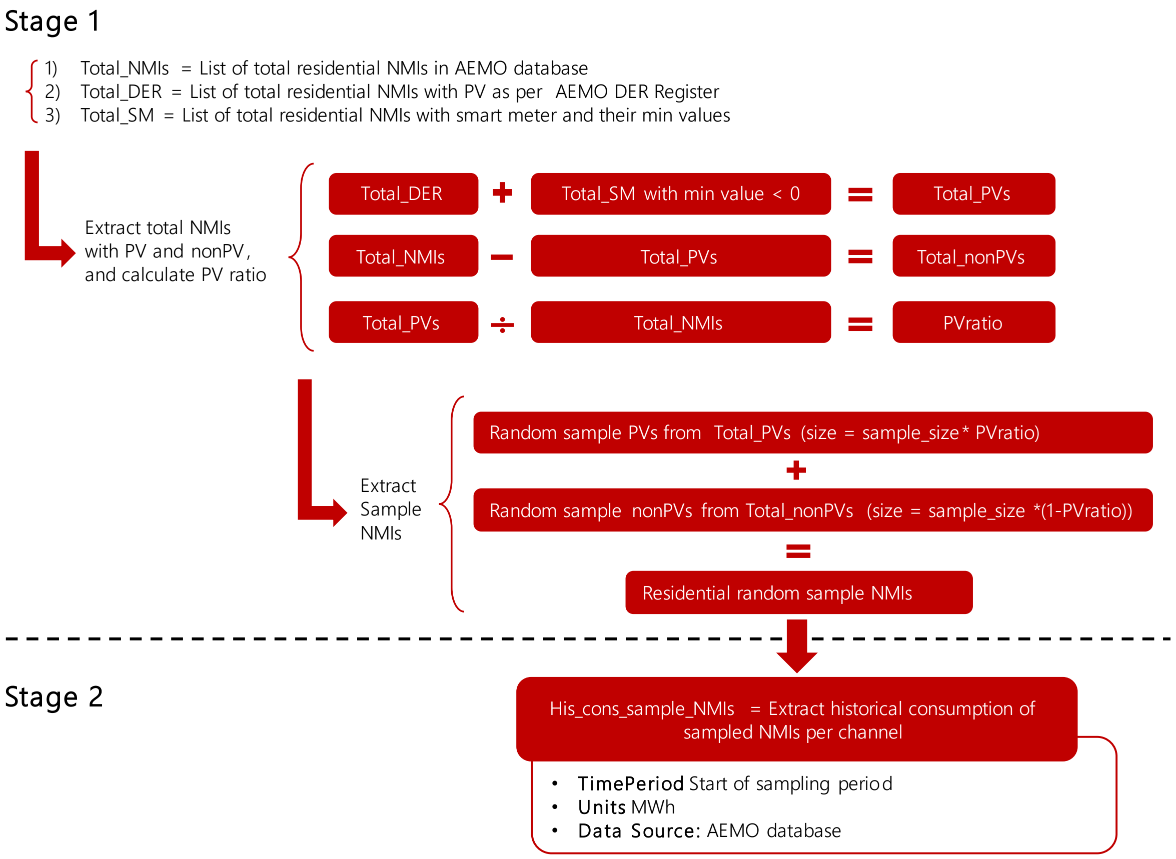
AEMO sampling methodology

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 or a smaller number of meters for a sub-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[59] 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 or sub-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.

[59] 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[60] 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 or sub-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 or sub-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:

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

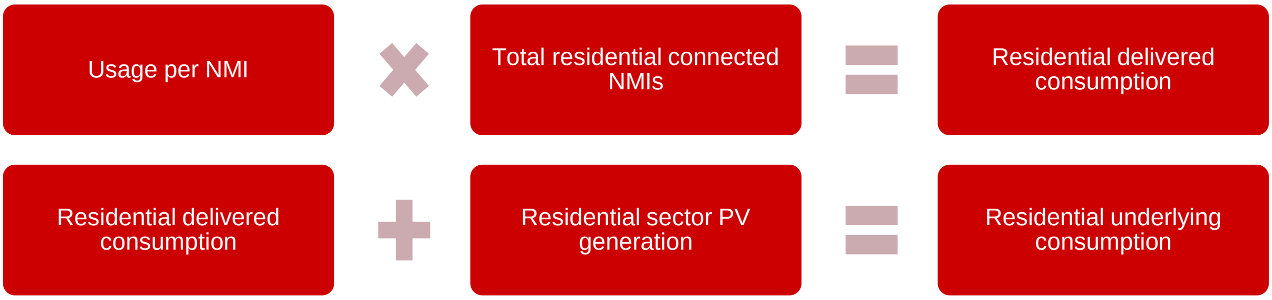
A6.3 Scale to a regional or sub-regional residential-business split

