FORECASTING METHODOLOGY INFORMATION PAPER

2016 NATIONAL ELECTRICITY FORECASTING REPORT

Published: **July 2016**

AEMO
AUSTRALIAN ENERGY MARKET OPERATOR

IMPORTANT NOTICE

Purpose

AEMO has prepared this document to provide information about the methodology, data and assumptions used to produce the *2016 National Electricity Forecasting Report*, as at the date of publication.

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Acknowledgement

AEMO acknowledges the support, co-operation and contribution of all participants in providing data and information used in this document.

Version control

Version	Release date	Changes
1	29/7/2016	

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CHAPTER 1. INTRODUCTION

The *National Electricity Forecasting Report* (NEFR) provides independent electricity consumption forecasts over a 20-year forecast period for the National Electricity Market (NEM), and for each NEM region. This report outlines the methodology used in the annual operational consumption, maximum demand, and minimum demand forecasting process for the 2016 NEFR.

1.1 Key definitions

AEMO forecasts are reported as:

- **Annual operational consumption**[1]:
  - Includes electricity used by residential and business (commercial and industrial) consumers, and distribution and transmission losses.
  - Includes electricity drawn from the electricity grid, supplied by scheduled, semi-scheduled and significant non-scheduled generating units , but not generation from rooftop photovoltaic (PV) and other small non-scheduled generation (SNSG).[2]
  - Is measured in gigawatt hours (GWh).
  - Is presented on a "sent-out"[3] basis (that is, the electricity supplied to the market, excluding generator auxiliary loads from the total output of generators).
- **Operational maximum (minimum) demand**: the highest (lowest) level of electricity drawn from the transmission grid at any one time in a year. It is measured on a daily basis, averaged over a 30 minute period. Maximum and minimum demand is measured in megawatts (MW), and the forecasts are also presented this year on a "sent-out" basis.[4]

In the 2016 NEFR, consumption and demand forecasts are based on this sector breakdown:

- **Residential**: Residential customers only.[5]
- **Business**: Includes industrial and commercial users. Recognising different drivers affecting forecasts, the business sector is further split into:
  - Liquefied Natural Gas (LNG) – associated with the production of LNG for export.
  - Coal mining – customers mainly engaged in open-cut or underground mining of black or brown coal.
  - Manufacturing – traditional manufacturing business sectors, with energy-intensive operations and electricity consumption growth that is projected to be flat due to ongoing economic restructuring (see Section 2.2 for more details). This excludes food and beverage manufacturing, which is growing, and projected to continue growing, with population.
  - Other business – business customers not covered by the categories above, which broadly are projected to grow with population in the forecast period. This group is dominated by services businesses, such as education, health care, telecommunications, and finance services, and also includes transport and construction services. Food and beverage manufacturing is a projected growth sector that is included in this group.

[1] More detailed definitions are available at: http://www.aemo.com.au/media/Files/Other/planning%202016/Operational%20Consumption%20definition%20%202016%20update.pdf

[2] Rooftop PV and SNSG generally covers generators smaller than 30 MW.

[3] Measured at the connection point between the generating system and the network.

[4] In previous NEFRs, maximum demand was presented on as "as generated" basis. Forecast components to calculate forecasts "as generated" are available on AEMO's online dynamic interface: http://forecasting.aemo.com.au.

[5] In previous NEFRs, residential demand was combined with commercial and light industrial demand as "residential and commercial" demand.

Other key definitions used in the 2016 NEFR are:

- **Probability of exceedance (POE)**: the likelihood a maximum or minimum demand forecast will be met or exceeded.
  - The 2016 NEFR provides 10% POE maximum demand forecasts, which are expected to be exceeded, on average, one year in 10.
  - Minimum demand forecasts are based on a 90% POE, which are expected to be met or exceeded, on average, nine years in 10 (meaning the actual demand is expected to be below the forecast minimum only, on average, one year in 10).
- **Rooftop photovoltaic (PV)**: A system comprising one or more PV panels, installed on a residential or commercial building rooftop to convert sunlight into electricity for use by that customer. PV systems larger than 100 kW but smaller than 30 MW are included in the small non-scheduled generation (SNSG) forecast. The 2016 NEFR does not consider utility-scale solar (larger than 30 MW), which generates to the grid.
- **Benefits index**: To track changing household use of technology, AEMO developed a benefits index as a measure of the energy services that electric appliances provide. This index reflects the utility that electricity users get from using appliances, based on the number of appliances, the hours of use, and their capacity (for example, light output, volume of refrigeration/freezer capacity, television screen size). This work is based on electricity usage data at individual appliance categories from the Australian Government Department of Industry, Innovation and Science, published in 2015 in the *Residential Baseline Study for Australia 2000 – 2030*.[6]

1.2 Summary of scenarios/sensitivities

AEMO has updated its scenarios framework for forecasting and planning publications. Following this update, all AEMO's major reports[7] are exploring a range of sensitivities that represent likely pathways for Australia across weak, neutral, and strong economic and consumer outlooks (assumptions are detailed below).

Table 1 2016 NEFR sensitivities

Driver	Weak sensitivity	Neutral sensitivity	Strong sensitivity
Population growth	ABS projection[8] C	ABS projection B	ABS projection A
Economic growth	Weak	Neutral	Strong
Consumer	Low confidence, less engaged	Average confidence and engagement	High confidence and more engaged
Electricity network charges – five years	Current AER determinations, fixed after five years		
Electricity retail costs and margin	Assume current margins throughout		
Technology uptake	Hesitant consumer in a weak economy	Neutral consumer in a neutral economy	Confident consumer in a strong economy
Energy efficiency uptake	Low	Medium	High

[6] Available at: http://www.energyrating.gov.au/document/report-residential-baseline-study-australia-2000-2030.
[7] *National Electricity Forecasting Report, National Gas Forecasting Report, NEM Electricity Statement of Opportunities, Gas Statement of Opportunities*, and *National Transmission Network Development Plan*.
[8] Australian Bureau of Statistics, 2013, *Population Projections, Australia 2012 (base)*, cat. no. 3222.0.

1.3 Changes since the 2015 NEFR

1.3.1 New forecasting methods

This NEFR continues a major shift in AEMO's forecasting methods that commenced with the *2015 National Gas Forecasting Report* (NGFR). AEMO is delivering more detailed "bottom-up" models that embrace a mix of economic and technical methods to better capture the continuing transformation of the energy supply and demand system.

This transformation, since the mid-late 2000s, has been driven by changes in technology that:

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

Business consumption has also been impacted by changes in the Australian economy, with the Global Financial Crisis[9], mining boom, and subsequent commodity price collapse all contributing to a continued transition away from energy-intensive industry.

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

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

- Is highly aggregated (so does not provide fine detail).
- Is historic (so may not be indicative of a changing future).
- Does not reveal dynamics that originate beyond the grid.

This approach has made it harder, in the changing energy environment, to quickly detect and understand key trends.

In response, AEMO is now integrating new data streams from beyond the grid, such as:

- Consumer energy meter data.
- Complementary data from other agencies and sources, like national account data from the Australian Bureau of Statistics, to support greater understanding of structural change in the economy.

By integrating detailed data from beyond the grid, AEMO can shift to finely segmented "bottom-up" forecasting approaches that embrace forward-looking economic and structural methods, and rely less on historic data that may not be indicative of Australia's next generation economy and consumer.

1.3.2 Policy assumptions

Australia has set a target to reduce carbon emissions by 26–28% below 2005 levels by 2030, which builds on the 2020 target of reducing emissions by 5% below 2000 levels.

The Energy Council of the Council of Australian Governments (COAG) has agreed that the contribution of the electricity sector should be consistent with national emission reduction targets, and has advised that a 28% reduction from 2005 levels by 2030 is an appropriate assumption for AEMO to use in forecasting and planning. For the 2016 NEFR, AEMO has assumed the achievement of this target will be supported by energy efficiency trends[10], electricity pricing trends, and coal-fired generator retirements.

[9] Global Financial Crisis (GFC) refers to the period of severe prolonged economic downturn tracing back to the collapse of the United States housing market in 2007.

[10] This includes the expected impacts of the National Energy Productivity Plan (NEPP) targeting a 40% improvement in energy productivity between 2016 and 2030.

While it is not yet known if abatement costs will affect prices, AEMO's modelling has assumed a partial impact in the 2016 NEFR forecasts, with retail prices assumed to increase by approximately 2.5% per annum[11] for the 10 years from 2020.

1.3.3 Technology assumptions

The 2016 NEFR includes forecasts for the uptake and use of battery storage technologies, assuming this is implemented with an energy management system that manages charging and discharging operations.

Rooftop PV projections now include forecasts of panel age, and 2016 NEFR forecasts consider derated generation efficiency as a result of panel age.

Electric vehicle uptake forecasts are not included in the 2016 NEFR. AEMO is, however, using the published forecasts as the baseline for an electric vehicles impact assessment in a separate 2016 *Insight* publication.

1.3.4 Survey and interviews from the largest energy users

AEMO continues to survey and interview the largest industrial energy users to inform its energy and demand forecasts. In the 2016 NEFR, the survey has been used to inform near-term and highly probable adjustments to the separately-determined business sector forecasts.

Forecast adjustments are now probability-weighted, based on:

- Discussions with the relevant energy users.
- An assessment of economic conditions relevant to the industry sectors, users, and the forecast sensitivities (weak/neutral/strong).

1.3.5 Consumer behaviour

AEMO has implemented the following improvements to its modelling of consumer behaviour:

- **Energy efficiency savings**: AEMO has refined energy efficiency projections and their representation in the forecast models. In the 2015 NEFR, a small post-model adjustment was included for energy efficiency, to add to an amount that was assumed to be captured in the historic data inputs to a regression-based model of consumer demand. The 2016 NEFR uses new, forward-looking economic forecasting models to model the full amount of projected energy efficiency savings. Projected savings have been separately forecast at an appliance level, and have been tuned to ensure consistency with consumer trends, as measured in recent meter data.

  The projections now include a 20% rebound effect[12], based on observed meter data trends. Rebound refers to an increase in consumption that is enabled by the lower operating cost of energy-efficient appliances.
- **Price elasticity of demand:** Price elasticity of demand adjustments are now only applied for permanent increases in price, measured through the bill of a typical consumer. Estimates have been revised down to avoid overlap with energy efficiency, recognising that energy efficiency represents a structural response to price that is occurring with shorter time-lags. Temporary price changes, such as price reductions due to lower network charges, are no longer assumed to trigger a permanent consumption response.
- **Consumption response from rooftop PV and battery storage:** The 2016 NEFR includes an assumed increase in consumption resulting from the impact of lower-cost energy, made available from rooftop PV and battery storage. Energy consumption is assumed to increase by 10% of the energy generated by rooftop PV. Similarly, energy consumed from batteries is assumed to

[11] Before inflation.
[12] For the neutral sensitivity. The strong and weak sensitivities use 30% and 10% respectively in most cases.

increase by 10% for energy charged from sunshine, and by 5% for energy charged from the grid during off-peak periods.

- **West-facing rooftop PV panels:** The projected uptake of capacity is now assumed to shift towards increasing westerly panel orientation, in response to projected consumer incentives from peak prices during the evening. The forecast assumes that 10% of new installed capacity by 2035–36 will be west-facing.

1.3.6 Maximum and minimum demand

The first minimum demand forecasts were included in the 2015 NEFR for South Australia. The 2016 NEFR extends last year's work to include all NEM regions.

The maximum and minimum demand forecasts are based on a new simulation work flow. Models of 30-minute demand have been reviewed, removing load closures from the historical dataset. The models were used in a weather simulation procedure able to produce a statistical distribution of half-hourly demand. Half-hourly demand was then forecast using integrated growth models for the individual components and drivers of demand.

1.3.7 LNG

Since 2015, AEMO has revised down electricity use by Queensland's LNG export industry, to reflect operational data now available as the facilities have moved into production.

CHAPTER 2. BUSINESS ANNUAL OPERATIONAL CONSUMPTION

This chapter outlines the methodology used to develop annual operational consumption forecasts for the business sector, which comprises both industrial and commercial users.

AEMO classified business users according to the Australian and New Zealand Standard Industrial Classification (ANZSIC)[13] code. Recognising different drivers affecting forecasts, the business sector was divided into two main categories:

- Manufacturing (excluding food and beverage manufacturing): as defined in Division C of the ANZSIC code, with energy-intensive operations and electricity consumption growth that is projected to be flat or to decline due to ongoing economic restructuring.
- Other business: this group is dominated by services businesses, such as education, health care, telecommunications, and financial services, and also includes transport and construction. Food and beverage manufacturing, which generally is projected to grow with population in the forecast period, was included in this group.

Within the manufacturing category, the forecast for the LNG manufacturing sector was produced separately.

The coal mining sector forecast was also produced separately within the other business category.

Changes to business forecasts in the 2016 NEFR include:

- Recognising structural changes in the economy by identifying business sectors exhibiting different levels of growth and modelling them separately. This disaggregated approach mitigates the risk of bias which could otherwise arise due to the dominating effect of certain sectors.
- Developing three new econometric models to forecast business consumption:
  - A short-term base model for total business consumption for the first year in the forecasting horizon.
  - Two long-term models for the two main categories (manufacturing and other business).
- Surveying and interviewing most large industrial customers, seeking advice on near-term and highly probable adjustments to forecasts.
- Expanding post-model adjustments to account for emerging factors, such as growth of rooftop PV and battery storage, and energy efficiency growth.

2.1 Data sources

Electricity consumption data

Business electricity consumption data had two sources:

- AEMO's meter data.
- The Energy Statistics Data (ESD)[14] published by the Office of the Chief Economist. The ESD provided a means to segment total business consumption into the main categories of manufacturing and other business sectors.

[13] For more information on ANZSIC code classifications, refer to the ABS website: http://www.abs.gov.au/ausstats/abs@.nsf/0/20C5B5A4F46DF95BCA25711F00146D75?opendocument.

[14] http://www.industry.gov.au/Office-of-the-Chief-Economist/Publications/Pages/Australian-energy-statistics.aspx.

Public data sources

AEMO's long-term forecast models used macroeconomic variables. AEMO sourced information on these economic indicators from publicly-available data.[15]

Other data sources

AEMO used consultant projections for some inputs.[16] For the business sector models this included:

- Retail electricity price projections.[17]
- Household disposable income forecasts.
- Gross state product forecasts.
- Energy efficiency forecasts.
- Rooftop PV generation forecasts.

2.2 Methodology

2.2.1 Process overview

AEMO took a hybrid modelling approach to forecast business consumption:

- First, a short-term base model was developed to forecast 2015–16 annual underlying consumption[18], which was calibrated using 2014–15 daily data, to provide a starting point for the forecast not affected by historic long-run macroeconomic trends, structural economic changes, and economic shocks.
- Two long-term models for the manufacturing sector and the other business sector were then developed to estimate the elasticities of demand corresponding to various economic drivers, which captured and quantified the potential impacts of different economic drivers on electricity consumption. These models used annual data from 2001–02 to 2013–14.
- AEMO obtained forecasts of various economic drivers, externally or internally, and applied the corresponding elasticities of demand to produce annual consumption forecast beyond 2015–16.[19]
- Post-model adjustments were made to account for potential impacts that were not captured in the models, including plant expansion/closure and energy efficiency growth.
- Finally, consumption met by rooftop PV generation and battery storage was removed to get delivered consumption.[20]

Figure 1 shows the steps undertaken to derive the underlying business consumption forecast. Figure 2 shows the compilation process to get from underlying consumption forecast to operational consumption forecast.[21]

[15] Please see Table 32 in Appendix K for a list of references to datasets used.
[16] Please see Table 32 in Appendix K for a list of references to datasets used.
[17] Please see Appendix B.
[18] Underlying demand is defined as behind the meter consumption for a household or business. Please see Appendix A for a full list of demand definitions.
[19] Forecasts for the LNG manufacturing sector and the coal mining sector are produced separately.
[20] See Appendix A for a full list of demand definitions.
[21] See Appendix A for a full list of demand definitions.

Figure 1 Process flow for business consumption forecasts

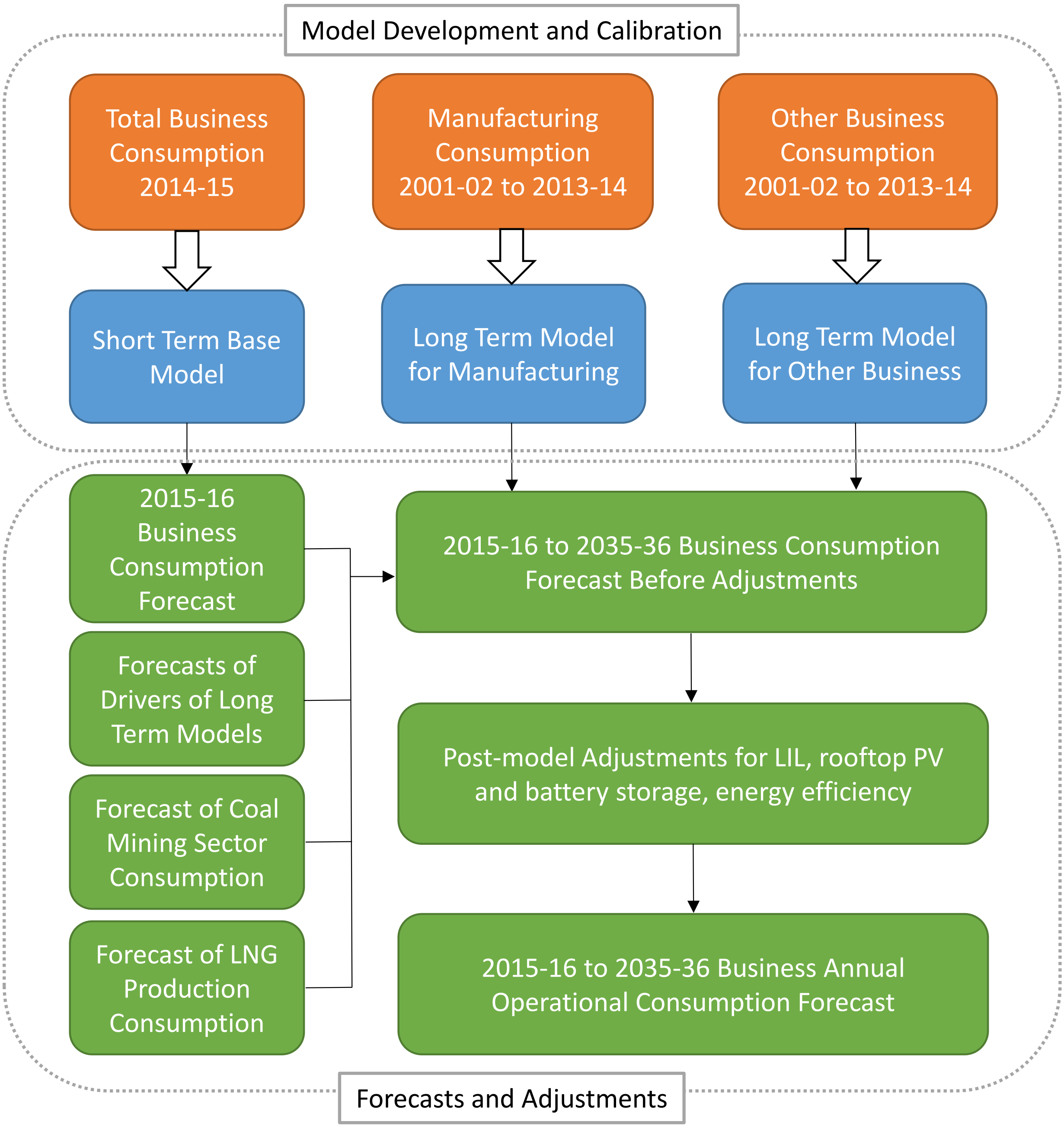
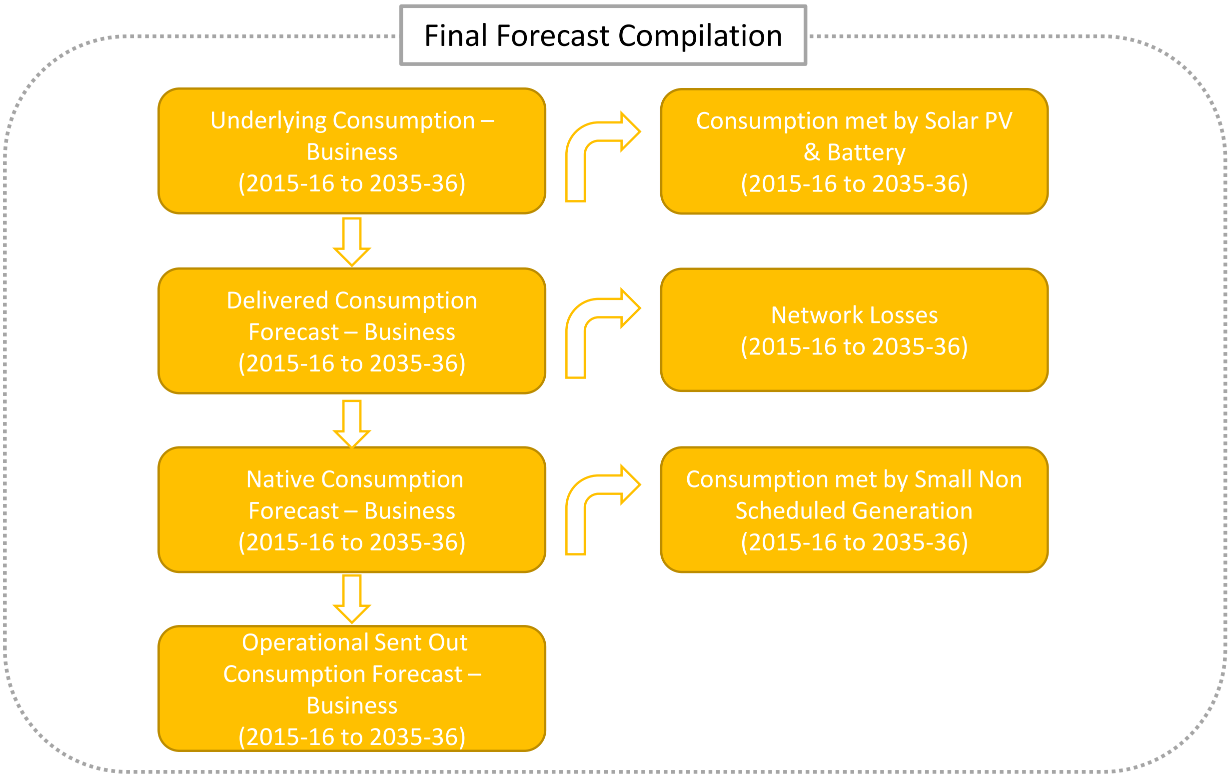


Figure 2 Process flow business forecast compilation



2.2.2 Short-term base model

A short-term base model was developed to forecast 2015–16 business consumption as the starting point of the 20-year forecast. This forecast reflected the most current business conditions, and was weather normalised. The short-term model was segmented by summer and winter to produce more fine-tuned elasticity parameters for heating degree days (HDD) and cooling degree days (CDD).[22]

The econometric models are presented below, where i indicates days.