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 or sub-regional level using the total number of residential-connected NMIs.

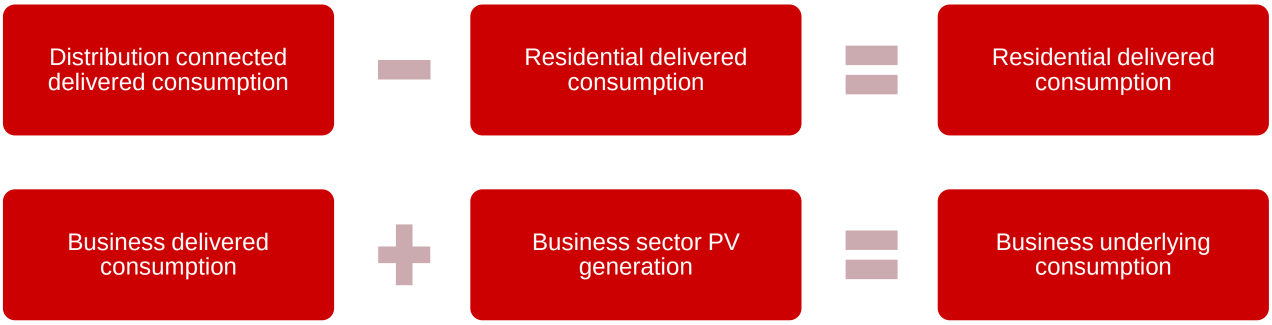
Residential underlying consumption is then calculated by adding residential PV generation (and other CER devices, if material) as estimated for each region or sub-region (refer to Appendix A3) to the residential delivered consumption:

60 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 or sub-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.

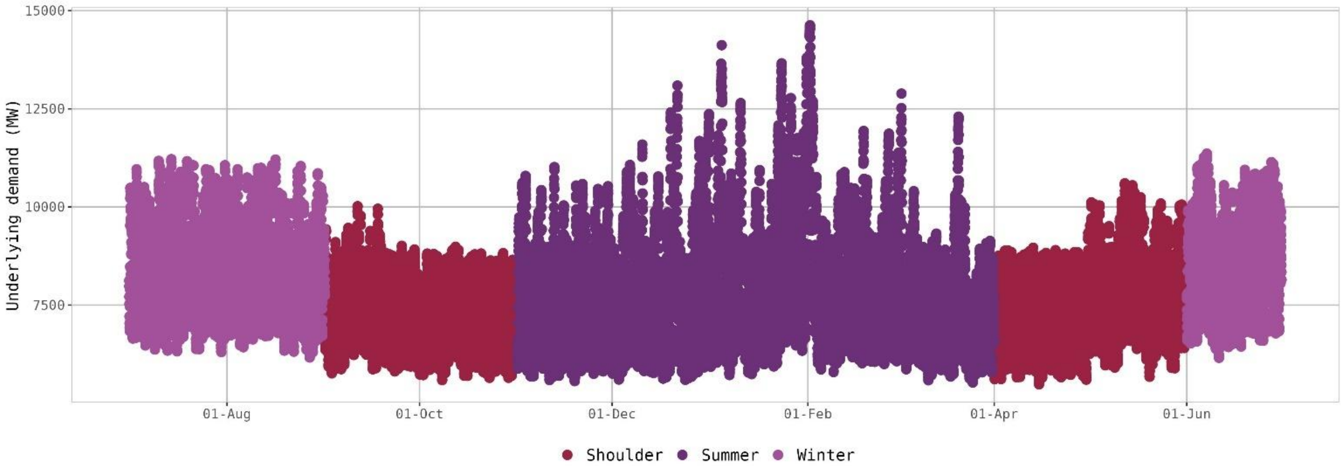


A7. Demand trace scaling algorithm

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.