Winter model

This comprised the months of April to September:

$$Bus\_Con_i = \beta_0 + \beta_1 HDD_i + \beta_2 CDD_i + \beta_3 Holiday_i + \beta_4 Saturday_i + \beta_5 Sunday_i + \varepsilon_i$$

Summer model

This comprised the months of October to March:

$$Bus\_Con_i = \beta_0 + \beta_2 CDD_i + \beta_3 Holiday_i + \beta_4 Saturday_i + \beta_5 Sunday_i + \varepsilon_i$$

The variables were defined as shown in Table 2.

[22] Exceptions to this were Queensland, which produces statistically insignificant estimates for HDD, and Tasmania, which has no CDD. For these states, a single full year model was used.

Table 2 Variable description of short term base model

Variable names	ID	Units	Description
Business Consumption	Bus_Con	MWh	Total business consumption including rooftop PV but excluding network losses.
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 public holidays	Holiday	{0,1}	A dummy variable that captures the ramp-down in industrial processes, and consequently in electricity consumption, during public holidays.
Dummy for Saturdays	Saturday	{0,1}	A dummy variable that captures the ramp-down in industrial processes, and consequently in electricity consumption, on Saturdays.
Dummy for Sundays	Sunday	{0,1}	A dummy variable that captures the ramp-down in industrial processes, and consequently electricity consumption, on Sundays.

The following steps outline how business consumption forecast for 2015–16 was derived.

Step 1. Historical business consumption data

Business consumption is met by electricity from both the grid and off-grid rooftop PV generation.

Transmission losses and distribution losses were removed from the meter data to get real consumption from the grid. Then the consumption from rooftop PV generation was added to get the total business consumption. A further adjustment was made to account for business closures. For all businesses that had closed before the time of modelling, their consumption was removed from the historic data.

Step 2. Econometric models for each state

For each state, daily data from 2014–15 was used to estimate the coefficients of the econometric models. The length of the data used was intentionally short, so the parameters reflected the most current business conditions and were not influenced by long-term factors such as policy shocks or technology changes.

Step 3. 2015–16 business consumption forecast

The elasticity parameters derived in step 2, in conjunction with weather forecasts, were used to project the 2015–16 consumption. This formed the starting point of the long-term forecasts.

2.2.3 Long-term models

Long-term model for manufacturing

This model was used to estimate the impacts of various economic drivers on manufacturing electricity consumption over the long term.

The econometric model was as follows, where t indicates years:

$$\ln(Man\_C_t) = \beta_0 + \beta_1 \ln(Input\_PPI_t) + \beta_2 \ln(GSP_t) + \delta_1 GFC_t + \varepsilon_t$$

The variables were defined as shown in Table 3.

Table 3 Variable description of long term model for manufacturing

Variable names	ID	Units	Description
Manufacturing consumption	Man_C	GWh	Manufacturing sector consumption.
Input Producer Price Index	Input_PPI	Index	An input PPI measures the rate of change in the prices of goods and services purchased as inputs by the producer for the manufacturing sector.
Gross State Product	GSP	$ million (FY 2012 real term)	GSP is a measurement of the economic output of a state. It is the sum of all value added by industries within the state.
Dummy for the Global Financial Crisis	GFC	{0,1}	A dummy variable that captures the economic shock from the Global Financial Crisis.

The coefficients β_1 and β_2 can be interpreted as the elasticities of manufacturing consumption corresponding to respective explanatory variables. More precisely, they give the percentage change in manufacturing consumption in response to a 1% change in Input PPI and GSP respectively (all else being equal).

Long-term model for other business

This model was used to estimate impacts of various economic drivers on other business electricity consumption over the long term. The econometric model was as follows[23], where t indicates years:

$$\ln(Other\_C_t) = \beta_0 + \beta_1 \, ln(POP_t) + \beta_2 \, ln(HDI_t) + \beta_3 \, ln(Elec\_P_t) + \delta_1 HDD_t + \delta_2 CDD_t + \delta_3 GFC_t + \varepsilon_t$$

The variables were defined as shown in Table 4.

Table 4 Variable description of long term model for other business

Variable names	ID	Units	Description
Other consumption	Other_C	GWh	Other business sector consumption.
Population	POP	Persons	Population level of a state (net of deaths, births, and migration).
Household disposable income	HDI	$ million (FY 2012 real term)	Real level of money that households have available for spending and saving after income taxes have been deducted.
Electricity price	Elec_P	$/MWh	Retail electricity price for business users.
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 the Global Financial Crisis	GFC	{0,1}	A dummy variable that captures the economic shock from the Global Financial Crisis.

The coefficients β_1, β_2, and β_3 can be interpreted as the elasticities of other business consumption corresponding to respective explanatory variables. More precisely, they give the percentage change in other business consumption in response to a 1% change in population, household disposable income, and electricity price respectively (all else being equal).

After the coefficients of the long-term models were estimated for each state, the following steps were followed to derive consumption forecasts. The process applied to both the manufacturing consumption forecast and the other business consumption forecast.

[23] Note that HDD is not included in the model for Queensland and CDD is not included in the model for Tasmania.

Step 1. Economic drivers

AEMO first obtained forecasts of the economic drivers.[24]

Step 2. Annual percentage change of economic drivers

The annual percentage change of the economic drivers from the forecast was then calculated.

Step 3. Annual percentage change in consumption

AEMO then calculated the annual percentage change in electricity consumption in response to changes in the economic drivers, using the elasticities of demand estimated from the long-term models.

Step 4. Derive annual consumption forecast

Using the 2015–16 business consumption forecast as the starting point, the annual consumption forecast over the 20-year forecast horizon was then derived, using results from Step 3.

Step 5. Total business forecast

The forecasts of manufacturing consumption and other business consumption were combined to get the total business consumption forecast.

2.2.4 Coal mining sector consumption forecast

AEMO sent surveys to coal mining companies responsible for about 4,000 gigawatt hours (GWh) of electricity consumption in 2013–14 (representing about two-thirds of all electricity used by coal mining companies in the NEM). Responses were received from around 2,300 GWh, or almost 60% of the load surveyed. AEMO also talked to some companies providing port terminal services for the coal industry.

Since a significant portion of coal mines in the NEM states were covered through the survey process, the consumption forecast for the coal mining sector was based on survey results. For the remainder of coal mining consumption, AEMO forecast growth – in line with the survey results[25] – to be 1% in 2015–16, followed by no growth for three years, then growth of:

- 0.5% pa in the neutral scenario.
- 1.5% pa in the strong scenario.
- -0.5% in the weak scenario.

2.2.5 LNG production consumption forecast

Electricity consumption by the LNG industry was modelled separately by Lewis Grey Advisory.[26]

2.2.6 Post-model adjustments

Post-model adjustments were made to account for potential impacts that were not captured in the models.

The following adjustments were considered:

- Near-term and highly probable adjustments of large industrial load (LIL).
- Growth of business sector energy efficiency.
- Growth of rooftop PV and battery storage.

[24] Please refer to Table 32 in Appendix K for the sources of the forecasts.
[25] But taking into account some additional growth for new projects.
[26] Lewis Grey Advisory. *Projections of Gas and Electricity Used in LNG*, April 2016. Available at: http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/National-Electricity-Forecasting-Report .

Adjustment of Large Industrial Load (LIL)

In the NEM, large industrial customers within the manufacturing and mining sectors make up a very significant component of consumption. While major changes to large industrial operations are relatively infrequent, when they do occur they have a significant impact on regional forecasts.

To better understand the key drivers of consumption by such customers, and accommodate their outlook in the forecast, AEMO surveyed and interviewed the largest industrial consumers in the NEM.[27] The structured survey approach helped AEMO to understand how these customers would be likely to respond to changing market conditions (such as changing electricity prices), and to analyse the potential effect of these responses on electricity consumption.

LIL information sources

AEMO used the following information sources when developing LIL consumption forecasts:

- LIL questionnaire responses.
- Detailed discussion with LILs.
- Publicly-available information and announcements.
- Historical data from AEMO's Market Management System.

The following LIL survey process was used.

Step 1. Initial survey

AEMO distributed a survey to each identified LIL, requesting historical and forecast electricity consumption information. The survey asked for forecasts of annual electricity consumption and site maximum demand, under three scenarios:

- Neutral – reflecting the most likely forecast levels based on their current understanding and expectations about key drivers such as electricity prices, commodity prices, economic growth, and the Australian dollar remaining at US$0.75.
- Strong – reflecting higher production and electricity consumption under more favourable economic conditions than in the neutral scenario, such as higher GDP growth, and significantly increasing commodity prices over the next five years, tempered by the Australian dollar increasing to US$0.95.
- Weak – reflecting lower production and electricity consumption from the network under less favourable economic conditions than in the neutral scenario, such as lower GDP growth and commodity prices that remain approximately at current levels, although ameliorated somewhat by a depreciation in the Australian dollar to US$0.65.

The surveys also included a questionnaire that asked the LILs to rate how external drivers, including the cost of renewable technologies and energy efficiency, impact upon their business performance.

Step 2. Detailed interviews

Following the survey, AEMO conducted an interview process to review and discuss the responses.

On the basis of these interviews and surveys, AEMO made adjustments to the econometric forecasts for step changes such as expansions and closures which would not be captured by the econometric models. This was done as a post-model adjustment.

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

Adjustments for growth of rooftop PV and battery storage

Electricity generated by rooftop PV replaces electricity drawn from the grid, and thus reduces forecast business consumption.[28] AEMO's forecast of capacity for rooftop PV and battery storage was based on advice from external consultancy Jacobs.[29]

Adjustments for business sector energy efficiency

Savings from energy efficiency gains in the business sector reduce forecast business consumption.[30] The energy efficiency savings forecast was provided by Pitt & Sherry.[31]

2.2.7 Strong and weak scenarios

Strong and weak scenario sensitivities were developed in accordance with the characteristics of strong and weak economies:

- A strong economy is characterised by strong population growth, high consumer confidence, strong economic growth and also a strong Australian dollar.
- A weak economy is characterised by moderate population growth, low consumer confidence, weak economic growth and also a weak Australian dollar.

To quantify the inputs for the scenarios, AEMO approximated 90% POE and 10% POE reference periods from recent history, and assumed the Australian economy would transition from its current point to the respective scenarios over the five-year period from 2015–16 to 2020–21.

2.2.8 Desalination plant consumption forecast

Desalination plants use large amounts of electricity when operating at close to capacity. According to material in the public arena, desalination plants on average use about 4 MWh of power for every million litres of fresh water produced[32], depending on factors such as water salinity, temperature and quality, number of passes through osmosis, and transfer pumping included.

The amount of water required for desalination depends more on climatic conditions than on economic growth (although the latter does have impact through population growth and non-residential usage). AEMO therefore used the same assumptions for the neutral, strong, and weak scenarios, apart from in Victoria, where different demand assumptions were made based on different population growth assumptions. AEMO made assumptions on the type of operation and amount of desalinated water produced each year, based on discussions with plant operators, and materials in the public arena.

AEMO is forecasting significant usage of electricity for desalination only at the Victorian Desalination Plant, based on the water order to produce 50 GL in 2016–17.[33] Technical analysis in the *Water for Victoria* discussion paper suggests that two further water orders of 50 GL would be expected in the following two years, followed by a hiatus and then increasing use over time with growth in population and reduction in catchment availability.[34] The desalination plant consumption forecast was included in the adjustment of large industrial load (see Section 2.2.6).

[28] Please refer to Appendix C for more details.
[29] Jacobs. *Projections of uptake of small-scale systems*, June 2016. Available at: http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/National-Electricity-Forecasting-Report
[30] Please see Appendix D for more details.
[31] Pitt & Sherry. *Estimating the Effects of Energy Efficiency Policies and Programs on Usage of Electricity and Gas*, June 2016. Available at: http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/National-Electricity-Forecasting-Report .
[32] http://www.bloomberg.com/news/articles/2013-05-01/energy-makes-up-half-of-desalination-plant-costs-study.
[33] Aquasure Media Release, "Victorian Desalination Project called into service", 8 March 2016. Available at: https://www.aquasure.com.au/uploads/files/water%20order-1457491174.pdf. Viewed: 13 July 2016.
[34] Department of Environment, Land, Water and Planning discussion paper, *Water for Victoria*, 16 March 2016. Available at: http://haveyoursay.delwp.vic.gov.au/water-for-victoria/documents/32650/download. Viewed: 13 July 2016.

2.2.9 Automotive vehicle manufacturing exit

With the announced closure of Toyota and Holden in 2017–18[35], the complete closure of the automotive vehicle manufacturing industry becomes a highly probable scenario. AEMO consulted the Computable General Equilibrium (CGE) modelling analysis, used by the Productivity Commission[36], to estimate the impact of the automotive manufacturing industry closure on annual electricity consumption. The process undertaken is outlined below.

Analysis of CGE Modelling Results

The CGE modelling results suggest the impact of automotive vehicle manufacturing closures will be predominantly felt in Victoria and South Australia. The modelling assumed the complete closure takes place over 2017–18.

AEMO used the CGE analysis on employment to estimate an electricity consumption per employee measure. This was then used to back-calculate the loss in electricity consumption due to closure of the automotive vehicle manufacturing industry (see the following section).

Although the Productivity Commission has estimated that employment in the economy as a whole will return to pre-closure levels by 2025–26, given the conservative growth outlook for manufacturing, AEMO has assumed that this will occur in other sectors of the economy and not in manufacturing.

Given that assumption, AEMO has used the CGE modelling results to estimate a permanent loss of consumption in manufacturing attributed to closures in the automotive vehicle manufacturing industry.

Estimating electricity consumption impacts

To estimate the total electricity consumption impact of automotive vehicle manufacturing industry closures, AEMO:

- Estimated electricity consumption per employee, by estimating the electricity input into the manufacturing process and spreading this across the number of employees.
- Aggregated this by projections from the Productivity Commission.

To estimate the electricity per employee measure, AEMO first estimated historic total electricity use in the industry. The Input-Output tables published by the Australian Bureau of Statistics (ABS)[37] contain dollar value estimates of inputs used in the production process for the supply of an output good, on an industry basis.

AEMO used this dataset to:

- First, estimate the direct and indirect[38] electricity consumption into the automotive vehicle manufacturing industry in dollars.
- Then, using a composite price ($/MWh) value, back-derive electricity consumption in that year.

Then, using the CGE analysis results and the ABS data for total employment, AEMO scaled electricity consumption to derive the total electricity consumed by employees in the industry, in Victoria and South Australia, then apportion this consumption by region.

After deriving the electricity consumption values using public data sources, AEMO validated the results through consultation with major automotive vehicle manufacturing industrial loads. After the validation process, AEMO used these calculations to adjust the final forecasts.

[35] ABC News, “Toyota to close: Thousands of jobs to go as carmaker closes Australian plants by 2017” (2014). Available: http://www.abc.net.au/news/2014-02-10/toyota-to-pull-out-of-australia-sources/5250114. Viewed 20 July 2016.
[36] Productivity Commission, “Australia’s Automotive Manufacturing Industry”, 2014; Productivity Commission Enquiry Report. Available: http://www.pc.gov.au/inquiries/completed/automotive/report/automotive.pdf. Viewed 20 July 2016.
[37] Australian Bureau of Statistics, Australian National Accounts: Input-Output Tables, 2012-13, “Table 2:Use Table- Input by Industry and Final Use Category and Supply by Product Group””. Available: http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/5209.0.55.0012012-13?OpenDocument. Viewed 20 July 2016.
[38] Gas consumed by other inputs used in the production process for automotive vehicle manufacturing.

CHAPTER 3. RESIDENTIAL ANNUAL OPERATIONAL CONSUMPTION

This chapter outlines the methodology used in preparing residential annual consumption forecasts for each NEM region, reported in the 2016 NEFR.

A generic forecast approach applied to all regions, with the single exception that there is no forecast cooling consumption for Tasmania because of cooler weather conditions in this region.

Residential consumption represents about 30% of total annual consumption in each region. It has been declining in recent years, due to:

- Increased penetration of rooftop PV panels.
- Appliance and building energy efficiency savings attributed to Federal and State energy efficiency programs.
- Increased residential prices (energy bill stress) also put downward pressure on household electricity consumption.

Residential consumption is affected by prevailing weather conditions, which impact heating consumption in winter months and/or cooling consumption in summer. The weather impact on annual consumption becomes more pronounced with increased penetration of reverse-cycle air-conditioners. While reverse-cycle air-conditioners were used predominantly for space cooling in the past, these appliances are also increasingly used for household heating.

Residential consumption forecasts over the next 20 years depend on these key drivers:

- Forecast growth in new connections increasing consumption.
- Forecast penetration of PV and battery storage, and forecast energy efficiency savings, offsetting consumption.

Because residential consumption is so sensitive to weather conditions, the forecasts are based on forecast standard weather conditions, measured in annual heating and cooling degree days, specific to each region.

3.1 Data sources

Residential consumption forecasts require a large set of input data.[39]

Two types of data were required for residential consumption forecasts.

First, the following actual data for 2013–14 and 2014–15 was required for each region to analyse the consumption trend:

- Quarterly total residential daily connections for each region (see Appendix E). Daily connections were estimated by interpolation of the quarterly values
- Estimates of daily de-rated generation from all registered and installed PV panels in each region (see Appendix C).
- Total delivered consumption to all residential customers in the region (see data definition in Appendix A).
- Daily actual weather measured in daily HDD and CDD (see Appendix F).
- Forecast annual weather standards measured in annual HDD and CDD (see Appendix F).

The following input data was required for forecasting annual residential annual consumption 2015–16 to 2035–36 for each region.

- Forecast annual (end of June) residential connections (see Appendix E).

[39] Please refer to Appendix B through to Appendix F for the relevant sources.

- Forecast annual heating and cooling degree days (see Appendix F).
- Forecast residential retail electricity prices (see details in Appendix B).
- Forecast annual energy efficiency savings for residential base load, heating and cooling consumption (see Appendix D).
- Forecast gas to electric appliance switching.[40]
- Forecast de-rated and normalised annual rooftop PV generation and storage (see Appendix C).
- Forecast electricity appliance uptake (see Appendix E).

3.2 Methodology

3.2.1 Process overview

Figure 3 shows the steps undertaken to derive the underlying residential consumption forecast. Figure 4 shows the compilation process to get from underlying consumption forecast to operational consumption forecast.[41]

[40] AEMO. *2015 National Gas Forecasting Report Methodology Information Paper*. Available at: http://www.aemo.com.au/Gas/National-planning-and-forecasting/National-Gas-Forecasting-Report .
[41] See Appendix A for a full list of demand definitions.