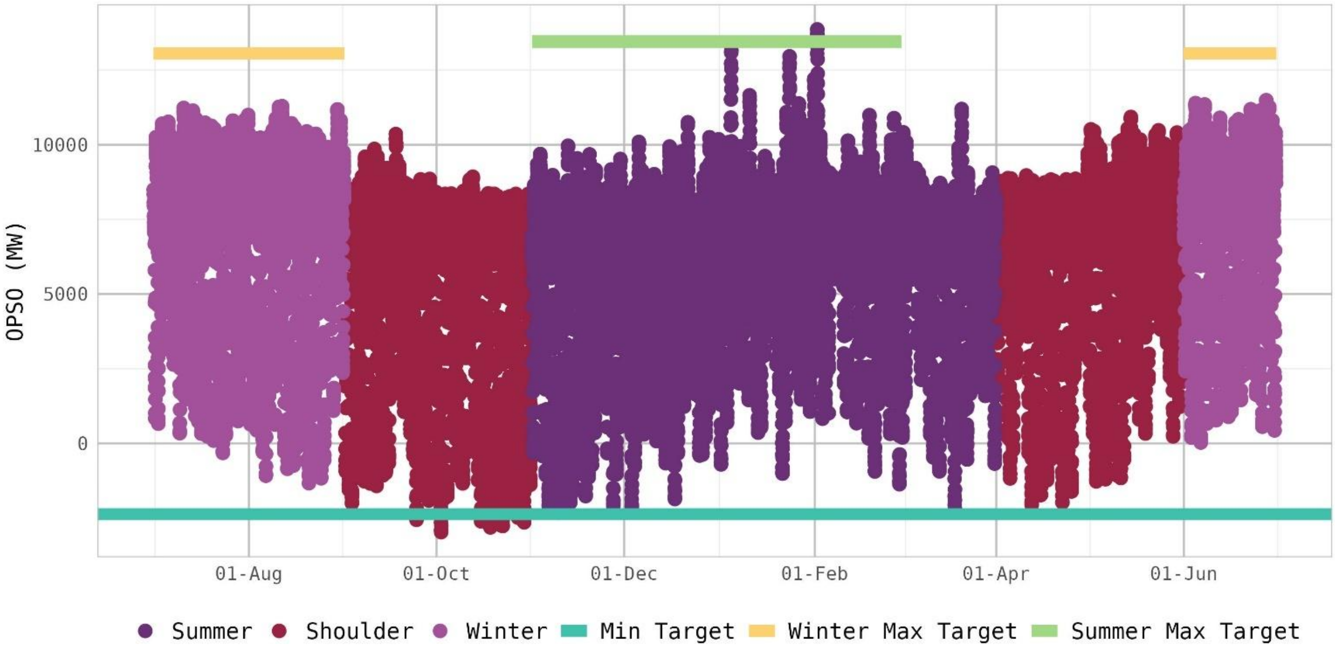
The example begins with a financial-year time series derived from the half-hourly model for underlying demand. This underlying demand trace is shown in Figure 29.

Figure 29 Synthetic trace for underlying demand



The forecast technology components are then added back to the underlying 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, ESS and EVs is appropriately applied to each half-hour to derive the unreconciled OPSO trace. Figure 30 shows the unreconciled OPSO trace along with the timing of when the minimum and maximum targets are applied.

Figure 30 Prepared demand trace



The trace scaling algorithm is then used to grow the unreconciled OPSO trace to meet demand targets. Since there are negative operational demands in this example, first it adds a fixed amount equal to at least the maximum negative value to all periods to increase all periods to at least 0 MW. This factor is then removed after completing the growing process. The targets of the unreconciled OPSO trace, and as well as the trace adjusted for negative demand, are summarised in Table 8. All targets represent an increase to the reference trace except for Summer Max in this example, but negative growth (particularly of minimum demand) may occur.

Table 8 Prepared demand trace and targets

	Prepared trace Unreconciled OPSO trace	Target	Unreconciled OPSO trace adjusted for negative demand	Targets adjusted for negative demand
Summer Max (MW)	13,862	13,450	25,744	25,331
Winter Max (MW)	11,490	13,057	23,372	24,938
Minimum (MW)	-2,970	-2,370	8,911	9,512
Energy (GWh)	52,631	57,481	156,714	161,565

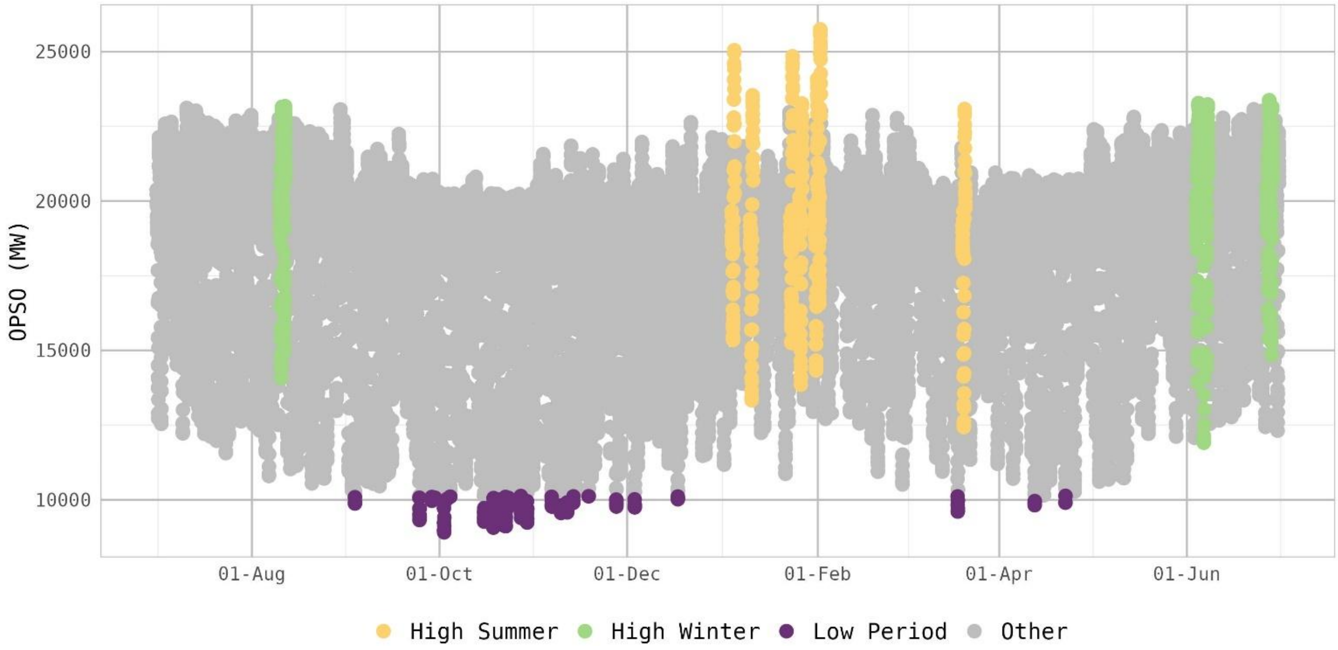
The series is then categorised into *n* highest-demand days in summer (using daily maximum as the reference), *n* highest demand days in winter, *p* lowest demand half-hour periods. In this example,

n = 7 days

p = 120 half-hour periods

The day-type categorisation (High Summer, High Winter, Low Period and Other) is displayed in Figure 31.

Figure 31 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 unreconciled OPSO adjusted for negative demand trace* using the information from Table 8.

Table 9 Scaling ratios (GWh)

Day-type category	Unreconciled OPSO trace adjusted for negative demand	Target/Base ratio
Summer high days	3,242	0.98
Winter high days	3,277	1.07
Low periods	586	1.07

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 adjusted for negative demand*.