Figure 3 Process flow for residential consumption forecasts

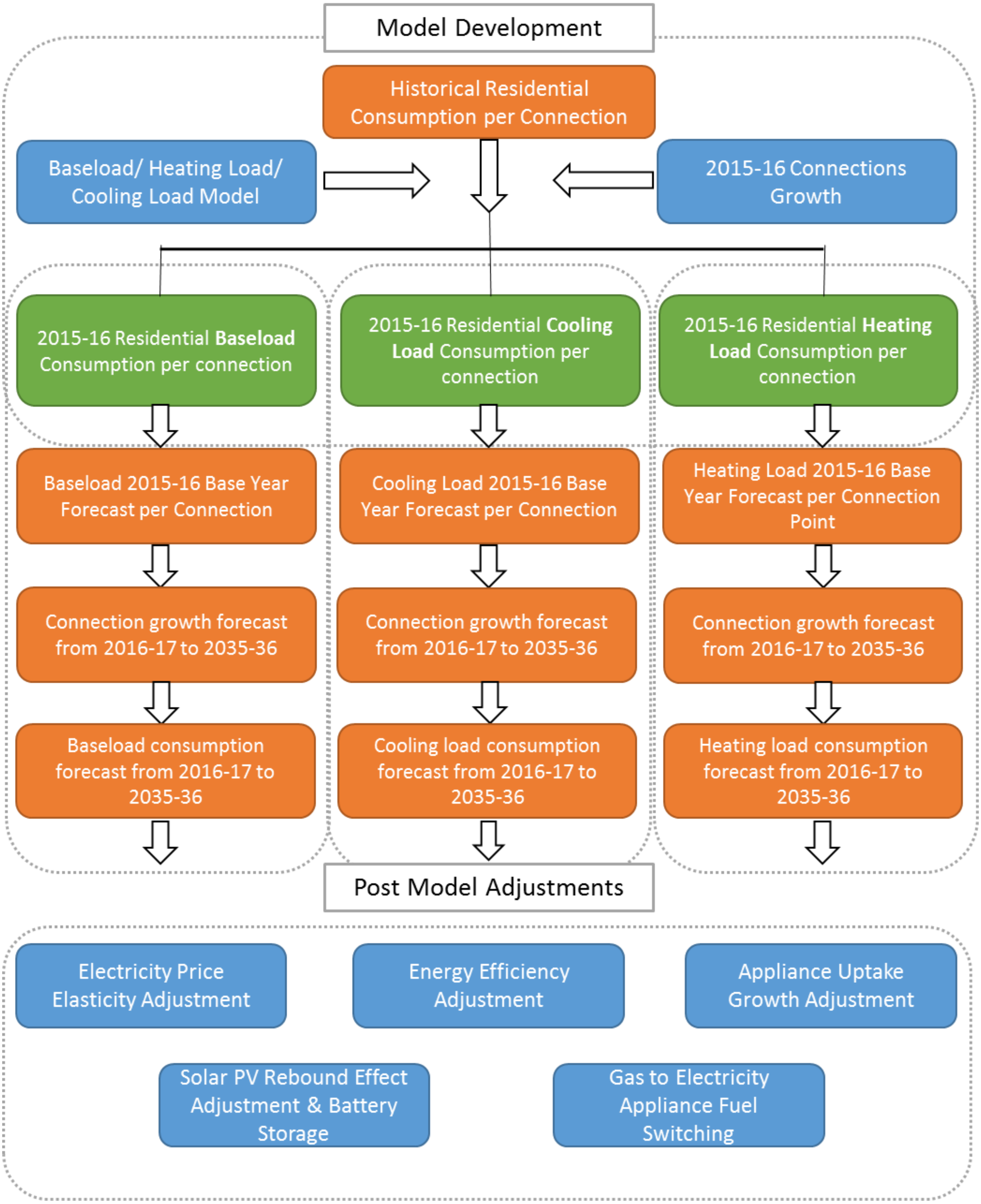
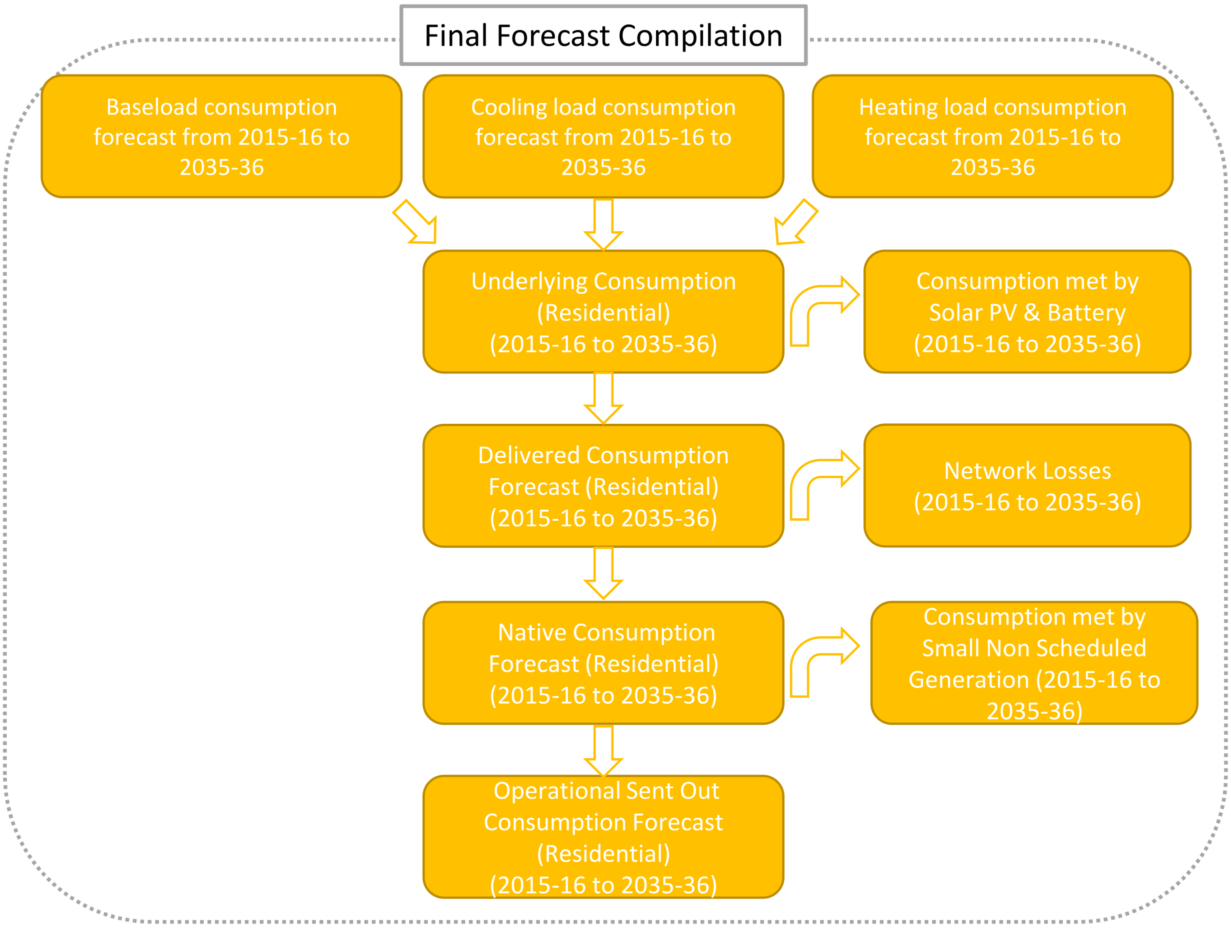


Figure 4 Process flow for residential forecast compilation



3.2.2 Process data

The input data described in section 3.1 was processed to provide the required data for analysis and forecasting process.

The analysis of the historical residential consumption trend used average weekly consumption per connection, and average weekly CDD and HDD. This was achieved by the following steps:

- **Step 1:** Calculated daily average underlying consumption (= sum of daily delivered and daily de-rated generation) in each region.
- **Step 2:** Daily underlying consumption was divided by total daily connections to create daily underlying consumption per residential connection.
- **Step 3:** For regression analysis of the consumption trend:
  - The calculated daily underlying consumption per connection was averaged for each week of each financial year, resulting in 53 observations in each year.
  - Daily HDD and CDD was also averaged to create average weekly HDD and CDD.

For the purpose of forecasting annual consumption:

- Forecast residential retail prices are expressed as percentages of growth relative to the base year 2015–16.
- The forecast impacts of annual energy efficiency savings, appliance fuel switching, PV generation, and PV storage are expressed as growth relative to the base year 2015–16.

3.2.3 Trend in residential consumption

This part of the analysis included the following steps.

Step 1: Regression analysis of weekly underlying consumption per connection

This was performed for each financial year separately to produce estimates of base load, heating, and cooling consumption per residential connection for these years.

The following regression model assumed that:

- The weekly average base load is constant across all weeks of each year and does not vary according to seasons.
- There is a linear relationship between weekly average consumption and HDD and CDD.

$$Res\_Con_{t,y} = \beta_{0,y} + \beta_{1,y}HDD_{t,y} + \beta_{2,y}CDD_{t,y} + \varepsilon_{t,y}$$

where

$Res\_Con_{t,y}$= average daily underlying consumption per residential connection for week t and year y

$HDD_{t,y}$ = average heating degree day for week t and year y

$CDD_{t,y}$ = average cooling degree day for week t and year y

$\varepsilon_{t,y}$ = error term for week t and year y

$\beta_{0,y}$ = estimate of base load per residential connection for year y

$\beta_{1,y}$ = estimate of heating consumption per residential connection for year y

$\beta_{2,y}$ = estimate of cooling consumption per residential connection for year y

t = 1, 2, …52 (or 53) denotes the week number in year y

y = 2014, 2015 for financial year 2013–14 and 2014–15 respectively

Step 2: Weather normalise underlying annual consumption per connection 2013–14 and 2014–15

Weather normalised underlying annual consumption per connection for each year was obtained using the regression coefficients obtained in the previous step, and forecasting annual HDD and CDD.

The weather normalised underlying annual consumption per connection was then used to assess consumption changes across these years, without the impact of weather conditions and installed rooftop PV generation.

3.2.4 Forecast regional residential underlying annual consumption 2015–16 to 2035–36

AEMO applied a “growth” model to generate the 20 years annual residential forecasts. In brief:

- The weather normalised underlying annual consumption per connection for the base year 2015–16 was used to grow the forecast base load, heating, and cooling consumption separately.
- The forecasts took into account the impact of the modelled consumption drivers. Some added to forecast consumption (for example, electricity appliance uptake, and gas to electricity appliance switching). Others acted to reduce residential consumption (such as forecast electricity retail price increases, and forecast energy efficiency savings driven by both Commonwealth and State government energy policies).
- Forecasts were based on forecast annual HDD and CDD standards.

The following steps were performed.

Step 1: Estimate weather normalised underlying annual consumption per connection for base year 2015–16

The analysis in section 3.2.3 produced the weather normalised average annual consumption per connection for 2013–14 and 2014–15. The estimated consumption for 2013–14 was used to project that for 2015–16, taking into consideration the estimated impact of changes to electricity retail price, modelled energy efficiency savings in appliances and enhanced building thermal efficiency, and growth in electricity appliance uptakes between 2013–14 and 2015–16.

BL_NMI_{2016}, HL_NMI_{2016}, CL_NMI_{2016} denote the estimated underlying annual base load, heating, and cooling per residential connection for 2015–16.

Step 2: Produce "Base case" underlying annual residential consumption forecasts

The "base case" annual forecasts were driven purely by connection forecasts. This means the underlying annual consumption per connection will not change over the forecast horizon, being unaffected by the external driving factors.

The forecast "base case" annual base load, heating, and cooling consumption for each financial year y was obtained by multiplying the estimated BL_NMI_{2016}, HL_NMI_{2016}, CL_NMI_{2016} by the forecast residential connections for that year. These are denoted by $Base\_BL_y$, $Base\_HL_y$, $Base\_CL_y$.

Hence the forecast base case underlying annual consumption forecast for year y was the sum of the above three components:

$$Base\_Total_y = Base\_BL_y + Base\_HL_y + Base\_CL_y$$

Step 3: Estimate impact of forecast electrical appliance uptakes

Penetration of electrical appliances is forecast to increase over the next 20 years. Growth in electrical appliance uptake was expressed as appliance uptake indices for each forecast year (=1 for 2015–16). The increased uptake can either increase forecast annual base load (for example, fridges and televisions) or weather-sensitive load (such as reverse-cycle air-conditioners).

The forecast impacts due to forecast growth in appliance stock in year y are denoted by AP_BL_y, AP_HL_y, AP_CL_y for base load, heating, and cooling respectively.

Hence the forecast total consumption increase due to appliance growth for year y was the sum of the above three components:

$$AP\_Total_y = AP\_BL_y + AP\_HL_y + AP\_CL_y$$

Step 4: Estimate impact of gas to electric appliance switching

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

The impact of appliance fuel switching was reported in AEMO's 2015 NGFR[42] and the approach is discussed in the *2015 NGFR Methodology Information Paper*.[43] The following adjustments were made to convert the loss in gas load to a forecast gain in electricity consumption:

- 50% of the forecast reduction in gas consumption attributed to gas hot water heating was assumed.
- Gas to electric heating efficiency was estimated to be 20% to 25%, assuming 70% to 80% efficiency for gas furnace and 25% of heat loss through the duct systems for gas central heating.

[42] AEMO. *2015 National Gas Forecasting Report*. Available at: http://www.aemo.com.au/Gas/National-planning-and-forecasting/National-Gas-Forecasting-Report.

[43] AEMO. *2015 National Gas Forecasting Methodology Information Paper*. Available at: http://www.aemo.com.au/Gas/National-planning-and-forecasting/National-Gas-Forecasting-Report .

The annual impact of gas to electric appliance switching for year *y* is denoted by FS_BL_y, FS_HL_y for hot water and heating load respectively.

Hence the forecast total consumption increase due to gas to electric appliance switching for year *y* was the sum of the above two components:

$$FS\_Total_y = FS\_BL_y + FS\_HL_y$$

Step 5: Estimate PV rebound effect

It was assumed that households with installed rooftop PV are likely to increase consumption, enabled by reduced operating costs attributed to PV. This was assumed to be 10% of the forecast PV generation, denoted by PV_RB_y for year y.

Step 6: Estimate impact of forecast residential retail prices

Changes in retail price will affect consumer behaviour for household electricity consumption.

Price elasticity was assumed to be -0.1, applying equally to base load, heating, and cooling. That is, 1% change in price will result in 0.1% change in annual residential consumption.

Residential prices have been forecast to fall for the first five years to 2020, and increase for the remainder of the forecast period. Price impacts were estimated in the case of increases, but not for temporary price reductions.

Forecast price impact for year *y* is denoted by $Price\_BL_y$, $Price\_HL_y$, $Price\_CL_y$ for base load, heating and cooling respectively.

Hence the forecast price impact on forecast underlying annual consumption for year *y* was the sum of the above three components:

$$Price\_Total_y = Price\_BL_y + Price\_HL_y + Price\_CL_y$$

Step 7: Estimate impact of energy efficiency savings

Energy efficiency is one of the key factors behind the slowdown of electricity consumption seen in recent years across developed countries, including Australia. It is therefore an important input into the forecast of future electricity consumption in the NEM.

Energy efficiency savings are driven by:

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

AEMO engaged consultants Pitt & Sherry to estimate historical and forecast energy efficiency savings associated with these program. The consultants' energy efficiency savings represent the expected achievable energy efficiency savings with the consumption rebound effects assumed to be 20% for the neutral scenario (see Appendix D for more information).

The energy efficiency savings are denoted by EE_BL_y, EE_HL_y, EE_CL_y for base load, heating and cooling respectively.

Hence the forecast energy efficiency savings for year y were the sum of the above three components:

$$EE\_Total_y = EE\_BL_y + EE\_HL_y + EE\_CL_y$$

Step 8: Forecast underlying annual consumption

Forecast underlying annual consumption for each region was derived from the "base case" forecasts calculated in Step 2, and adjusted to:

- Add the forecast impact of consumption adders described in Step 3 to 5 (appliance uptake, gas to electric appliance switching, PV rebound effect).

- Subtract the impact of consumption reducers described in Steps 6 to 7 (Price impact, energy efficiency savings).

Hence, the forecast underlying annual consumption for year y was:

$$Underlying\_Total_y = Base\_Total_y + AP\_Total_y + FS\_Total_y + FS\_Total_y - Price\_Total_y - EE\_Total_y$$

3.2.5 Forecast regional residential delivered annual consumption 2015–16 to 2035–36

Forecast delivered annual consumption refers to underlying consumption, adjusted down for consumption offset due to PV and battery storage (see Appendix C for more information):

$$Delivered\_Total_y = Underlying\_Total_y - PV\_Total_y - Storage\_Total_y$$

CHAPTER 4. MAXIMUM AND MINIMUM DEMAND

This chapter outlines the methodology used to develop forecasts of maximum and minimum demand (MD[44]) for each year. Forecasts of maximum and minimum demand
are an important input for assessing future system capabilities and planning any investment in electricity infrastructure.

The 2016 NEFR represented a major milestone for MD forecasts by AEMO, with improvements compared to previous forecasts. Following an extensive engagement process with key external stakeholders, AEMO identified a set of core improvements:

- Develop "bottom-up" models that are based on end-point metering data and more reflective of consumer behaviour.
- More closely integrate annual energy forecasts and MD forecasts.
- Improve preparation of input data, removing known large industrial closures and structural changes in the electricity system.

Based on these requirements, AEMO decided for the first time not to engage consultants to undertake this model development, but to develop these models in-house. This allowed for the following main improvements:

- Modelling and forecasting of MD split by end-use, allowing better, more granular modelling of the impact of energy efficiency.
- Closer integration of half-hourly models with the annual consumption forecasts described in Chapters 2 and 3.
- Models tuned to a recent period to strip the effects of structural changes such as large industrial closures, energy efficiency improvements, and penetration of climate control appliances.
- Fully-integrated model for rooftop PV generation and battery storage usage.
- Ability to fine-tune models and develop in-depth diagnostic tools.

4.1 General overview of the method

MD has been presented on a "sent-out" basis, in contrast to the "as generated" operational demand basis used in previous NEFR publications[45].

Maximum demand is highly dependent on weather conditions, implying that future values have a high degree of randomness. Because of this, the maximum demand analysis is carried out with a probabilistic methodology and results are presented in POE terms. For any given season:

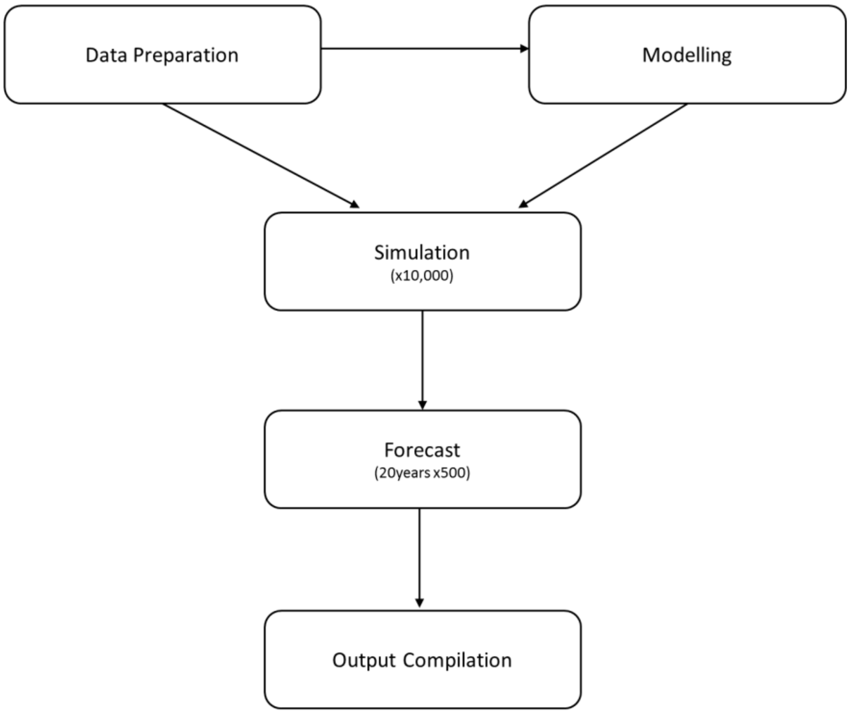
- A 10% POE MD projection is expected to be exceeded, on average, one year in 10.
- A 50% POE MD demand projection is expected to be exceeded, on average, five years in 10.
- A 90% POE MD demand projection is expected to be exceeded, on average, nine years in 10.

As a consequence, the most extreme (highest) value presented for maximum demand will be the 10% POE, while for minimum demand the most extreme (lowest) will be the 90% POE.

The general work flow of the analysis is presented in Figure 5. It is similar to the one adopted in the 2015 NEFR[46,47], although the implementation is different at a number of stages.

[44] In the rest of this chapter, the label MD will be used to indicate the maximum and the minimum demand indistinctly.
[45] See Appendix A for a full set of demand definitions, including the definition of "underlying" and "delivered" demand.
[46] AEMO. *2015 NEFR Forecasting Methodology Information Report*. Available at http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/National-Electricity-Forecasting-Report .
[47] R.J. Hyndman and S. Fan, "Monash Electricity Forecasting Model", June 2015. Available at: http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/National-Electricity-Forecasting-Report .

Figure 5 General work flow of the MD analysis for the 2016 NEFR



For each NEM region, 48 models of demand corresponding to each half-hour in the day were developed. These models describe the relationship between underlying demand and independent variables including calendar effects (public holidays, day of the week, and month in the year) and weather effects.

The modelling stage was followed by a simulation stage, where numerous instances of weather patterns were simulated based on historical weather patterns using a resampling technique.

- The correlation between historical weather variables and solar radiation at the surface was completely preserved at this stage.
- The simulated weather patterns produced in this way were then used as input into the models defined at the previous stage, resulting in a series of realisations of possible half-hourly demand patterns.
- At the same time, solar radiation patterns were used to simulate rooftop PV and battery storage effects.

The demand patterns then evolved using information from the residential and business forecasts described in Chapter 2 and 3. This forecasting stage represented one of the main differences to last year's methodology, as it was performed independently for different components of demand, separated by end-use.

The forecast demand components, PV generation, and battery charging were then assembled together to produce numerous 20-year, half-hourly profiles of delivered demand.[48]

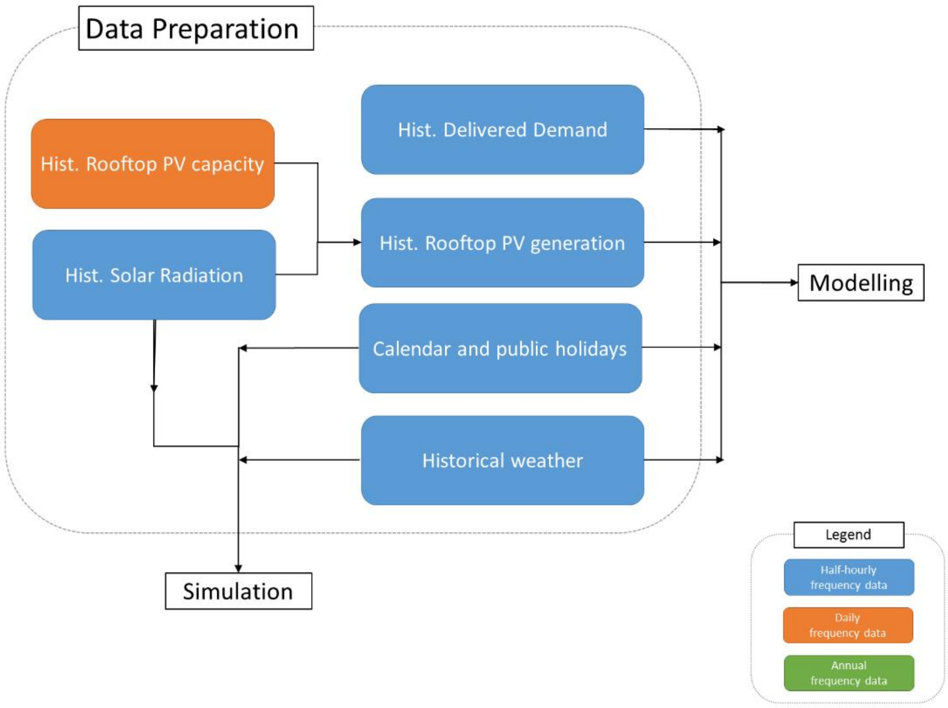
In the last stage of the analysis, the maxima and minima of the delivered demand were extracted from each simulated half-hourly pattern and used to build probability distributions. The POEs of maximum and minimum demand were then extracted from these distributions. Final corrections for contribution of network losses and Small Non-Scheduled Generation (SNSG) were applied to compute the POE for operational MD.