Table 10 Resulting energy (GWh)

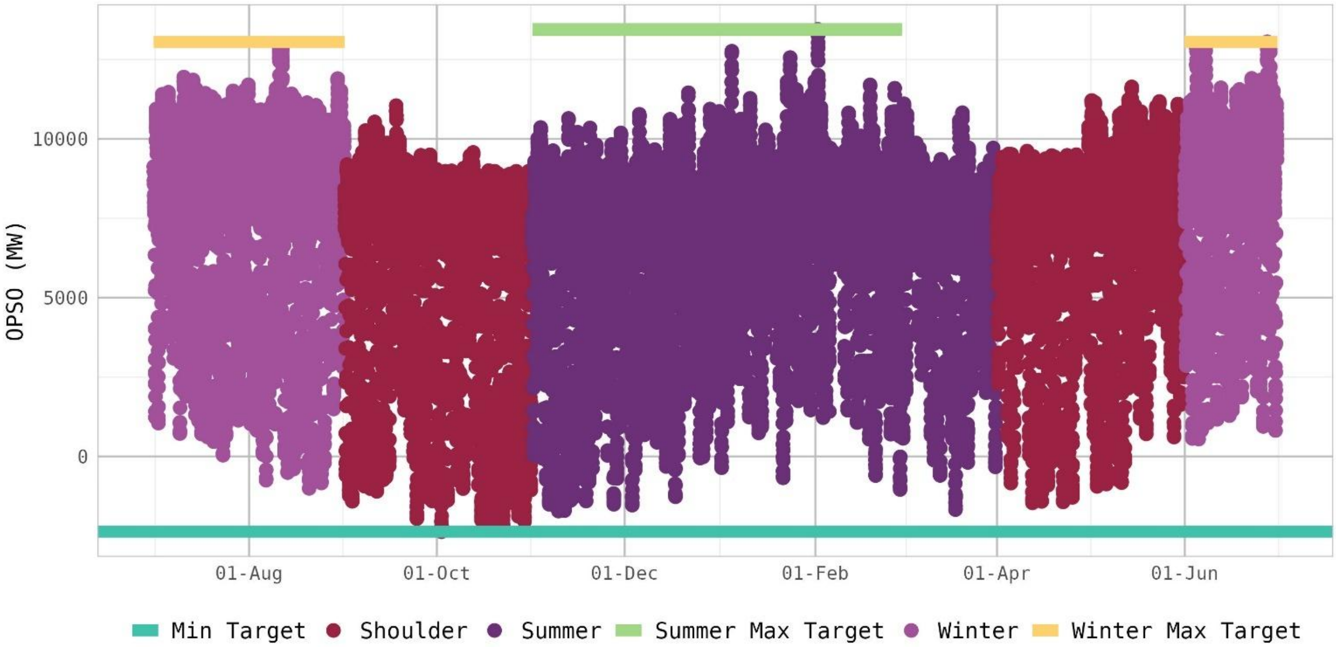
	Resulting value
Summer high days	3,190.42
Winter high days	3,497.20
Low periods	622.33
Remaining energy difference	154,254.82

The remaining energy difference from Table 10 equates to a 1.03% 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 32.

Table 11 Check of grown trace against targets

	Unreconciled OPSO trace adjusted for negative demand	Targets adjusted for negative demand	Grown trace (adjusted for negative demand)
Summer Max (MW)	25,744	25,331	25,331
Winter Max (MW)	23,372	24,938	24,938
Minimum (MW)	8,911	9,512	9,512
Energy (GWh)	156,714	161,565	161,565

Figure 32 Grown trace and targets



The check summarised in Table 11 reveals that all targets have been met. In this example the algorithm converged in a single iteration. As explained in the methodology section, after each iteration, the algorithm assesses whether the targets have been achieved. If not, the process is repeated until they are achieved.

Following the second pass, the process moves to the third pass, where electrification is added to OPSO.