[48] See Appendix A for a full set of demand definitions, including the definition of "underlying" and "delivered" demand.

4.2 Data preparation stage

The basic inputs to the work flow were 30-minute historical time series of weather variables, solar radiation, and delivered demand, that were later used to define the demand models and run the simulations (see Figure 6).

Figure 6 Detailed work flow of data preparation stage for MD



Weather data was provided by the Bureau of Meteorology (BoM).[49] The dataset used in the 2016 NEFR extended from 1 January 2000 to 31 March 2016, providing more than 15 years of detailed weather information.

The analysis used, as a proxy for weather conditions ("weather standard"), the heating and cooling degree variables (HDeg and CDeg, respectively). The heating and cooling degree variables were defined as:

$$HDeg = \tilde{T} - T_H$$
$$CDeg = T_C - \tilde{T}$$

where $\tilde{T}$ indicates the average temperature over the past three hours and T_H and T_C are critical heating and cooling temperatures that depend on the region and the time of the day.

This formulation of the weather standard indicates that residential and business loads react to extreme weather conditions by increasing the power of their climate control devices only when the temperature goes out of a "comfort zone", inducing a threshold effect. The adoption of a rolling average temperature allowed AEMO to model the behavioural effect that the response to very high or very cold temperatures is not instantaneous, but depends on the perceived accumulation of heat (or cold). Allowing finely granular critical temperatures that depend on the geographical area and time of the day also allowed AEMO to better model the great variety of consumer behaviours across the NEM.

[49] Each NEM region was approximated by a reference weather station. See Appendix F for a detailed list.

The BoM also provided satellite half-hourly data for solar radiation at the surface, that is, taking into account clouding effects. The data set covered the same historical period as the weather data.

These figures were used in a model of rooftop PV generation developed by the University of Melbourne[50], which converts them in an estimated half-hourly generation of a 1 KW solar panel unit. This normalised generation was then multiplied by the total installed capacity in the NEM region, to obtain the total PV generation for the region.

Historical daily values of installed PV capacity were provided by the Clean Energy Regulator (CER). It was assumed that the existing battery storage capacity in the NEM is negligible, and neglected for historical purposes.

The half-hourly demand data was extracted from AEMO's Market Settlement and Transfer Solution (MSATS) system. The demand data was aggregated at the NEM regional level, and stripped of network losses and SNSG contribution.

The resulting demand ("delivered" demand) was an estimate of what households and business must effectively withdraw from the network grid. After correcting for rooftop PV generation, AEMO obtained half-hourly traces of "underlying" demand, corresponding to the energy effectively used on premises.

Unlike in previous NEFRs, all the half-hourly data was expressed in local time, allowing better alignment of the modelling with consumption patterns and consumers' behaviour taking place in real life.

4.3 Modelling stage

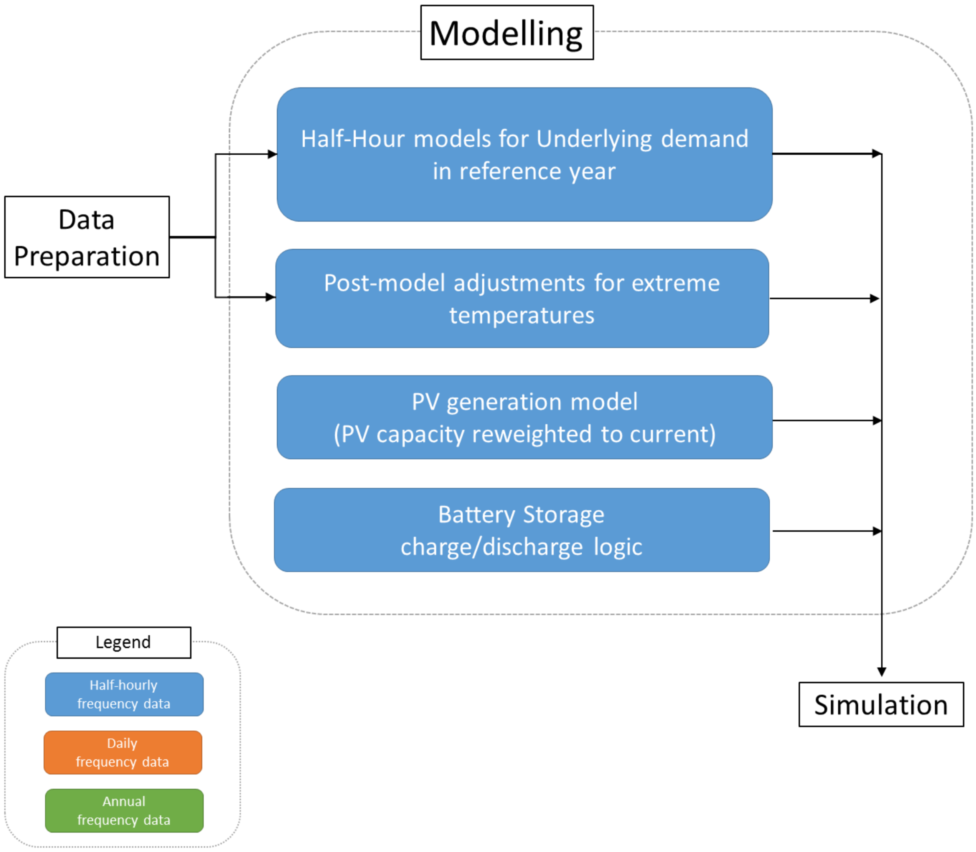
The key components of the modelling stage are summarised in Figure 7.

AEMO chose to base the modelling on underlying demand, because it is the type of demand more directly driven by socio-economic-technological factors like demographics, economic drivers, fuel switching, and energy efficiency gains.

The model expressed the relationship between demand and predictor variables related to the day of the year (including whether it is a public holiday or not) and the weather standard.

[50] See Appendix C.2 for more details and references of the model.

Figure 7 Detailed work flow of modelling stage for MD



For every NEM region, 48 models were developed, one for each half-hour in the day. Many different formulations of the models were explored. Models were always linear in the parameters, but more complex polynomial formulations have been investigated. For the same formulation, different values of critical temperature for the HDeg and CDeg were scanned. This extensive analysis was performed to find the most accurate description of the electricity demand.

The discriminant used to select the model was the adjusted R^2:

- Typical values of adjusted R^2 observed are in the range of 0.80 – 0.90.
- When different models gave very similar adjusted R^2 (less than 0.01 difference in adjusted R^2), the Akaike Information Criterion was also used to select the best-performing model in a specific half-hour period.
- There were occurrences characterised by very closely performing models, all of them satisfactorily describing the observed data. In these cases, AEMO decided to try to use the same model formulation across the largest number of contiguous half-hour periods.

Estimation of the coefficients and model selection was carried out using only the most recent subset of data (from July 2014 to March 2016). This strategy was in line with the strategy adopted for forecasting residential and business annual operational consumption (see Chapters 2 and 3). The aim was to have a reference starting point for the forecasts that would most accurately represent the current characteristics of the system, removing biases coming from different system conditions in the previous years (such as the effects of energy efficiency, different stock of climate control appliances, and different business sector breakdown).

Extreme weather conditions happen only rarely, and might not have occurred in the considered time range. Because of this, the models might not be accurate in case of very high or very low temperatures. This concern was addressed through post-model adjustments, computed with the following procedure:

1. Select historical weather data and underlying demand from the past ten years.
2. For each financial year, compute a scale factor dividing the average demand in the financial year by the average demand of the reference period July 2014 to March 2016.
3. Normalise demand in a half-hour by the scaling factor calculated at step 2.
4. Select only half-hour periods where temperature went above a correction temperature of 30 degrees (33 degrees for Victoria).
5. Run the models just extracted from the reference period, and compute the residuals of the demand.
6. Study the residuals and extract a correction factor to be applied to the model estimation when the temperature goes above the correction temperature.

Rooftop PV half-hourly model

The model that converts solar radiation to a value of electricity generated by a unit-sized rooftop PV system has been developed by the University of Melbourne. It is described in more detail in Appendix C.2.

While the normalised PV generation used to estimate actual values was tuned on the geographic distribution of rooftop PV installations at the historical time, in the simulation stage of the MD analysis the PV generation was reweighted, to better represent the current distribution of the panels. Due to limited time available to integrate the north-west blend of panel orientation in the workflow, a pure north-facing panel orientation was assumed in the MD analysis.

Battery storage half-hourly model

See Appendix C.3 for a detailed description of the charge/discharge logic assumed.

4.4 Simulation stage

Having a model that estimated the demand at a given half-hour provided weather conditions and calendar effects, the simulation stage focused on incorporating in the analysis the inherent variability of weather conditions and demand patterns. The main components of this stage are shown in Figure 5.

The procedure, similar to the 2015 NEFR[51,52], obtained a large number of possible weather realisations by resampling historical weather values, using a "double season block" bootstrapping procedure.[53]

A simulated year was built by randomly selecting 26 fortnightly weather patterns ("weather blocks"), ensuring that the weather block was assigned to the corresponding time of the year. The data used for this procedure amounted to the full historical data set described in Section 4.2. As discussed in more detail in Appendix F.3, in the absence of a specific study, no warming trend has been assumed for the forecast years.

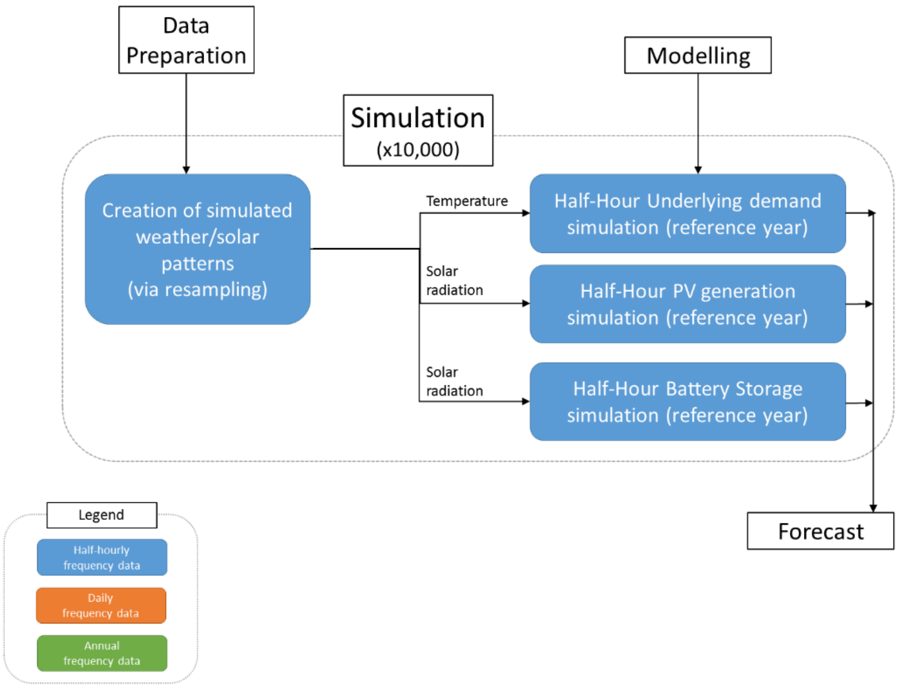
The main difference from the 2015 NEFR procedure was that historical values of solar radiation and normalised generation were resampled at the same time of the weather conditions. This allowed AEMO to fully preserve the correlation between weather patterns and solar panel generation, improving the accuracy of the simulation procedure.

[51] AEMO. *2015 NEFR Forecasting Methodology Information Report*. Available at: http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/National-Electricity-Forecasting-Report .

[52] R.J. Hyndman and S. Fan, "Monash Electricity Forecasting Model", June 2015. Available at: http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/National-Electricity-Forecasting-Report .

[53] Bootstrapping is a statistical technique used to estimate the statistical properties of stochastic variables by means of a procedure of random sampling with replacement. Using the bootstrapping procedure, one can estimate the typical range of values of the weather variables from the empirical distribution of the weather data.

Figure 8 Detailed work flow of simulation stage for MD



The process simulated ten thousand different possible instances of weather and solar patterns. These simulations were then fed into the models described in Section 4.3, to calculate the estimated underlying demand.

When the simulated demand was computed, the process kept track of its three components:

- The contribution from terms in the model depending on CDeg (cooling component).
- The contribution from terms depending on HDeg (heating component).
- The part that does not depend on the temperature (baseload component).

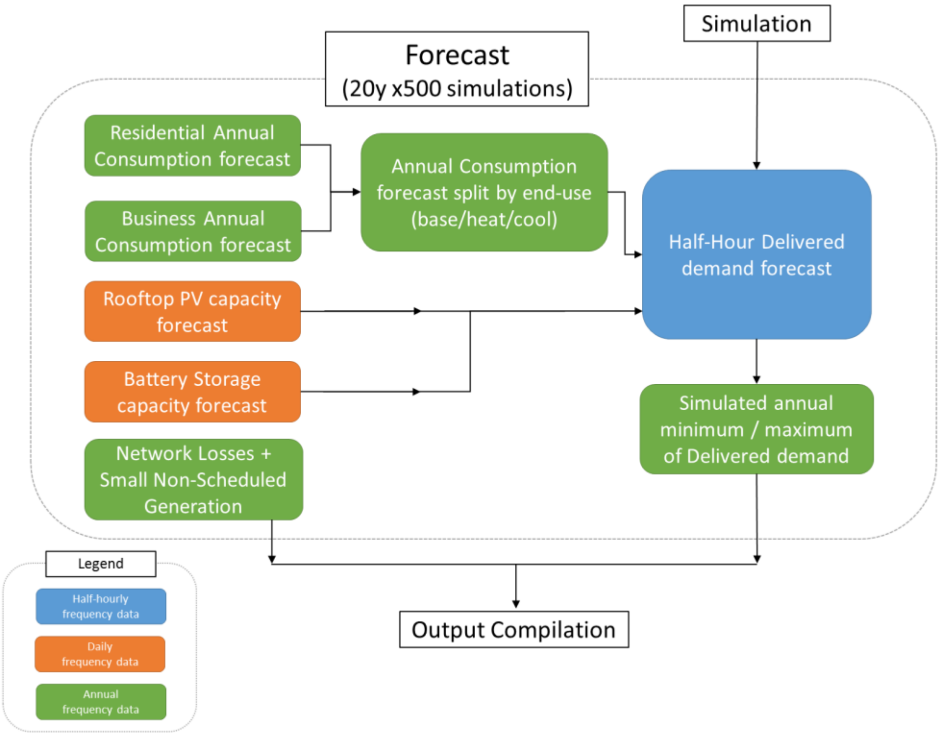
This split enabled AEMO to model independently the drivers of MD by end-use, better incorporating their different technological, economic, and behavioural drivers. The mean prediction of the model components were randomly smeared by the standard errors of the model regression coefficients to consider the random variations of demand under the same weather conditions.

The normalised PV generation and normalised battery charging profile were calculated simultaneously using the resampled solar radiation data as input, and the solar generation model reweighted for current installations (see Section 4.3).

4.5 Forecasting stage

The simulated half-hourly traces produced at the end of the simulation stage were representative for the conditions of the system during the reference period. To forecast future system behaviour, they were rescaled based on the results of the other 2016 NEFR components. This procedure is in the flowchart shown in Figure 9.

Figure 9 Detailed work flow of forecasting stage for MD



The 10,000 simulations were divided into 20 groups of equal size, corresponding to the 20 years of the forecast horizon. The residential and business forecasts for underlying annual consumption were aggregated by end-use component (baseload/heating/cooling component).

The growth rate relative to the reference period (2014–15) was first calculated for each forecast year and component, and then applied to the corresponding set of 500 simulated traces. The result was a set of 500 forecast underlying demand traces for every considered future year. This procedure allowed AEMO to weight appropriately any systemic change affecting a specific consumers' end-use sector.

In a similar fashion, 500 different normalised PV and battery half-hourly profiles were prepared for every forecast year and scaled by the forecast installed PV and battery storage capacity. The future installed capacity for both rooftop PV and battery was estimated by external consultancy Jacobs, as described in Appendix C. The only modification specific to the MD analysis was to apportion daily the annual increase in capacity on a pro-rata basis. This avoided unnatural step changes at the boundaries of future financial years caused by the rapid uptake of rooftop PV estimated by the analysis. It was checked from the historical CER records that the rate of installations is not strongly unbalanced across the year.

The half-hourly forecast PV and battery traces were subtracted from the underlying demand, obtaining 500 series of twenty-years-long half-hourly delivered demand traces.

Network losses for MD

To compute the operational MD, AEMO estimated the contribution of distribution and transmission losses at times of peak.

For transmission losses, the procedure followed was the same used in the 2015 NEFR. For each NEM region, the relative contribution of transmission losses to operational demand was calculated for the ten highest half-hourly demand over the past five years. The transmission loss correction was calculated averaging the historical relative contributions and assumed to be constant over the forecast horizon.

For distribution losses, AEMO relied on information prepared by the NEM distribution network service providers (DNSPs) and collected from either public sources (reports to AER, public documentation) or via direct enquiries to the DNSP by AEMO. The loss correction factors of DNSPs in the same NEM region were combined with an average weighted by the electricity volume of each DNSP network. The distribution losses correction factors were also assumed to be constant over the forecast horizon.

Table 5 Loss correction factors for MD expressed as percentage of operational demand

	NSW	QLD	SA	TAS	VIC
Distribution network	5.0%	4.9%	6.0%	5.4%	5.6%
Transmission network (Summer)	3.3%	3.6%	1.7%	3.1%	2.6%
Transmission network (Winter)	2.2%	3.0%	2.6%	4.0%	2.4%

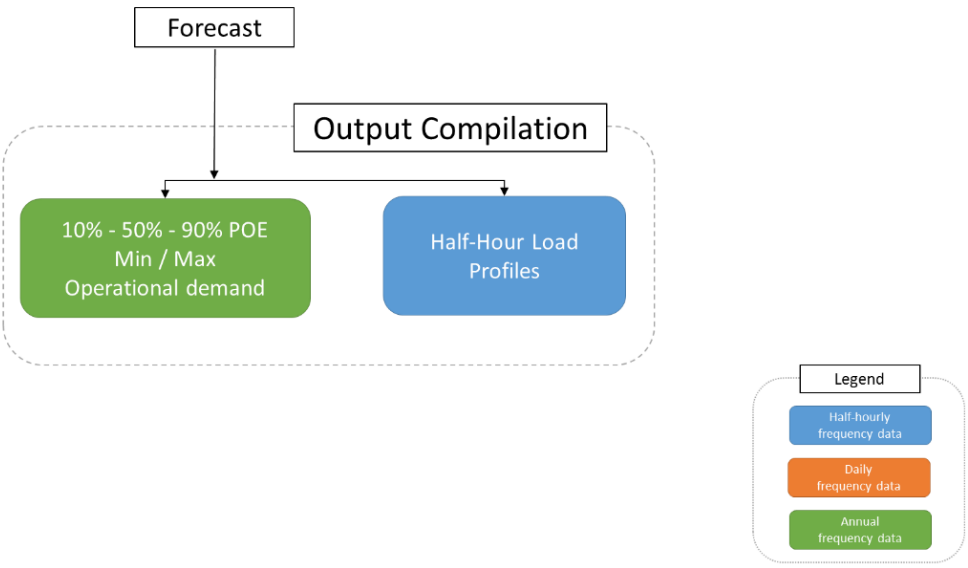
Small Non-Scheduled Generation contribution to MD

See Appendix G for a detailed description of the SNSG forecasts, including the contribution at the times of maximum and minimum demand.

4.6 Output compilation stage

The simulated traces contained a rich set of information that could be used to extract the POE for maximum and minimum demand, following the work flow presented in Figure 10.