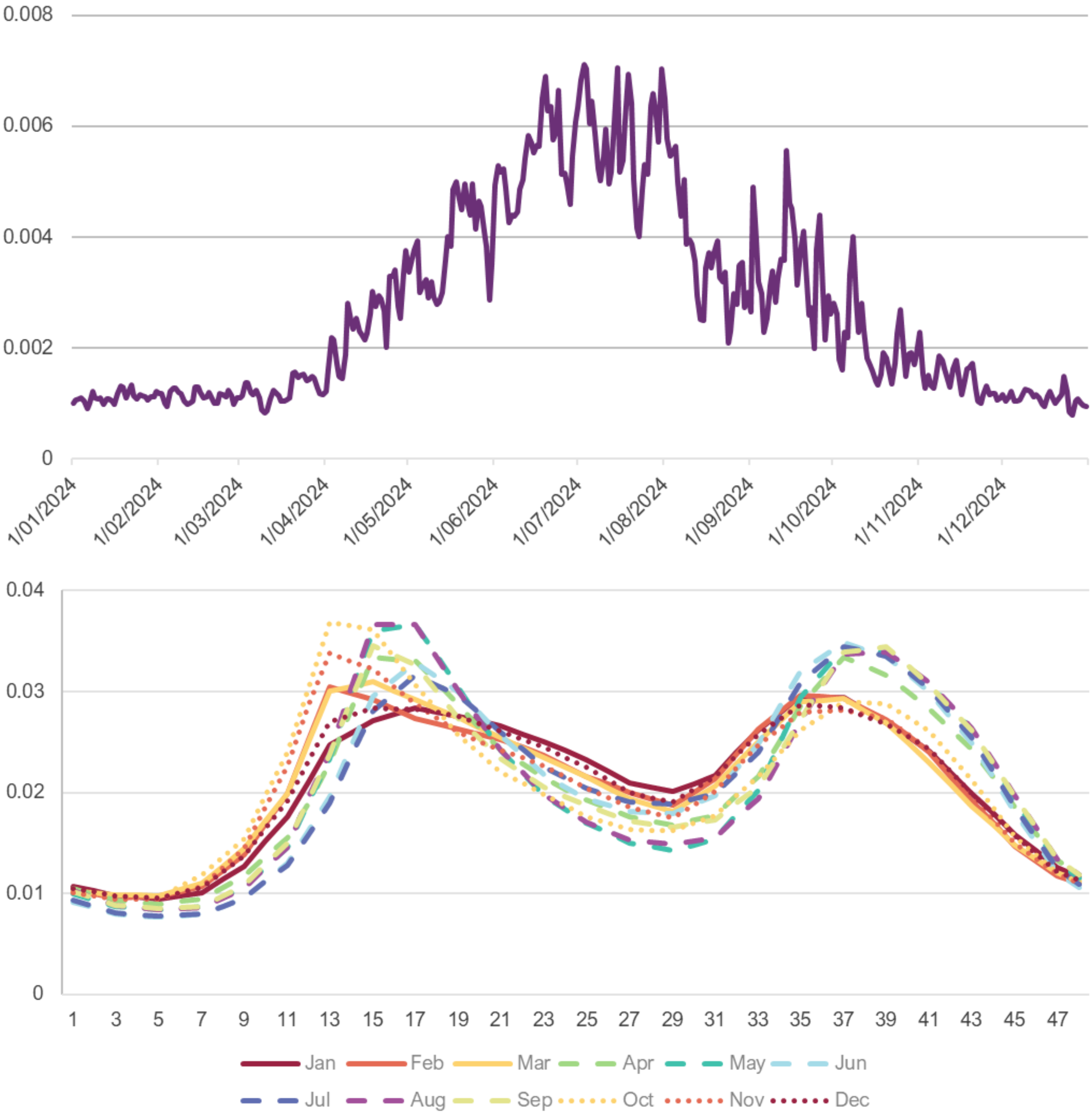
As explained in the IASR, newly electrified loads are assumed to mirror existing gas temporal consumption patterns, and are added as follows:

- 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 year, peaking in winter with heating loads, and diurnally with a morning and evening peak. Annual residential electrification is disaggregated to half-hourly values through a two-stage process:

- First, annual residential electrification is disaggregated into daily values using the proportion of daily gas consumption to annual gas consumption, based on daily tariff V gas consumption data from the reference year in each region.
- Second, daily electrification was further disaggregated to half-hourly values. Half-hourly weight profiles are derived from hourly tariff V gas consumption data interpolated to half-hourly values from Victoria in 2024 for each month of the year. The half-hourly profile shape is dependent on temperature, with distinct seasonal patterns and shift of day-light savings forward or backward.