Figure 10 Detailed work flow of the output compilation stage for MD

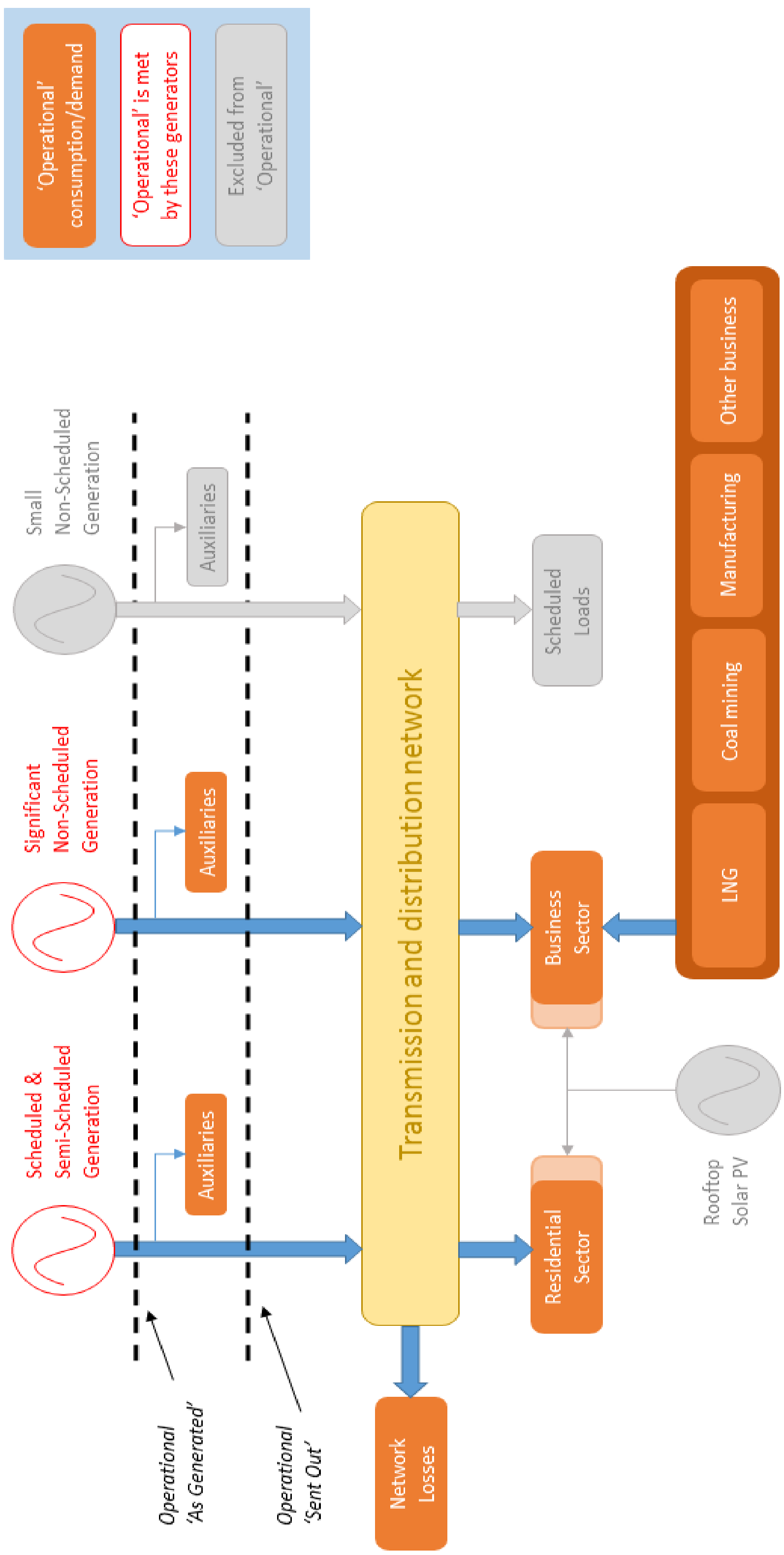


For every year of the forecast horizon, the maxima and minima of the simulated delivered demand traces were noted – keeping different records for the season when the maximum and minimum occurred. In this way, a distribution of the 500 simulated maxima (minima) for a given region, forecast year and season was constructed. The 10%, 50% and 90% quantiles of the distribution corresponded to the desired 90% POE, 50% POE, and 10% POE, respectively. To quote the maximum and minimum of the operational demand, corrections for network losses and SNSG (calculated as described in Section 4.5) were applied to the POE values.

APPENDIX A. DEMAND DEFINITIONS

Demand Type	Definition	Description
Underlying	Actual customer consumption	Actual consumption on premises (“behind the meter”) ignoring effect of rooftop PV and battery storage.
Delivered	Underlying – PV – battery	What the consumer (either residential or business) must withdraw from the electricity grid.
Native	Delivered + (network losses)	Total generation that must be fed into the electricity grid.
Operational “as sent-out”	Delivered – (Small Non-Scheduled Generation) + (network losses)	Total generation by scheduled / semi-scheduled / significant non-scheduled generators needed to meet system demand.
Operational “as generated”	(Operational “as sent out”) + (auxiliary loads)	Total generation by scheduled / semi-scheduled / significant non-scheduled generators needed to meet system demand and demand on generator premises.

Figure 11 Flow chart with components of operational demand in the NEM



APPENDIX B. PRICES

B.1 Gas prices for Gas Powered Generators (GPG)

Delivered gas price projections for Gas Powered Generators (GPG) were provided by consultancy CORE Energy ("CORE"). These were used by consultancy Jacobs ("Jacobs") as an input into a NEM market simulation model that estimates wholesale market costs.

The methodology report for CORE Gas Prices is available on the AEMO website.[54]

B.2 NEM wholesale and retail electricity prices

For the 2016 NEFR, the wholesale and retail price modelling was undertaken by Jacobs. Using delivered gas price projections for GPG provided by CORE, Jacobs estimated wholesale market costs. From there, Jacobs developed their wholesale and retail electricity prices.

The methodology report for Jacobs Retail Prices is available on the AEMO website.[55]

[54] CORE Energy Group. AEMO – Gas Price Consultancy, August 2015. Available at: http://www.aemo.com.au/Gas/National-planning-and-forecasting/National-Gas-Forecasting-Report .

[55] Jacobs. *Retail Electricity Price History and Projections*, May 2016. Available at: http://www.aemo.com.au/Gas/National-planning-and-forecasting/National-Gas-Forecasting-Report .

APPENDIX C. ROOFTOP PV AND STORAGE

C.1 Rooftop PV installed capacity modelling

C.1.1 Installed capacity forecast:

AEMO's 2016 forecast of installed capacity for rooftop PV was based on advice from external consultancy Jacobs. Jacobs' report provides details of the approach.[56]

The main drivers behind the forecast rooftop PV uptake are:

- Financial incentives, such as Small Technology Certificates (STCs) and feed-in tariffs (FiTs).
- Declining installation costs:
  - Short-term cost reductions are expected to come mainly in non-hardware "soft costs", including marketing and customer acquisition, system design, installation labour, permitting and inspection costs, and installer margins.
  - In the longer term, cost reductions are expected to come from better system efficiencies and cost reductions from production of PV system components.
- An increase in retail electricity tariffs from 2020 (see Appendix B.2).
- Projected steady population growth across most states in Australia, allowing for more rooftop PV systems to be adopted before saturation is reached.

C.1.2 Effective capacity forecast

As solar panel output is expected to degrade over time, AEMO has built a stock model of the installations forecast by Jacobs, to be able to calculate the average age of the panels. Based on the average panel age, AEMO has calculated the effective rooftop PV capacity, taking into account the projected degradation by region and across the NEM.

Table 6 Effective capacity (after allowing for reduced efficiency of aged panels) – rooftop PV (MW)

	NSW and ACT	QLD	SA	TAS	VIC	NEM
2016–17	1,278	1,737	718	113	1,094	4,939
2020–21	2,112	2,580	1,024	188	1,850	7,754
2025–26	3,262	3,807	1,467	302	2,970	11,807
2030–31	4,452	5,141	1,787	428	4,157	15,965
2035–36	5,513	6,066	1,942	526	5,004	19,049

Further to this, AEMO adapted has assumed a westerly shift in rooftop panel orientation, commencing from zero at the start of 2016–17 and resulting in 10% of Jacob's capacity projections having a westerly panel orientation by 2035–36. This reflects AEMO's assumptions that:

- Consumer incentives will continue to evolve over the period.
- Grid-supplied electricity will increase in cost, relative to the value of exporting rooftop PV generation to the grid before the evening peak.
- West-facing panels, which better align rooftop PV generation with the period of peak consumption and assumed higher energy cost, will remain economic for installation and use and add approximately 10% to generation output during the late afternoon compared to north-facing panels.

[56] Jacobs. *Projections of uptake of small-scale systems*, June 2016. Available at: http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/National-Electricity-Forecasting-Report .

C.2 Rooftop PV generation forecasts

Forecasts of rooftop PV generation are estimated by multiplying the forecast of effective capacity with a forecast of normalised generation for a standardised 1 KW unit of effective capacity (refer to section C.1.2). This product is separately calculated for each region and sector (residential and business).

C.2.1 Normalised generation and rooftop PV generation forecast

AEMO has developed, with the University of Melbourne, a rooftop PV generation model which, for each region, estimates the historic 30-minute generation of installed systems. This model produces a measure of total generation, as well as the average generation of a notional 1 KW unit of capacity.[57]

For the production of forecasts for the NEFR, this model has been modified and extended in the following way to produce a forecast of rooftop PV generation:

1. **Re-weighted normalised generation.**

   The University of Melbourne rooftop PV generation model was modified so its measure of normalised generation was 're-weighted' from the spatial and temporal character of installed capacity at each time-step from 1 January 2000, to that which is indicative of actual installed capacity as of summer 2015–16. This step normalised the measure of historic generation per unit of capacity so it corrected for a possible technology diffusion bias that diminishes with time. For PV, this corrected for a possible greater tendency of earlier installations to occur in more affluent suburbs with lower installation inefficiency (due to panel orientation and shading, for example).

2. **Re-directed and re-weighted normalised generation.**

   The modified model was run to produce a 're-weighted' measure of normalised generation for each 30-minute period from 1 January 2000. It was then run again with a 90 degree panel orientation shift to produce a westerly measure of normalised generation.

3. **50% POE forecast of normalised generation.**

   The 30-min data from Step 2 was used to determine an annual probability distribution for normalised generation, from which the 50% POE was used in the annual consumption forecasts.

4. **Rooftop PV generation forecast.**

   For annual consumption the output of Step 3, representing a 50% POE measure of annual normalised generation, was multiplied with the annual forecast of rooftop PV installed capacity to produce a forecast of annual PV generation. Two forecasts were produced, one with a northerly orientation, and one with a westerly orientation. For forecasts of annual consumption, the northerly and westerly forecasts were combined to forecast the generation outcomes of a westerly shift. This shift started with zero input from the westerly data at the start of the 20-year forecast period, with a linear adjustment to achieve a 10% input from the westerly data at the end of this outlook period.

C.3 Storage modelling

C.3.1 Installed capacity forecast

The forecast capacity of Integrated PV and Storage Systems (IPSS) was also based on external advice from Jacobs.[58] The IPSS forecast captures new combined PV and storage installations only. The model does not consider rooftop PV being retrofitted with battery storage.

[57] Details of the model can be found on AEMO's website http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting

[58] Jacobs. *Projections of uptake of small-scale systems*, June 2016. Available at: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report.

- Uptake of IPSS is forecast to start slowly and pick up especially after 2020, in both the residential and the commercial sectors, reaching around 3.8 GW installed at the end of the 20-year forecast period.
- The forecast penetration of IPSS is not uniform in all states. A key factor in uptake projections is that the existing high installed capacity of residential rooftop PV in some states prevents a higher penetration of integrated battery storage, since no retrofitting of batteries to existing systems has been considered in the model.

Table 7 Installed capacity – Integrated PV and storage systems (MW)

	NSW and ACT	QLD	SA	TAS	VIC	NEM
2016–17	7	9	1	0	7	24
2020–21	178	181	77	12	164	613
2025–26	442	402	279	33	495	1,651
2030–31	719	637	424	55	901	2,736
2035–36	1,004	847	517	67	1,348	3,783

Table 8 Installed capacity – battery storage (MWh)

	NSW and ACT	QLD	SA	TAS	VIC	NEM
2016–17	33	39	4	2	33	111
2020–21	306	312	135	21	284	1,058
2025–26	762	696	489	58	859	2,864
2030–31	1,245	1,104	742	96	1,565	4,752
2035–36	1,741	1,469	902	116	2,343	6,571

The key drivers behind IPSS uptake are:

- Cost reductions from economies of scale and increased competition.
- A projected transition to a time-of-use tariff structure that provides cost-reflective pricing and enables consumers to gain greater value from IPSS, as they could charge during low cost time periods and discharge during high cost time periods.

C.3.2 Storage charging/discharging

Projecting the contribution of battery storage to consumption and maximum/minimum demand depends heavily on the assumed charging and discharging profile.

This profile represents, for each 30-minute period, a proportion of the energy storage capacity of Integrated PV and Storage Systems (see section C.3.1).

The following explains AEMO's assumptions and method for determining the forecast for battery storage and discharge:

1. Charging and discharging profile.
   a. It was assumed a battery storage system is installed with an energy management system that will schedule charging and discharging.
   b. The charge/discharge logic assumed alignment with deemed dispatch costs in the wholesale market (so charging when dispatch costs are lowest and discharging when they are highest).
   c. There are three charging/discharging periods:
      i, Overnight: charging to 25% capacity (or specified) for discharge during the day. Even charging from 30-minute intervals 1 to 12 (of 48 per calendar day, starting at midnight). Even discharge during intervals 13 to 34.

ii, Daytime: charging when clear-day solar radiation is >50 watts per square metre (W/m^2), with clear-day radiation used as a charging weight, to a cap of 500 W/m^2. Discharge during intervals 35 to 46. Discharge occurs with an even/flat profile, stepped up/down at each end over 3 intervals with a unit gradient.

1. A clear-day radiation model was used to create a diffuse charging bias. Diffuse radiation remains relatively consistent on cloudy days. Also, by capping radiation to ~50% it brings the clear-day estimate closer to typical received radiation. If the day is fully cloudy, the model will slightly over charge because diffuse radiation can vary between 10% and 30% on a cloudy day. But this could happen in the real world –the programming logic may not be so dynamic – and overcharging may be close to optimal anyway if future retail prices and incentives move to align with the daily solar cycle.

iii, Overlapping charge in the evening: Allowing greater capacity use over the day when solar conditions are sustained into the evening peak period. The daytime charging/discharging logic is assumed into the evening period when clear-day radiation is sustained above 50 W/m^2.

2. Round trip efficiency. This was assumed to be 90%, implemented via the charging and discharging profile, such that the sum of the discharge profile for the calendar day is 10% less than the sum of the charging profile. A round trip efficiency factor was used to enable this adjustment (0.9), applied on a 30-minute basis to the discharge profile.
3. Price elasticity of demand (PED). A price elasticity of demand adjustment was made that further adjusted the discharge profile for an assumed increase in consumption resulting from a lower cost of stored energy compared to the cost of grid-supplied energy. This was proxied by reducing the level of discharge by an elasticity factor. This had the effect of causing consumption to be higher.
   a. Daytime charging: AEMO used a PED[59] of -0.1. This reduced the discharge factor to 90% of the outcome from Step 2.
   b. Overnight charging: AEMO used a PED of -0.05. This reduced the discharge factor to 95% of the outcome from Step 2.

[59] A PED of -0.1 means a 1% increase in price is associated with a 0.1% reduction in consumption.

APPENDIX D. ENERGY EFFICIENCY

D.1 Projected energy efficiency

AEMO contracted consultancy Pitt & Sherry to provide a forecast for expected energy efficiency savings over the next 20 years.[60]

D.1.1 Scope of work

The analysis projected savings from two types of energy efficiency measures:

- Policy measures addressing the energy efficiency of appliances.
- Building energy efficiency measures.

The assessment covered:

- Savings from existing federal energy efficiency programs as well as state-based programs in Victoria, South Australia and New South Wales.
- Both the residential and commercial sectors, but does not include industrial energy efficiency. However, energy efficiency at all major industry sites is covered through AEMO's industrial load forecasting process, where surveys and interviews with individual companies have been used to estimate energy consumption from these sites going forward.

D.1.2 Methodology

Energy efficiency impacts were estimated for individual programs.[61] The starting point was typically the Regulation Impact Statements leading to program approval. That means savings were estimated based on projected appliance sales or building owners/developers' responses to changes in building requirements. However, where possible these projections have been verified with actual sales data and information about compliance.

The estimated savings were split into heating use, cooling use, and baseload use. Base load is the non-temperature sensitive demand, covering categories such as water heating, lighting, white goods, and home entertainment.

Most assessments were national, and savings had to be split into regional estimates. For cooling and heating energy use, savings were split between states based on appliance penetration and state specific cooling and heating needs.[62] Baseload type appliances were generally split by population, unless there are significant differences in appliance penetration (water heating is one such exception, where some states have less electric and more natural gas-based water heating).

The assessment also included an allowance for future programs, expecting additional initiatives to be implemented over time to assist meeting the target set in the National Energy Productivity Plan (NEPP) for a 40% improvement in energy productivity between today and 2030. The level of additional programs assumed was the same across baseload, heating and cooling, but varied between the three sensitivities as shown in Table 9.

Table 9 Assumptions on additional future energy efficiency programs for the three sensitivities

	Weak	Neutral	Strong
Additional programs driven by NEPP	No additional programs assumed	Increase forecasts savings linearly from 2016–17 to reach 10% in 2035–36	Increase forecasts savings linearly from 2016–17 to reach 20% in 2035–36

[60] Pitt & Sherry. *Estimating the Effects of Energy Efficiency Policies and Programs on Usage of Electricity and Gas*, June 2016. Available at: http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/National-Electricity-Forecasting-Report .

[61] For appliances, this included minimum performance standards for air conditioners and standby energy use and the ban of general purpose incandescent light bulbs. For buildings, this included the National Australian Built Environment Rating System (NABERS) rating scheme for commercial buildings and star rating for residential houses.

[62] For this cooling degree days (CDD) and heating degree days (HDD) were used.

D.2 Energy efficiency

The 2015 NEFR used a long-run regression model of historical data trends to forecast consumption. This method meant that historic energy efficiency trends were captured by the model and then projected. Forecast changes in the historic energy efficiency trends were managed by applying a post-model adjustment that was then added to the forecast.[63]

Recent history has made this approach challenging for capturing energy efficiency trends, due to the coincidence of many changes that are hard to separate in a regression model. These include increasing energy efficiency, increasing energy bill inflation, business closures from the macro-economic shocks of the Global Financial Crisis, and falling costs of electric devices that make energy efficiency more accessible within shorter periods of time (such as LED light globes).

The 2016 NEFR has used a forward-looking method that enables the full strength of the energy efficiency forecasts to be applied. AEMO considers that this method provides a more accurate measure and application of the impact of energy efficiency on its forecasts.

AEMO used back-casting to calibrate the energy efficiency forecasts to recent meter data trends, and also to test the accuracy of the post model adjustment method from the 2015 NEFR. This analysis found that AEMO's previous method did not apply the full strength of energy efficiency.

This analysis also indicated a potential rebound effect from previous energy efficiency initiatives. The rebound effect refers to an increase or bounce-back of consumption, enabled by lower cost use. Based on calibration against these historical years, AEMO has estimated the rebound effect to be around 20%, meaning the effective savings from energy efficiency would be 80% of the forecast estimate. This is used in the neutral sensitivity. Table 10 shows the assumptions used for the other sensitivities.

Table 10 Assumed energy efficiency rebound by sensitivity

	Weak	Neutral	Strong
Residential energy efficiency rebound	10% (0% for SA)	20%	30% (45% for SA)
Business energy efficiency rebound	20%	20%	20%

[63] AEMO. *2015 Forecasting Methodology Information Paper.* Available at: http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/National-Electricity-Forecasting-Report .

APPENDIX E. NEW CONNECTIONS AND UPTAKE OF ELECTRIC APPLIANCES

Key drivers for residential demand are the forecast number of connections (households with electricity connection), the projected uptake and use of electrical appliances per connection, and the energy use of the various appliances, to deliver the required energy services.

Figure 12 Breakdown of drivers for changes in residential demand

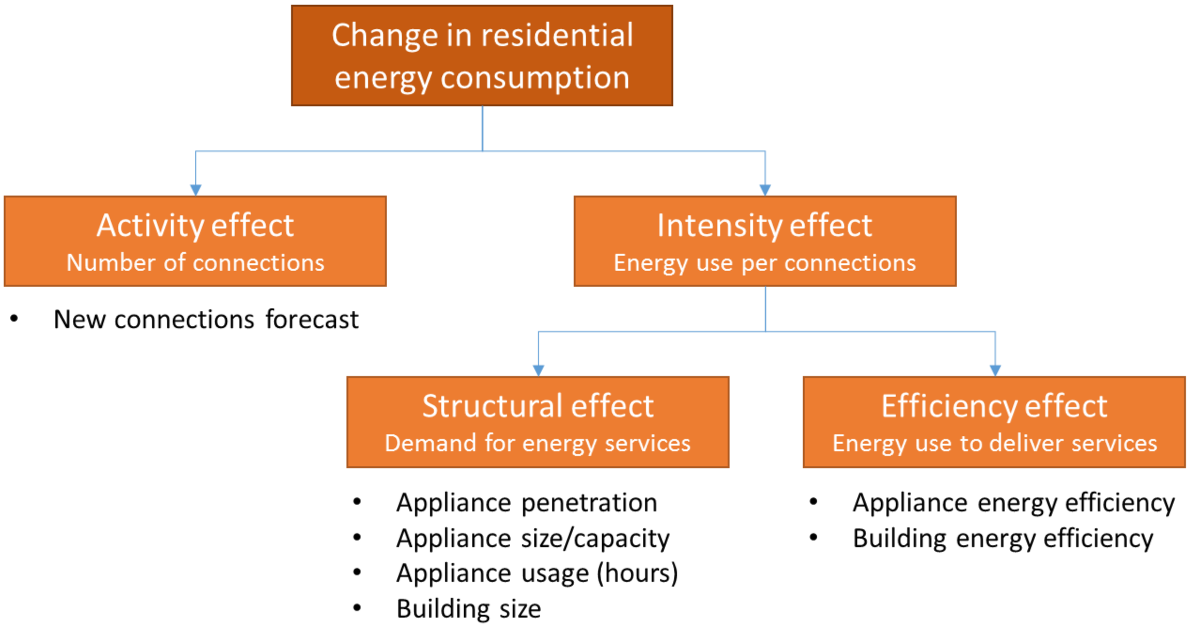


Figure 12 illustrates how residential demand may change due these factors:

- Activity effect – captured change in the number of electricity connections (in practise, this is corresponds to households).
- Structural effect – this captured the demand for various energy services per household. These services could be, for example, space cooling/heating, hot water, refrigeration, and lighting.
- Efficiency effect – this captured the energy used by appliances to meet the demand for services at the households. As appliances get more efficient – and buildings get better insulation, the energy consumed to deliver the services is reduced.

The new connections forecast and appliance uptake and use projections are explained below. More information about energy efficiency is in Appendix D.

E.1 New connections

The increase in the number of connections is one of the main elements of the residential energy consumption forecast. The growth in the number of connections tends to push upwards the total demand, counterbalancing downward drivers like energy efficiency gains and rooftop PV. The number of new connections is driven by demographic and social factors like population projections and changes in the household structure.

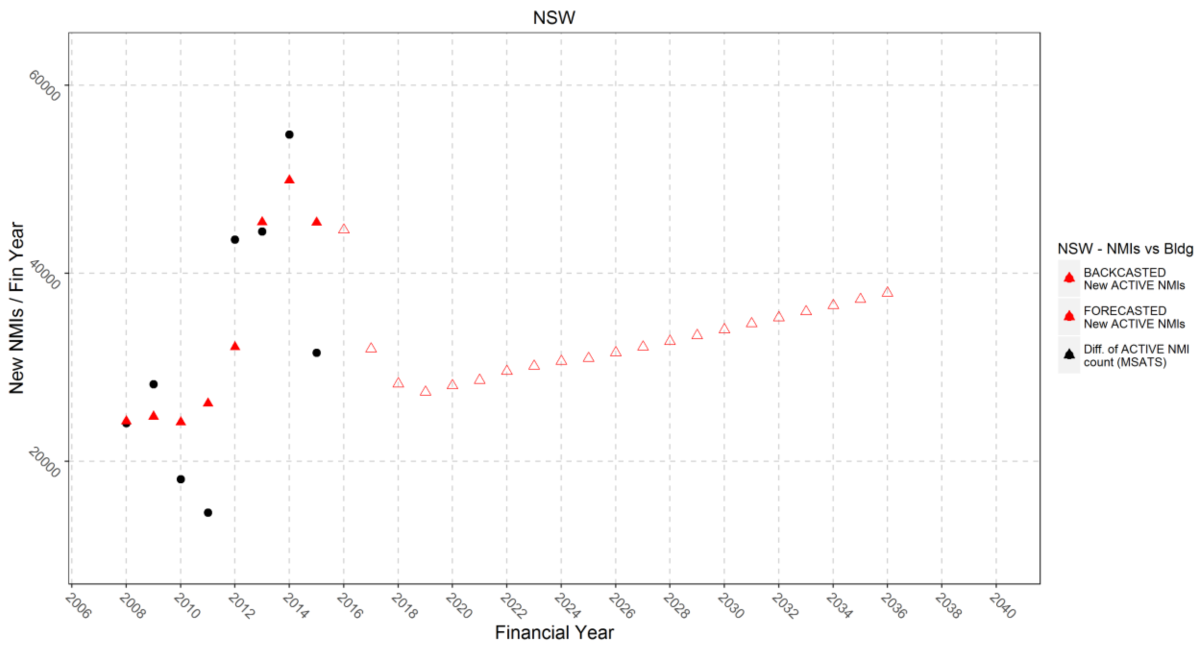
The net change of active electricity meters was used as a proxy for the number of new electricity connections. Historical figures of the net change of active electricity meters were taken from AEMO database systems.[64]

The number of new connections in a given year was correlated to the growth of the dwelling stock in the NEM region. Forecasts of dwelling stock growth were provided by the Housing Industry Association (HIA). These forecasts used as inputs the population projections from the ABS economic trends, recent data of building stocks, and surveys to key participants in the construction sector. The forecasts from HIA have been modified by AEMO so the long-term growth rate converges smoothly into the growth rate of the long-term ABS population projections.[65] HIA provided forecasts for the period 2015–16 to 2025–26. Beyond 2026, the number of connections was forecast using the same year-on-year growth rate as the ABS population projections.

The historical quarterly data of new dwelling construction was correlated to the actual net change of active meters via a linear model. The model took into account the fact that in times of intense expansion of the dwelling stock (like what was observed in the Melbourne and Sydney areas over the past years) a certain fraction of houses is not immediately occupied and stays disconnected from the electricity grid. The forecasts of new constructions were then used in the model to predict the number of future new connections (see Figures 13 and 14).

The forecast of residential connections was obtained from the total number of connections, using a scaling factor that describes the fraction of meters assigned to the residential sector. AEMO has data that allows it to study the historical values of such ratio. The fraction of residential meters is stable and the observed trends are very mild. The trend observed in the past five years was extrapolated in the future. Over the 20-year time horizon of the forecast, the fraction of residential meters is expected to change by at most a couple of per cent, emphasising again the stability of such quantity (see Figures 15 and 16**)**.

Figure 13 Modelling and forecast of total number of new annual connections in New South Wales



[64] Tasmania entered the NEM at a later stage compared to the other regions. The historical data for Tasmania has been uploaded to AEMO's systems at a later stage, making impossible to build historical time series before 2014.
[65] Australian Bureau of Statistics, 2013, Population Projections, Australia 2012 (base),cat. no. 3222.0.

Figure 14 Modelling and forecast of total number of new annual connections in Victoria

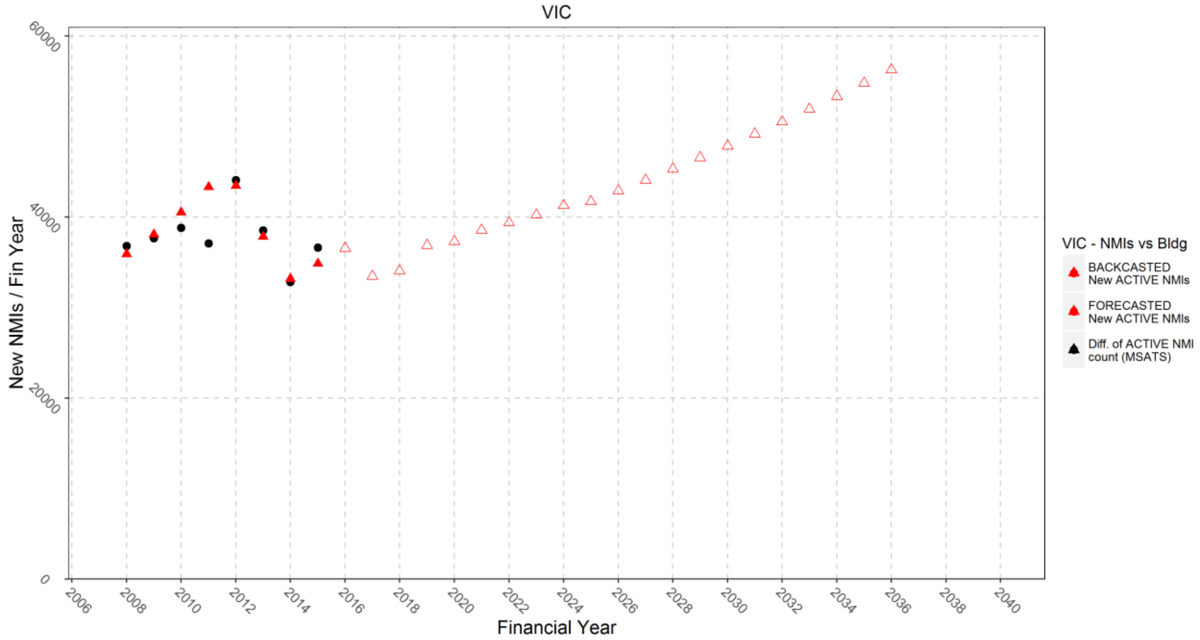


Figure 15 Historical and forecast values of the fraction of residential over total new annual connections in New South Wales

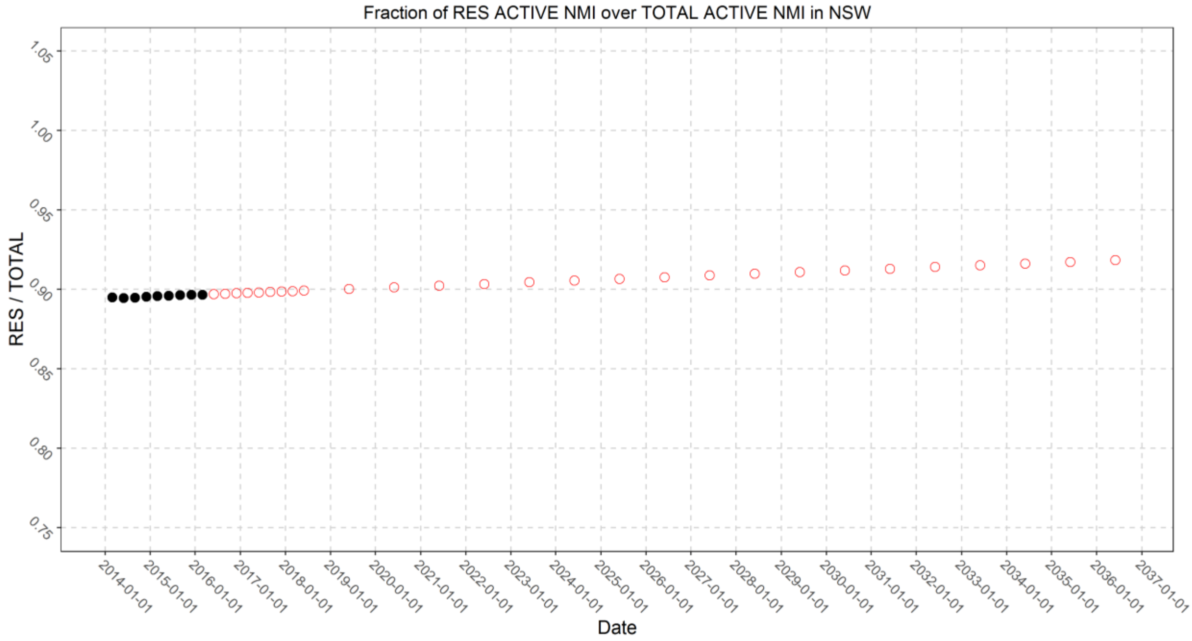
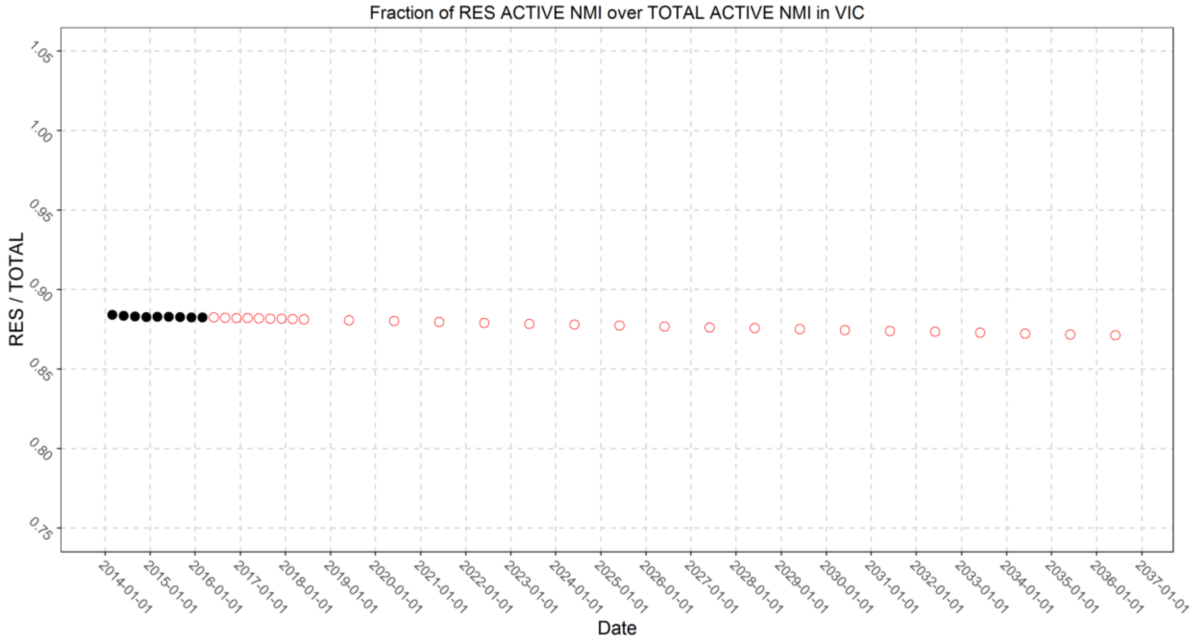


Figure 16 Historical and forecast values of the fraction of residential over total new annual connections in Victoria



E.2 Uptake and use of electric appliances

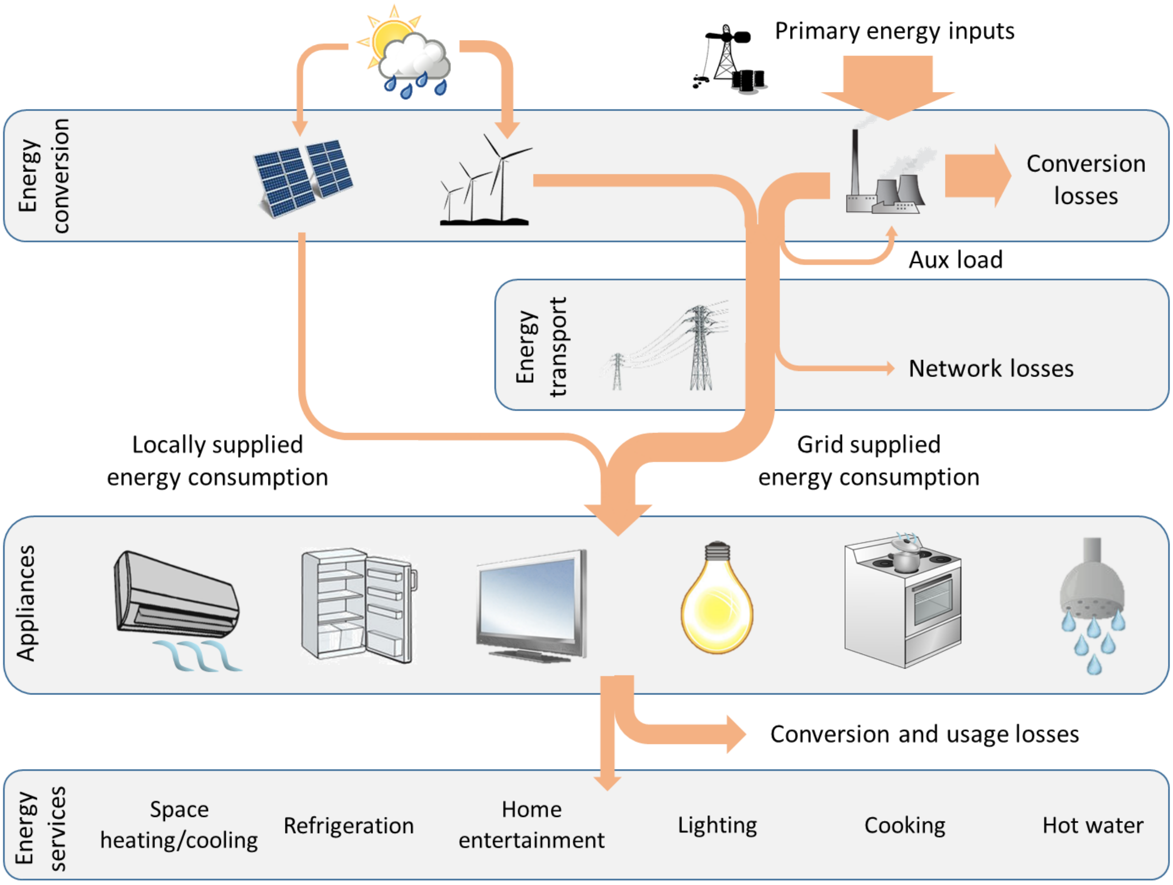
For this NEFR, AEMO was able to get access to electricity usage data down to individual appliance categories, due to its new data collaboration with the Australian Government Department of Industry, Innovation and Science.[66]

AEMO has used this appliance data to forecast growth in electricity consumption by the residential sector (see earlier discussion around Figure 3).

The data allowed AEMO to estimate changes to the level of energy services supplied by electricity per households across the NEM. Energy services here is a measure based on the number of appliances per category across the NEM, their usage hours, and their capacity and size. Figure 17 illustrates the difference between energy services and energy consumption.

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

Figure 17 Energy services vs energy consumption



E.2.1 Appliance growth calculation

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

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

The calculated demand for energy services by appliance group was converted into a growth index with 2015–16 being the base year (index = 100). These indices were combined into a composite index for all appliances based on their relative estimated energy consumption in the base year. As the index captures the benefits to users from the appliance use, it is also referred to as the benefits index.

The table below shows the appliances covered by the calculations.

Table 11 Appliances covered in the calculation of energy services listed by category and subgroup

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

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

E.2.2 Difference between sensitivities

In addition to forecast changes in appliance uptake and use for known appliance categories, AEMO has added to the composite index a small increase in growth from “new” appliance types/categories (not shown specifically in Table 11), representing yet unknown technologies that are expected to hit the market over the forecast period and affect electricity demand.

The three sensitivities had different assumptions of how much these new and yet unknown appliances would add to the composite appliance growth index.

- Weak sensitivity: No additional growth from unknown appliances
- Neutral sensitivity: Up to 4% additional growth from unknown appliances for base load and cooling, half of that for heating
- Strong sensitivity: Up to 8% additional growth from unknown appliances for base load and cooling, half of that for heating

Examples of the benefits index showing appliance composite index growth for New South Wales are shown in the following figures.

Figure 18 Forecast growth in NSW demand for cooling and heating services (Neutral sensitivity)

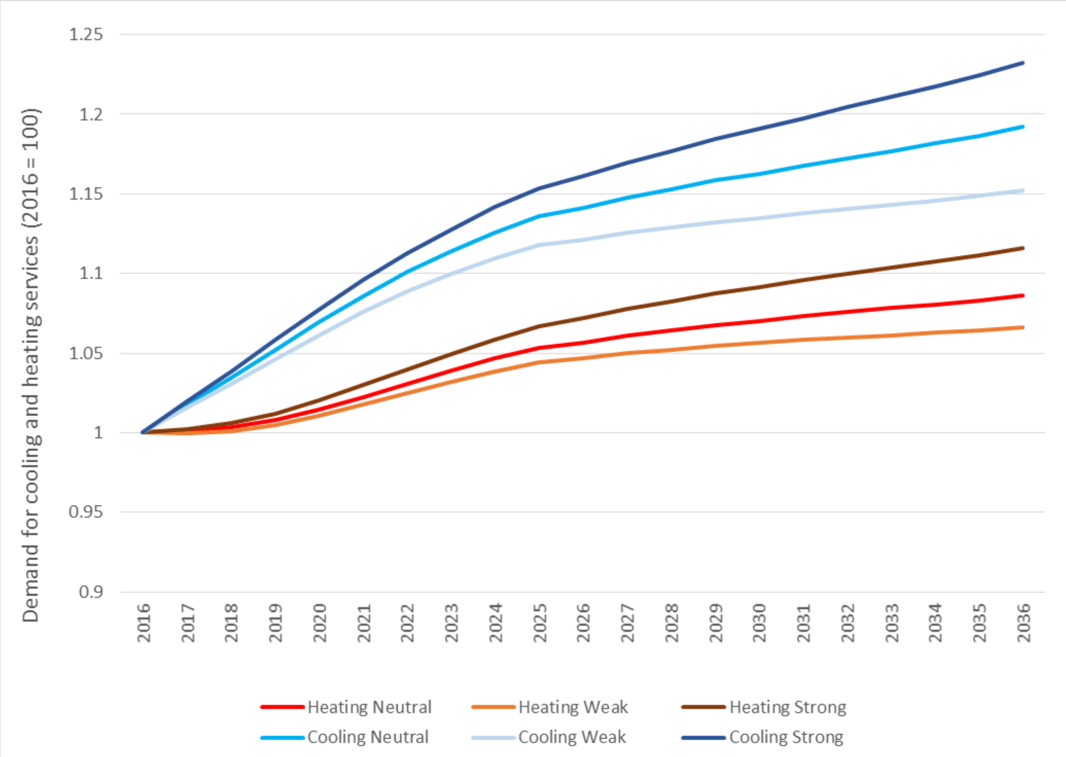
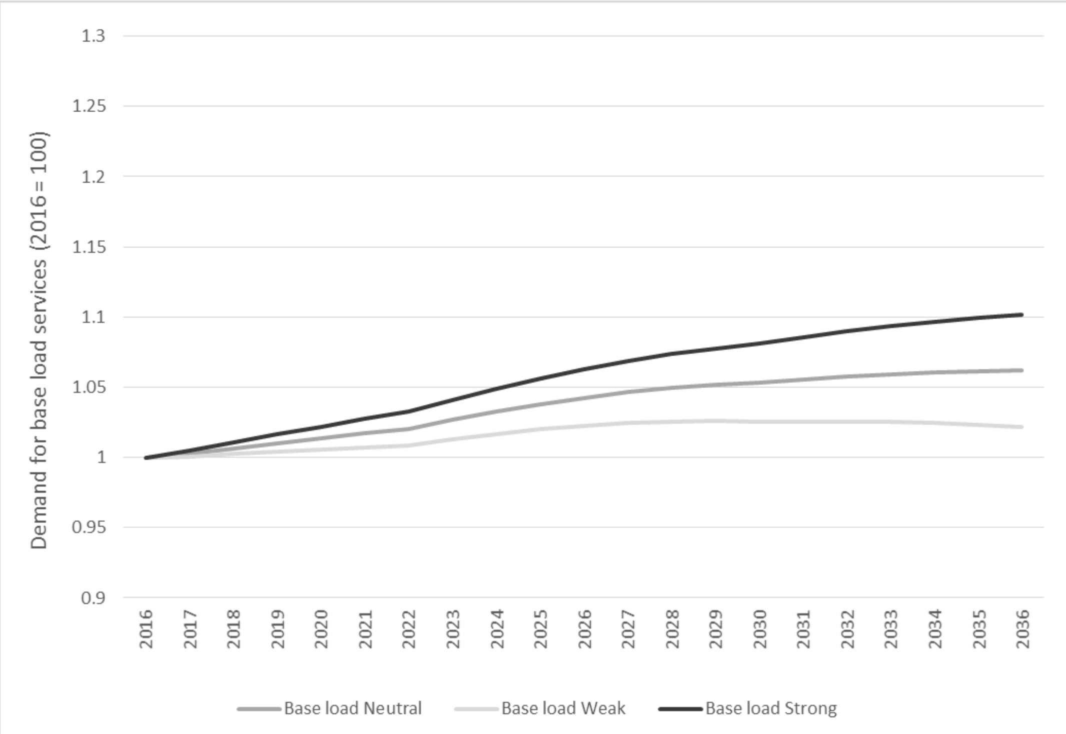


Figure 19 Forecast growth in NSW demand for base load services (Neutral sensitivity)



APPENDIX F. WEATHER AND CLIMATE

F.1 Heating Degree Days (HDD)

HDD is a measure of heating demand, defined by differencing air temperature from a critical temperature.[67]

The formula for HDD[68] is:

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

where $\overline{T}$ is average 30 minute temperature between 9:00 PM to 9:00 PM the following day and CT is the critical temperature threshold in relation to the relevant region.