This profile is used in other regions by adjusting the impact of temperature and day-light saving changes. Weightings used for disaggregating annual to half-hourly residential electrification are illustrated in Figure 33.

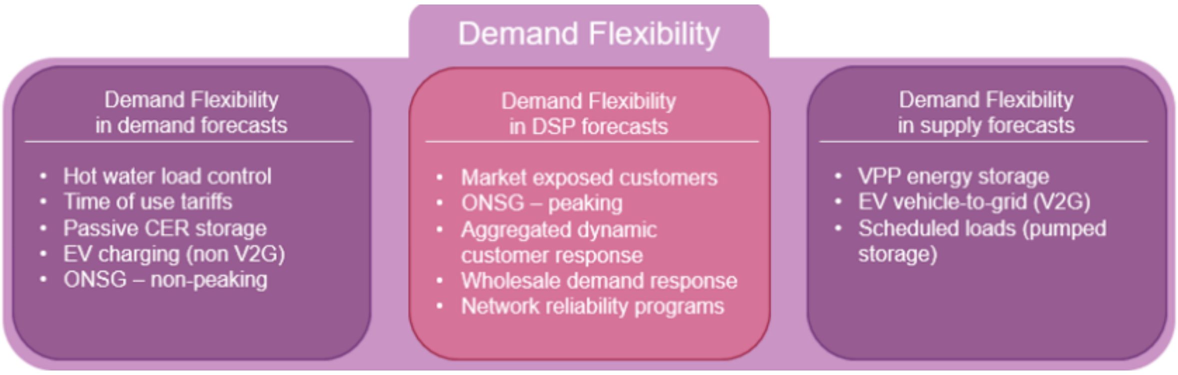
Figure 33 Weightings of annual to daily (top) and daily to half-hourly values (bottom) for residential electrification using historical gas consumption in 2024



A8. Demand flexibility

AEMO currently incorporates demand flexibility across various aspects of its forecasting approach:

- **Demand flexibility in demand forecasts**: Where demand flexibility does not respond to wholesale market price fluctuations but instead follows regular daily patterns (for example, hot water load control or EV charging control in response to TOU tariffs) it is incorporated within AEMO's maximum and minimum demand models. This reflects their consistent operational patterns, providing a stable offset within demand forecasts and capturing their contributions to overall load shape evolution.
- **Demand flexibility in demand side participation (DSP) framework**: Where demand flexibility aligns with wholesale market price or reliability-responsive demand, it is included within the DSP framework. This allows for demand adjustments in response to market signals.
- **Demand flexibility in supply forecasts**: Where demand flexibility responds to wholesale market incentives, rather than retail tariffs (for example, scheduled loads, VPP energy storage, EV VPP/V2G), it is incorporated within AEMO's supply forecasting dispatch models to align its modelled dispatch with the modelled wholesale market conditions.



Within the demand forecasting methodology, cyclical and uncoordinated demand flexibility is incorporated across several aspects including:

- Hot water load control.
- EV charging behaviours (not part of a VPP or V2G).
- Operating behaviour of 'uncoordinated' CER storage (not part of a VPP).
- Operation of a customer's own generation facilities (known as other non-scheduled generation (ONSG) (non-peaking)).

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	Consumer energy resources
COP	Coefficient of performance
DER	Distributed energy resources
DSP	Demand side participation
EDA	Exploratory data analysis
ESS	Energy storage systems
EV	Electric vehicle
FiTs	Feed-in tariffs
GFC	Global Financial Crisis
GWh	Gigawatt hour/s
HD	Heating degree
HDD	Heating degree day
HIA	Housing Industry Association
ISP	Integrated System Plan
kW	Kilowatts
LIL	Large industrial load/s
LNG	Liquefied natural gas
MD	Maximum demand
MMS	Market Management System
MW	Megawatt/s
NEM	National Electricity Market
NMI	National meter identifier
NSG	Non-scheduled generation
ONSG	Other non-scheduled generators
OPSO	Operational demand as sent out
POE	Probability of exceedance
PVNSG	PV non-scheduled generators
PVROOF	Rooftop PV
STC	Small-scale technology certificate
V2H	Vehicle-to-home discharging

Abbreviation	Full name
VPP	Virtual power plant
WEM	Wholesale Energy Market