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

The weather station temperature data was sourced from the Bureau of Meteorology[69] and the stations used are given below.

Table 12 Weather stations used for HDD

Region	Station Name
New South Wales	BANKSTOWN AIRPORT AWS
New South Wales	SYDNEY (OBSERVATORY HILL)
Queensland	ARCHERFIELD AIRPORT
Queensland	BRISBANE AERO
South Australia	ADELAIDE AIRPORT
South Australia	ADELAIDE (KENT TOWN)
Tasmania	HOBART (ELLERSLIE ROAD)
Victoria	MELBOURNE (OLYMPIC PARK)
Victoria	MELBOURNE REGIONAL OFFIE
Victoria	MELBOURNE AIRPORT

Table 13 Critical temperature based on region for HDD

Region	Critical Temperature in degrees C
New South Wales	17.0
Queensland	17.0
South Australia	19.0
Tasmania	16.0
Victoria	16.5

F.2 Cooling Degree Days (CDD)

CDD is a measure of cooling demand, defined by differencing air temperature from a critical temperature[70] (see Table 15).

The formula for CDD[71] is:

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

[67] Critical temperature is a threshold temperature for electricity heating.
[68] All the HDDs in a year are aggregated to obtain the *annual* HDD.
[69] Bureau of Meteorology Climate Data, http://www.bom.gov.au/climate/data/. Viewed: 14 December 2015.
[70] Critical temperature is a threshold temperature for electricity cooling.
[71] All the CDDs in a year are aggregated to obtain the *annual* CDD.

where $\overline{T}$ is average 30 minute temperature between 9:00 PM to 9:00 PM the following day, and CT is the critical temperature threshold in relation to the relevant region.

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

The weather station temperature data was sourced from the Bureau of Meteorology[72] and the stations used are given below.

Table 14 Weather stations used for CDD

Region	Station Name
New South Wales	BANKSTOWN AIRPORT AWS
New South Wales	SYDNEY (OBSERVATORY HILL)
Queensland	ARCHERFIELD AIRPORT
Queensland	BRISBANE AERO
South Australia	ADELAIDE AIRPORT
South Australia	ADELAIDE (KENT TOWN)
Tasmania	HOBART (ELLERSLIE ROAD)
Victoria	MELBOURNE (OLYMPIC PARK)
Victoria	MELBOURNE REGIONAL OFFIE
Victoria	MELBOURNE AIRPORT

Table 15 Critical Temperature based on Region for CDD

Region	Critical Temperature in degrees C
New South Wales	19.5
Queensland	20.0
South Australia	19.0
Tasmania	20.0
Victoria	18.0

F.3 Determining HDD & CDD Standards

Analysis of historic 365-day rolling HDD and CDD data indicated that warming trends across regions have stabilised since the early 2000s. For this reason, the 2016 NEFR used data from 2000 to 2016 to derive a median weather trend.

While the data indicates that the warming trend has stabilised, AEMO is yet to receive climate change advice on the direction of the warming trend going forward. Therefore, AEMO has assumed a stable trend, and has used 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:

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

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

where HDD_{365} is heating degree days over a 365 day period, based on a daily-rolling period starting from 1 January 2000 until 31 March 2016,

and POE50 is where 50% Probability of Exceedance is expected for the given total heating/cooling degree days within that 365 day period.

[72] Bureau of Meteorology Climate Data, http://www.bom.gov.au/climate/data/. Viewed: 14 December 2015.

Table 16 Annual HDD and CDD Standards for each region

Region	Annual HDD	Annual CDD
New South Wales	684.89	404.47
Queensland	257.02	667.29
South Australia	1,261.75	407.20
Tasmania	1,653.07	0.00
Victoria	862.94	328.95

APPENDIX G. SMALL NON-SCHEDULED GENERATION

Operational demand in NEFR forecasts represents consumption from residential and business consumers, supplied by scheduled, semi-scheduled, and significant non-scheduled generating units.[73]

The remainder of non-scheduled generators are referred to as small non-scheduled generation (SNSG). When calculating operational consumption, energy supplied by SNSG is subtracted from residential and business sector consumption.

4.6.1 Data sources

AEMO forecast SNSG generation based on the following data sources:

- AEMO's generation information pages.
- Publicly available information.
- Historical data.
- Projection of PV uptake.[74]

4.6.2 Methodology

The SNSG forecast to 2035–36 is split into two components:

- PV installations above 100 kW but below 30 MW. In previous years, this has been part of the rooftop PV forecast and not included as SNSG. Including it as SNSG provides better visibility of different segments of PV growth.
- 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. Forecast capacity was converted into

The PV component is forecast to grow at the same rate as the commercial rooftop PV forecast.

For the other technologies, AEMO has reviewed the list of generators making up the current SNSG fleet, and made some adjustments to add newly commissioned or committed generators, and to remove retired generators or units that may already be captured though net metering of the load it is embedded under. This resulted in a forecast capacity, for each NEM region, for each technology.

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

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

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

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

[73] Operational definition: http://www.aemo.com.au/media/Files/Other/planning%202016/Operational%20Consumption%20definition%20%202016%20update.pdf .
[74] Jacobs. *Projections of uptake of small-scale systems*, June 2016. Available at: http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/National-Electricity-Forecasting-Report .

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

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

Similarly, the forecast impact on maximum and minimum demand was calculated based on the technologies' historical generation at time of maximum or minimum demand.[75]

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

APPENDIX H. NETWORK LOSSES AND AUXILIARY LOAD FORECASTS

H.1 Network losses

H.1.1 Transmission losses forecast methodology

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

Analysis – annual losses

The approach taken was the same as in the 2015 NEFR. AEMO forecast annual transmission losses (Table 17) by using the historical normalised transmission losses averaged over the last five years. Annual transmission losses were normalised by electricity consumption by large industrial customers as well as residential and commercial customers.

Analysis – maximum demand

AEMO forecast transmission losses during maximum demand (Table 18) by averaging historical normalised transmission losses during the 10 highest operational demand intervals for both summer and winter over the past five years. A weighting factor was applied to ensure the trend of the forecast was more reflective of the more recent historical years.

Analysis – minimum demand

AEMO forecast transmission losses during minimum demand (Table 18) by averaging historical normalised transmission losses during the 10 lowest operational demand intervals for both summer and winter over the past five years. A weighting factor was applied to ensure the trend of the forecast was more reflective of the more recent historical years.

Table 17 Historical normalised transmission losses (annual energy)

Financial Year	NSW	QLD	SA	TAS	VIC
2000–01	2.15%	3.79%	2.30%	-	3.16%
2001–02	2.28%	4.34%	2.01%	-	3.00%
2002–03	2.23%	3.92%	2.31%	2.22%	3.70%
2003–04	2.51%	3.78%	2.44%	2.35%	3.51%
2004–05	2.59%	3.56%	2.32%	2.39%	3.19%
2005–06	2.77%	3.36%	2.34%	2.86%	2.99%
2006–07	2.75%	3.45%	2.10%	2.34%	2.71%
2007–08	2.92%	3.39%	1.88%	2.44%	2.43%
2008–09	2.68%	3.19%	2.21%	2.61%	2.68%
2009–10	2.78%	3.24%	2.35%	3.01%	2.88%
2010–11	2.47%	3.08%	2.32%	3.00%	2.90%
2011–12	2.42%	3.11%	2.37%	2.73%	3.00%
2012–13	2.14%	3.24%	2.40%	3.21%	2.72%
2013–14	1.99%	2.90%	2.67%	4.48%	2.97%
2014–15	2.14%	3.32%	2.95%	2.81%	3.10%
5-year average	**2.23%**	**3.13%**	**2.54%**	**3.25%**	**2.94%**

Table 18 Forecasts of normalised transmission losses for each NEM region during maximum and minimum demand

Demand Type	Duration	NSW	QLD	SA	TAS	VIC
Maximum Demand (Summer)	2016–17 to 2035–36	3.27%	3.61%	1.72%	3.08%	2.64%
Maximum Demand (Winter)	2016 to 2035	2.17%	2.97%	2.56%	4.03%	2.43%
Minimum Demand (Summer)	2016–17 to 2035–36	2.50%	3.22%	2.99%	2.73%	4.89%
Minimum Demand (Winter)	2016 to 2035	2.06%	2.76%	3.15%	2.71%	3.69%

H.1.2 Distribution losses

To calculate operational and native demand from estimated delivered demand (see Appendix A), distribution losses are needed in addition to transmission losses.

AEMO has used the losses shown in Table 19. These are estimated as a volume weighted average per region generally based on recent losses reported to the Australian Energy Regulator (AER) by distribution companies as part of the Distribution Loss Factor approvals process.

Table 19 Estimated average distribution losses in the NEM (in % of transmitted energy)

	NSW	QLD	SA	TAS	VIC
Losses (in %)	5.0 %	1.9%	6.0%	5.4%	5.6%

H.2 Auxiliary loads forecast methodology

Auxiliary loads forecast

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

Historical data

Analysis for auxiliary loads required historical data obtained from the wholesale market system – Market Management System (MMS). Since auxiliary loads were not directly measured, auxiliary loads were assumed to be equal to the difference between total generation as measured at generator terminals and that sent-out.

Analysis – annual energy

Similar to the 2015 NEFR, the annual auxiliary factor in each region was forecast based on historical data and the anticipated changes in the future generation mix[76] (Table 20). The auxiliary factor is defined as:

$$Auxiliary\ factor = \frac{Total\ auxiliary\ loads}{Operational\ consumption\ as - generated}$$

The annual auxiliary loads were then estimated by multiplying the expected auxiliary factor by operational consumption as forecast by the annual energy model.

Analysis – maximum demand

Auxiliary load forecasts during maximum demand (Table 21) were based on the average auxiliary factor. This factor was calculated by first determining the average of the historical auxiliary loads during the 10 highest operational demand intervals for both summer and winter over the past five years. A weighting factor was then applied to ensure the trend of the forecast was more reflective of the more recent historical years.

Analysis – minimum demand

Auxiliary load forecasts were not produced separately for minimum demand. This year, the model used the same factors as maximum demand. In future years, these will be calculated directly based on historical auxiliary load during minimum demand.

[76] Forecasts of the future generation mix were based on the 2015 *National Transmission Network Development Plan* (NTNDP) with minor changes.

Table 20 Forecasts of the auxiliary factor for each NEM region (annual energy)

Financial Year	NSW	QLD	SA	TAS	VIC
2016-17	4.66%	6.61%	3.34%	1.50%	8.99%
2017-18	4.67%	6.61%	1.09%	1.40%	8.91%
2018-19	4.39%	6.49%	1.13%	1.33%	8.78%
2019-20	4.09%	6.42%	0.91%	1.33%	8.73%
2020-21	4.12%	6.42%	1.02%	1.33%	8.73%
2021-22	4.03%	6.42%	1.03%	1.33%	8.73%
2022-23	4.08%	6.41%	1.03%	1.33%	8.73%
2023-24	4.12%	6.41%	1.04%	1.33%	8.74%
2024-25	4.15%	6.41%	1.04%	1.33%	8.73%
2025-26	4.17%	6.41%	1.04%	1.33%	8.73%
2026-27	4.19%	6.40%	1.04%	1.33%	8.73%
2027-28	4.19%	6.39%	1.04%	1.33%	8.73%
2028-29	4.23%	6.39%	1.06%	1.33%	8.74%
2029-30	4.24%	6.40%	1.08%	1.33%	8.74%
2030-31	4.25%	6.40%	1.06%	1.33%	8.73%
2031-32	4.26%	6.39%	1.06%	1.33%	8.73%
2032-33	4.27%	6.38%	1.06%	1.33%	8.73%
2033-34	4.26%	6.38%	1.08%	1.33%	8.73%
2034-35	4.27%	6.33%	1.09%	1.33%	8.74%
2035-36	4.26%	6.32%	0.00%	1.33%	8.72%

Table 21 Forecasts of the auxiliary factor for each NEM region during maximum demand

Demand Type	Duration	NSW	QLD	SA	TAS	VIC
Maximum Demand (Summer)	2015-16 to 2034-35	3.95%	5.32%	4.68%	1.65%	5.31%
Maximum Demand (Winter)	2015 to 2034	4.27%	5.67%	3.53%	1.50%	6.67%

APPENDIX I. GENERATORS INCLUDED

This appendix provides two lists of power stations for each NEM region, to separately identify the scheduled, semi-scheduled and non-scheduled generators that contributed to 2016 NEFR forecasts:

- The first lists the power stations used to develop operational consumption forecasts.
- The second lists the additional power stations used to develop native consumption forecasts.

I.1 New South Wales

Table 22 Power stations used for operational consumption forecasts

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Bayswater	2640	Steam Sub Critical	Black Coal	Scheduled
Blowering	70	Hydro - Gravity	Water	Scheduled
Boco Rock Wind Farm	113	Wind - Onshore	Wind	Semi-Scheduled
Broken Hill Solar	53.76	Solar PV	Solar	Semi-Scheduled
Capital Wind Farm	140.7	Wind - Onshore	Wind	Non-scheduled
Colongra	724	OCGT	Natural Gas Pipeline	Scheduled
Cullerin Range Wind Farm	30	Wind - Onshore	Wind	Non-scheduled
Eraring	2880	Steam Sub Critical	Black Coal	Scheduled
Gullen Range Wind Farm	165	Wind - Onshore	Wind	Semi-Scheduled
Gunning Wind Farm	46.5	Wind - Onshore	Wind	Semi-Scheduled
Guthega	60	Hydro - Gravity	Water	Scheduled
Hume NSW	29	Hydro - Gravity	Water	Scheduled
Hunter Valley GT	50	OCGT	Fuel Oil	Scheduled
Liddell	2000	Steam Sub Critical	Black Coal	Scheduled
Moree Solar Farm	57	Solar PV	Solar	Semi-Scheduled
Mt Piper	1400	Steam Sub Critical	Black Coal	Scheduled
Nyngan Solar Farm	102	Solar PV	Solar	Semi-Scheduled
Shoalhaven	240	Hydro - Gravity	Water	Scheduled
Smithfield Energy Facility	170.9	CCGT	Natural Gas Pipeline	Scheduled
Tallawarra	420	CCGT	Natural Gas Pipeline	Scheduled
Taralga Wind Farm	106.7	Wind - Onshore	Wind	Semi-Scheduled
Tumut 3	1500	Hydro - Gravity	Water	Scheduled
Upper Tumut	616	Hydro - Gravity	Water	Scheduled
Uranquinty	664	OCGT	Natural Gas Pipeline	Scheduled
Vales Point B	1320	Steam Sub Critical	Black Coal	Scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Woodlawn Wind Farm	48.3	Wind - Onshore	Wind	Semi-Scheduled

Table 23 Power stations (existing, SNSG) used for native consumption forecasts for New South Wales – in addition to those in Table 20

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Appin Power Plant	55.6	Spark Ignition Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
Awaba Power Station	1.1	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Bankstown Sports Club	2.1	Compression Reciprocating Engine	Diesel	Non-scheduled
Belconnen Landfill	1.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Broadwater Power Station	38.0	Steam Sub Critical	Bagasse	Non-scheduled
Broken Hill Gas Turbines	50.0	OCGT	Diesel	Non-scheduled
Brown Mountain	5.2	Hydro - Gravity	Water	Non-scheduled
Burrendong Hydro Power Station	19.0	Hydro - Gravity	Water	Non-scheduled
Burrinjuck Power Station	27.2	Hydro - Gravity	Water	Non-scheduled
Buttonderry Waste Facility	2.2	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Capital East Solar Farm	0.1	Solar PV	Solar	Non-scheduled
Condong Power Station	30.0	Steam Sub Critical	Bagasse	Non-scheduled
Copeton Hydro	20.0	Hydro - Gravity	Water	Non-scheduled
Crookwell Wind Farm	4.8	Wind - Onshore	Wind	Non-scheduled
EarthPower Biomass Plant	3.9	Spark Ignition Reciprocating Engine	Biomass recycled municipal and industrial material	Non-scheduled
Eastern Creek 2	7.9	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Eastern Creek Power Station	5.1	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Glenbawn Hydro	5.0	Hydro - Gravity	Water	Non-scheduled
Grange Avenue Landfill	1.3	Compression Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Hunter Economic Zone	29.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Jacks Gully Landfill	2.3	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Jindabyne Small Hydro	1.1	Hydro - Gravity	Water	Non-scheduled
Jounama Small Hydro	14.4	Hydro - Gravity	Water	Non-scheduled
Keepit Power Station	7.2	Hydro - Gravity	Water	Non-scheduled
Kincumber Landfill	1.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Lake Cargelligo CST	3.5	Solar Thermal	Solar	Non-scheduled
Lucas Heights I	5.4	Compression Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Lucas Heights II	17.3	Compression Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Mugga Lane Landfill	3.4	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Nine Network Willoughby	3.2	Compression Reciprocating Engine	Diesel	Non-scheduled
Nymbodia	5.0	Hydro - Gravity	Water	Non-scheduled
Oaky River Dam Hydro	5.0	Hydro - Gravity	Water	Non-scheduled
Pindari Hydro	5.7	Hydro - Gravity	Water	Non-scheduled
Royalla Solar Farm	20.0	Solar PV	Solar	Non-scheduled
St Georges League Club	1.5	Compression Reciprocating Engine	Diesel	Non-scheduled
Summerhill Waste Mgmt. Centre	2.2	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Teralba	3.0	Compression Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
The Drop Hydro	2.5	Hydro - Gravity	Water	Non-scheduled
Tower Power Plant	41.2	Spark Ignition Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
West Illawarra Leagues Club	1.0	Compression Reciprocating Engine	Diesel	Non-scheduled
West Nowra Landfill Gas Power Generation Facility	1.0	Compression Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Western Suburbs League	1.3	Compression Reciprocating Engine	Diesel	Non-scheduled
Wilga Park A	10.0	Spark Ignition Reciprocating Engine	Natural Gas - Unprocessed	Non-scheduled
Wilga Park B	6.0	Spark Ignition Reciprocating Engine	Natural Gas - Unprocessed	Non-scheduled
Woy Woy	1.1	Compression Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Wyangala A	20.0	Hydro - Gravity	Water	Non-scheduled
Wyangala B	4.0	Hydro - Gravity	Water	Non-scheduled

I.2 Queensland

Table 24 Power stations used for operational consumption forecasts for Queensland

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Barcaldine	37	OCGT	Natural Gas Pipeline	Scheduled
Barron Gorge	66	Run of River	Water	Scheduled
Braemar	504	OCGT	Coal Seam Methane	Scheduled
Braemar 2	519	OCGT	Coal Seam Methane	Scheduled
Callide B	700	Steam Sub Critical	Black Coal	Scheduled
Callide C	900	Steam Super Critical	Black Coal	Scheduled
Condamine A	144	CCGT	Coal Seam Methane	Scheduled
Darling Downs	644	CCGT	Coal Seam Methane	Scheduled
Gladstone	1680	Steam Sub Critical	Black Coal	Scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Kareeya	88	Run of River	Water	Scheduled
Kogan Creek	744	Steam Super Critical	Black Coal	Scheduled
Mackay Gas Turbine	34	OCGT	Diesel	Scheduled
Millmerran Power Plant	856	Steam Super Critical	Black Coal	Scheduled
Mt Stuart	424	OCGT	Kerosene Aviation fuel used for stationary energy	Scheduled
Oakey	282	OCGT	Diesel	Scheduled
Roma Gas Turbine	80	OCGT	Natural Gas Pipeline	Scheduled
Stanwell	1460	Steam Sub Critical	Black Coal	Scheduled
Swanbank E GT	385	CCGT	Coal Seam Methane	Scheduled
Tarong	1400	Steam Sub Critical	Black Coal	Scheduled
Tarong North	450	Steam Super Critical	Black Coal	Scheduled
Townsville Gas Turbine (Yabulu)	242	CCGT	Coal Seam Methane	Scheduled
Wivenhoe	500	Pump Storage	Water	Scheduled
Yarwun	154	CCGT	Natural Gas Pipeline	Scheduled[77]

Table 25 Power stations (existing, SNSG) used for native consumption forecasts for Queensland – in addition to those in Table 22

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Browns Plains Landfill	2.2	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Callide A4 Oxyfuel	30.0	Steam Turbine - Sub Critical	Black Coal	Non-scheduled
Daandine	30.0	Compression Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
German Creek	45.0	Spark Ignition Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
ISIS Central Sugar Mill	25.0	Steam Turbine - Sub Critical	Bagasse	Non-scheduled
Kareeya 5 Power Station	7.0	Hydro - Gravity	Water	Non-scheduled
Moranbah Generation Project	12.6	Compression Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
Moranbah North	45.6	Spark Ignition Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
Oaky Creek Power Station	20.0	Compression Reciprocating Engine	Coal Seam Methane	Non-scheduled
Racecourse Mill	48.0	Steam Turbine - Sub Critical	Bagasse	Non-scheduled
Rochedale Renewable Energy	4.2	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Rocky Point Green Energy	30.0	Steam Turbine - Sub Critical	Biomass	Non-scheduled
Roghan Road	1.2	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled

[77] The NEM registration classification of Yarwun Power Station Unit 1 (dispatchable unit ID: YARWUN_1) is a market non-scheduled generating unit. However, it is a condition of the registration of this unit that the Registered Participant complies with some of the obligations of a scheduled generator. This unit is dispatched as a scheduled generating units with respect to its dispatch offers, targets and generation outputs. Accordingly, information about YARWUN_1 is reported as scheduled generating unit information.

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
South Johnstone Sugar Mill	19.3	Steam Turbine - Sub Critical	Bagasse	Non-scheduled
Southbank Institute of Tech	1.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Suncoast Gold Macadameias	1.0	Steam Turbine - Sub Critical	Biomass	Non-scheduled
Tarong Power Station GT	15.0	OCGT	Diesel	Non-scheduled
Tully Sugar Mill	10.0	Steam Turbine - Sub Critical	Bagasse	Non-scheduled
Veoilia Ti Tree Bioreactor	3.3	Compression Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Victoria Mill	24.0	Steam Turbine - Sub Critical	Bagasse	Non-scheduled
Whitwood Road Renewable Energy Facility	1.1	Compression Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Windy Hill	12.0	Wind Onshore	Wind	Non-scheduled
Wivenhoe Small Hydro	4.5	Hydro - Gravity	Water	Non-scheduled

I.3 South Australia

Table 26 Power stations used for operational consumption forecasts for South Australia

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Angaston	50	Compression Reciprocating Engine	Diesel	Scheduled
Canunda Wind Farm	46	Wind - Onshore	Wind	Non-scheduled
Cathedral Rocks Wind Farm	66	Wind - Onshore	Wind	Non-scheduled
Clements Gap Wind Farm	56.7	Wind - Onshore	Wind	Semi-scheduled
Dry Creek Gas Turbine Station	156	OCGT	Natural Gas Pipeline	Scheduled
Hallett 1 (Brown Hill)	94.5	Wind - Onshore	Wind	Semi-scheduled
Hallett 2 (Hallett Hill)	71.4	Wind - Onshore	Wind	Semi-scheduled
Hallett 4 (Nth Brown Hill)	132.3	Wind - Onshore	Wind	Semi-scheduled
Hallett 5 (The Bluff)	52.5	Wind - Onshore	Wind	Semi-scheduled
Hallett GT	228.3	OCGT	Natural Gas Pipeline	Scheduled
Ladbroke Grove Power Station	80	OCGT	Natural Gas Pipeline	Scheduled
Lake Bonney Stage 2 Wind Farm	159	Wind - Onshore	Wind	Semi-scheduled
Lake Bonney Stage 3 Wind Farm	39	Wind - Onshore	Wind	Semi-scheduled
Lake Bonney Wind Farm	80.5	Wind - Onshore	Wind	Non-scheduled
Lonsdale	20	Compression Reciprocating Engine	Diesel	Scheduled
Mintaro Gas Turbine Station	90	OCGT	Natural Gas Pipeline	Scheduled
Mt Millar Wind Farm	70	Wind - Onshore	Wind	Non-scheduled
Osborne Power Station	180	CCGT	Natural Gas Pipeline	Scheduled
Pelican Point Power Station	478	CCGT	Natural Gas Pipeline	Scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Port Lincoln Gas Turbine	73.5	OCGT	Diesel	Scheduled
Pt. Stanvac	57.6	Compression Reciprocating Engine	Diesel	Scheduled
Quarantine Power Station	224	OCGT	Natural Gas Pipeline	Scheduled
Snowtown Wind Farm Units 1 And 47	98.7	Wind - Onshore	Wind	Semi-scheduled
Snowtown S2 North Wind Farm	144	Wind - Onshore	Wind	Semi-scheduled
Snowtown S2 South Wind Farm	126	Wind - Onshore	Wind	Semi-scheduled
Snuggery Power Station	63	OCGT	Diesel	Scheduled
Starfish Hill Wind Farm	34.5	Wind - Onshore	Wind	Non-scheduled
Torrens Island A	480	Steam Sub Critical	Natural Gas Pipeline	Scheduled
Torrens Island B	800	Steam Sub Critical	Natural Gas Pipeline	Scheduled
Waterloo Wind Farm	111	Wind - Onshore	Wind	Semi-scheduled
Wattle Point Wind Farm	90.8	Wind - Onshore	Wind	Non-scheduled

Table 27 Power stations (existing, SNSG) used for native consumption forecasts for South Australia – in addition to those in Table 24

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Amcor Glass, Gawler Plant*	4.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Blue Lake Milling Power Plant	0.5	Compression Reciprocating Engine	Diesel	Non-scheduled
Highbury Landfill*	1.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Pedler Creek Landfill	3.1	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
SA Water Hope Valley Terminal Storage Mini Hydro	2.5	Hydro - Gravity	Water	Non-scheduled
SA Water Seacliff Park Mini Hydro	1.2	Hydro - Gravity	Water	Non-scheduled
Tatiara Bordertown	0.5	Compression Reciprocating Engine	Diesel	Non-scheduled
Tea Tree Gully Landfill*	1.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Wingfield 1 Landfill	4.1	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Wingfield 2 Landfill	4.1	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled

* Deregistered during the 2015–16 financial year.

I.4 Tasmania

Table 28 Power stations used for operational consumption forecasts for Tasmania

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Bastyan	79.9	Hydro - Gravity	Water	Scheduled
Bell Bay Three	120	OCGT	Natural Gas Pipeline	Scheduled
Catagunya / Liapootah / Wayatinah	170.1	Hydro - Gravity	Water	Scheduled
Cethana	85	Hydro - Gravity	Water	Scheduled
Devils Gate	60	Hydro - Gravity	Water	Scheduled
Fisher	43.2	Hydro - Gravity	Water	Scheduled
Gordon	432	Hydro - Gravity	Water	Scheduled
John Butters	144	Hydro - Gravity	Water	Scheduled
Lake Echo	32.4	Hydro - Gravity	Water	Scheduled
Lemonthyme / Wilmot	81.6	Hydro - Gravity	Water	Scheduled
Mackintosh	79.9	Hydro - Gravity	Water	Scheduled
Meadowbank	40	Hydro - Gravity	Water	Scheduled
Musselroe Wind Farm	168	Wind – Onshore	Wind	Semi-Scheduled
Poatina	300	Hydro - Gravity	Water	Scheduled
Reece	231.2	Hydro - Gravity	Water	Scheduled
Tamar Valley Combined Cycle	208	CCGT	Natural Gas Pipeline	Scheduled
Tamar Valley Peaking	58	OCGT	Natural Gas Pipeline	Scheduled
Tarraleah	90	Hydro - Gravity	Water	Scheduled
Trevallyn	93	Hydro - Gravity	Water	Scheduled
Tribute	82.8	Hydro - Gravity	Water	Scheduled
Tungatinah	125	Hydro - Gravity	Water	Scheduled
Woolnorth Studland Bay / Bluff Point Wind Farm	140	Wind - Onshore	Wind	Non-scheduled

Table 29 Power stations (existing, SNSG) used for native consumption forecasts for Tasmania – in addition to those in Table 26

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Butlers Gorge	14.4	Hydro – Gravity	Water	Non-scheduled
Cluny	17.0	Hydro – Gravity	Water	Non-scheduled
Paloona	28.0	Hydro – Gravity	Water	Non-scheduled
Remount	2.2	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled

I.5 Victoria

Table 30 Power stations used for operational consumption forecasts for Victoria

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Bairnsdale	94	OCGT	Natural Gas Pipeline	Scheduled
Bald Hills Wind Farm	106.6	Wind - Onshore	Wind	Semi-scheduled
Bogong / Mckay	300	Hydro - Gravity	Water	Scheduled
Challicum Hills Wind Farm	52.5	Wind - Onshore	Wind	Non-scheduled
Dartmouth	185	Hydro - Gravity	Water	Scheduled
Eildon	135	Hydro - Gravity	Water	Scheduled
Hazelwood	1600	Steam Sub Critical	Brown Coal	Scheduled
Hume VIC	29	Hydro - Gravity	Water	Scheduled
Jeeralang A	212	OCGT	Natural Gas Pipeline	Scheduled
Jeeralang B	228	OCGT	Natural Gas Pipeline	Scheduled
Laverton North	312	OCGT	Natural Gas Pipeline	Scheduled
Loy Yang A	2180	Steam Sub Critical	Brown Coal	Scheduled
Loy Yang B	1000	Steam Sub Critical	Brown Coal	Scheduled
Macarthur Wind Farm	420	Wind - Onshore	Wind	Semi-scheduled
Mortlake Units	566	OCGT	Natural Gas Pipeline	Scheduled
Morton's Lane Wind Farm	19.5	Wind - Onshore	Wind	Non-scheduled
Mt. Mercer Wind Farm	131.2	Wind - Onshore	Wind	Semi-scheduled
Murray 1	950	Hydro - Gravity	Water	Scheduled
Murray 2	552	Hydro - Gravity	Water	Scheduled
Newport	500	Steam Sub Critical	Natural Gas Pipeline	Scheduled
Oaklands Hill Wind Farm	67.2	Wind - Onshore	Wind	Semi-scheduled
Portland Wind Farm	102	Wind - Onshore	Wind	Non-scheduled
Somerton	160	OCGT	Natural Gas Pipeline	Scheduled
Valley Power Peaking Facility	300	OCGT	Natural Gas Pipeline	Scheduled
Waubra Wind Farm	192	Wind - Onshore	Wind	Non-scheduled
West Kiewa	60	Hydro - Gravity	Water	Scheduled
Yallourn W	1480	Steam Sub Critical	Brown Coal	Scheduled
Yambuk Wind Farm	30	Wind - Onshore	Wind	Non-scheduled

Table 31 Power stations (existing, SNSG) used for native consumption forecasts for Victoria – in addition to those in Table 28

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Ballarat Base hospital	2.0	Spark Ignition Reciprocating Engine	Natural Gas Pipeline	Non-scheduled
Banimboola Power Station	12.2	Hydro - gravity	Water	Non-scheduled
Berwick Landfill	4.6	Other renewable	Landfill Methane / Landfill Gas	Non-scheduled
Broadmeadows Landfill	6.2	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Brooklyn Landfill	2.8	Spark Ignition	Landfill Methane / Landfill Gas	Non-scheduled
Cardinia Hydro Power Station	3.2	Hydro - Gravity	Water	Non-scheduled
Clayton	12.0	Spark Ignition	Landfill Methane / Landfill Gas	Non-scheduled
Codrington Wind Farm	18.2	Wind - Onshore	Wind	Non-scheduled
Coonooer Bridge Wind Farm	20.0	Wind - Onshore	Wind	Non-Scheduled
Corio Landfill	1.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Dandenong PEP	2.0	Spark Ignition Reciprocating Engine	Natural Gas Pipeline	Non-scheduled
Eildon Pondage Hydro	4.5	Hydro - Gravity	Water	Non-scheduled
Glenmaggie Hydro	3.8	Hydro - Gravity	Water	Non-scheduled
Hallam Road RE Facility	9.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Hepburn Wind Farm	4.0	Wind - Onshore	Wind	Non-scheduled
Longford	31.8	OCGT	Natural Gas Pipeline	Non-scheduled
Mornington Waste Disposal	0.8	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Rubicon	13.5	Hydro - Gravity	Water	Non-scheduled
Shepparton Waste Water	0.8	Spark Ignition Reciprocating Engine	Sewerage / Waste Water Gas	Non-scheduled
South East Water - Hallam Plant	0.3	Hydro - Gravity	Water	Non-scheduled
Springvale Landfill Gas Power Station	4.2	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Traralgon Network Support Station	10.0	Spark Ignition Reciprocating Engine	Natural Gas Pipeline	Non-scheduled
Tatura Biogas	1.1	Spark Ignition Reciprocating Engine	Sewerage / Waste Water Gas	Non-scheduled
Toora Wind Farm	21.0	Wind - Onshore	Wind	Non-scheduled
William Hovell Hydro Power Station	1.8	Hydro - Gravity	Water	Non-scheduled
Wollert Renewable Energy Facility	6.7	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Wonthaggi Wind Farm	12.0	Wind - Onshore	Wind	Non-scheduled
Wyndham Waste Disposal Facility	1.9	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Yarrawonga Hydro	9.5	Hydro - Gravity	Water	Non-scheduled

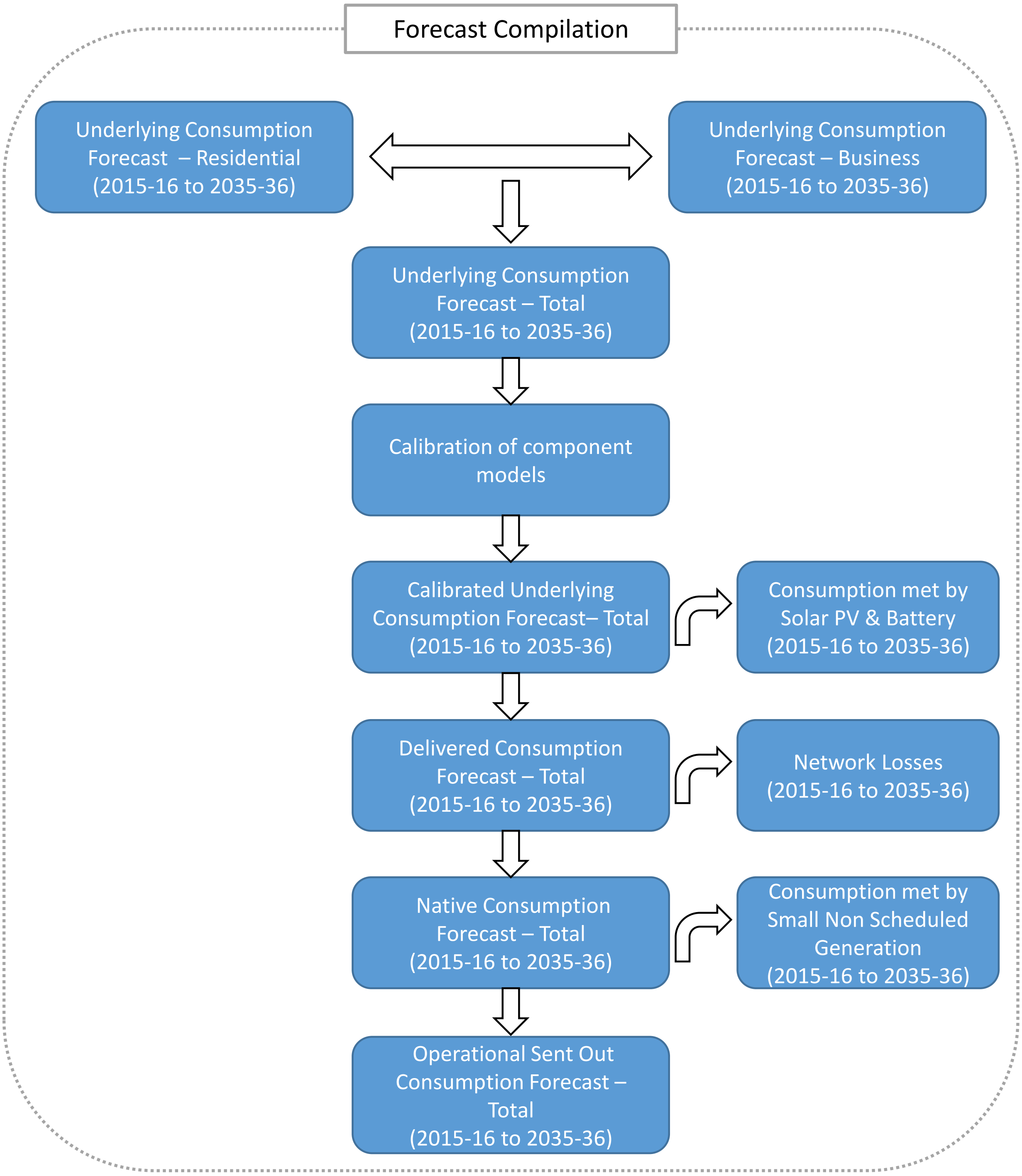
APPENDIX J. REGIONAL FORECAST COMPILATION

Once the business and residential forecasts were derived for each state and scenario, they were compiled to produce regional forecasts. The compiled forecasts went through a tuning process to normalise datasets and to calibrate with the latest operational data[78] and relevant benchmarks.[79] This process was also needed to best integrate components that may have been developed using alternative datasets.[80] The tuning process reveals the need for adjustments to specific model components, which are made as required.

The tuning process is explained in the diagram below.

[78] Operational consumption data was weather normalised.
[79] Benchmarks included alternative and prior year forecasts and other data that together could confirm or be used to refine key model assumptions and inputs.
[80] Examples include using ABS data in place of business consumption data. Other tuning adjustments included time-normalising across components in cases where these components used time series data that may have reflected different or overlapping periods of time.

Figure 20 Process flow for regional forecasts compilation



Forecast compilation

The forecast compilation began with an initial compilation of residential and business forecasts by region. These resulting total forecasts underwent a robustness check and were benchmarked against several measures, as outlined in detail below. The components in need of tuning were adjusted and re-aggregated to give the final compiled regional forecasts.

Model tuning process

AEMO's move to the use of more detailed, "bottom-up" models means there are now more components that must be integrated together. Bottom-up models refers to highly segmented models that when added together represent a total forecast for the region. To enable the aggregation of these segmented models, they must be internally consistent in terms of data, variables and assumptions. The tuning process is a key step in the compilation of regional forecasts.

The following tuning techniques were applied to the forecast components:

- **Time normalisation** – parameters for different components of regional forecasts may be developed using data with a varying time series range. This can be the case, for example, when historic data inputs have varying data cut-off dates causing differential time lags across model components. In some cases, the forecasts from these components need to be evolved to the starting year of the forecast outlook.
- **Weather normalisation** – forecast components assume weather inputs with a defined probabilistic level, such as 50% POE. To validate forecasts against recent historic data, this historic data needs to be adjusted to share a similar probabilistic basis, thereby enabling a consistent comparison between the actual data and forecast data.
- **Variable normalisation** – when alternative data sources are used as proxy variables to address data or information gaps, these data sources may have an inconsistent measurement basis requiring some adjustment. For example, the business forecasts use some electricity consumption data sourced from the Office of the Chief Economist that is measured differently from AEMO's definition of Operational Consumption.
- **Smoothing the transition from historic trends to modelled trends** – some forecast components may be developed using historic data that is not completely current or that uses parameter inputs that cause a step change when compared with trends in the latest available meter data. In this case, the level of the year 1 forecast may be reset, or relevant forecast components may be adjusted, to bridge consistency between recent historic trends and short-term forecast trends.
- **Calibration to weather normalised actuals for the region** – depending on the outcome of the weather normalisation of recent actual meter data, it may be the case that the levels of the year 1 forecast need to be reset to calibrate the forecasts with recently observed actual meter data.

APPENDIX K. DATA SOURCES

Table 32 Public datasets used in business consumption forecast

Indicator	Description	Units	Source	Forecast Provider
Input Producer Price Index	An input PPI measures the rate of change in the prices of goods and services purchased as inputs by the producer for the manufacturing sector.	Index	ABS Table 11 Input to the Manufacturing industries, division and selected industries, index numbers and percentage changes (64720.0) ; Series Title: Index Numbers; Manufacturing Division; Series ID: A2309054F	AEMO Internal
Gross State Product	GSP is a measurement of the economic output of a state. It is the sum of all value added by industries within the state.	$ million (FY 2015 real term)	Deloitte	Deloitte
Household Disposable Income	Real level of money that households have available for spending and saving after income taxes have been deducted.	$ million (FY 2012 real term)	KPMG	KPMG
Population	Population (net of births, deaths and migration)	No. of persons	ABS Table A1.Population projections, By age and sex, New South Wales - Series A (3222.0); ABS Table A2.Population projections, By age and sex, Victoria - Series A (3222.0); ABS Table A3.Population projections, By age and sex, Queensland - Series A (3222.0); ABS Table A4.Population projections, By age and sex, South Australia - Series A (3222.0); ABS Table A6.Population projections, By age and sex, Tasmania - Series A (3222.0); ABS Table A8.Population projections, By age and sex, Australian Capital Territory-Series A (3222.0);	ABS

Table 33 ANZSIC and business classification

ANZSIC Division ID	ANZSIC Division Name	AEMO Sector Category
A	Agriculture, Forestry and Fishing	Other
B	Mining	1. 06 Coal Mining is categorised as ‘Coal’ 2. All other mining is categorised as ‘Other’
C	Manufacturing	1. Food Product Manufacturing (ANZSIC Code: 11) & Beverage and Tobacco Manufacturing (ANZSIC Code: 12) are categorised as 'Other' 2. Industrial Gas Manufacturing (ANZSIC Class: 1811) is categorised as ‘LNG’. 3. All other manufacturing sub sectors are categorised under ‘Manufacturing’.
D	Electricity, Gas, Water and Waste Services	Other
E	Construction	Other
F	Wholesale Trade	Other
G	Retail Trade	Other
H	Accommodation and Food Services	Other
I	Transport, Postal and Warehousing	Other
J	Information Media and Telecommunications	Other
K	Financial and Insurance Services	Other
L	Rental, Hiring and Real Estate Services	Other
M	Professional, Scientific and Technical Services	Other
N	Administrative and Support Services	Other
O	Public Administration and Safety	Other
P	Education and Training	Other
Q	Health Care and Social Assistance	Other
R	Arts and Recreation Services	Other
S	Other Services	Other