Demand Forecasting Methodology Information Paper

June 2018

For the 2018 Gas Statement of Opportunities

Important notice

PURPOSE

AEMO has prepared this document to provide information about methodology and assumptions used to produce the 2018 Gas Statement of Opportunities under the National Gas Law and Part 15D of the National Gas Rules.

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VERSION CONTROL

Version	Release date	Changes
1	29/6/2018	

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1. Introduction

The Gas Statement of Opportunities (GSOO) incorporates regional gas consumption and maximum daily demand forecasts for the eastern and south-eastern Australian gas market of Queensland, New South Wales, Victoria, Tasmania, and South Australia. These forecasts represent demand to be met from gas supplied through the natural gas transmission system in southern and eastern Australia, and are the sum of a number of component forecasts, each having a distinct forecasting methodology. These components (defined in the Glossary) are:

- Liquefied natural gas (LNG).
- Gas-powered generation (GPG).
- Industrial.
- Residential and commercial.
- Network losses and other unaccounted for gas (UAFG).

For annual consumption, each of these component forecasts is modelled separately, and then summed at the regional level. Chapters 2 through 5 describe the methodologies used for each of the first four components. Network losses and other UAFG are covered in Appendix A3.

Maximum demand forecasts provide an annual projection of maximum daily demand for each region. The maximum demand methodology uses an integrated modelling approach that forecasts the component models jointly to produce a forecast of maximum coincident daily demand (see Chapter 6).

The GSOO provides three scenarios that consider strong, neutral and weak drivers of demand. These scenarios are in alignment with those used in AEMO's Integrated System Plan (ISP)[1]. Specific detail on scenarios used in the 2018 GSOO are available in the GSOO report, available on AEMO's website[2].

[1] https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/Integrated-System-Plan

[2] https://www.aemo.com.au/Gas/National-planning-and-forecasting/Gas-Statement-of-Opportunities

2. Liquefied Natural Gas (LNG) Consumption

This chapter briefly describes how future LNG consumption estimates are developed. In the preparation of the 2018 GSOO, AEMO engaged Lewis Grey Advisory (LGA) to estimate projections of gas and electricity consumption used in the production and export of LNG for the 20-year outlook. AEMO also engaged directly with the east coast LNG Consortia to obtain best estimates of the LNG forecasts over the short term[3]. The provision of this data directly from the LNG Consortia represents a significant improvement on previous gas forecasts.

The LNG component forecasts therefore are produced using a combination of short term estimates provided by industry, and long-term forecasts by provided by AEMO's consultants.

Prior to finalising AEMO's LNG forecasts, AEMO met with stakeholders that includes the Australian Competition and Consumer Commission, AEMO's Forecasting Reference Group and the Australian Petroleum Producers and Exploration Association and presented our domestic gas and LNG forecasting methodology in May 2018 at a workshop in Queensland.

The long-term LNG forecasts were developed using a range of public data and the outcomes of technical engagement with the LNG producers. A full explanation of the forecasting methodology applied by LGA for the 2018 GSOO is outlined in their December 2017 LGA report.[4]

In addition to improvements to the short-term forecasts through estimates directly from industry, the long-term estimates provided by LGA improved upon several key assumptions from the 2016 National Gas Forecasting Report (NGFR), including:

- The quantity of gas used to power liquefaction facilities is estimated for the 2018 forecasts using historical gas data acquired from AEMO's Gas Bulletin Board from 2014. Previously, the 2016 NGFR estimate was based on planning data. The application of historical gas data and the stability of electricity and gas consumption related to LNG plateau production for all three east coast LNG facilities, and have increased the estimates of the quantity of gas used to power liquefaction. The estimates increased from an average of approximately 6.7% for all 3 facilities in 2016[5] to approximately 9% of gas input for this report. [6]
- Additional gas consumption for the High scenario – the proposed seventh LNG export train was previously assumed to have no impact on the quantity of gas used for the transmission of gas to the Queensland LNG projects. AEMO has since received advice that to deliver gas to a seventh LNG export train would require additional mid-point compression along the transmission pipeline to the export facilities at Curtis Island, near Gladstone. This additional gas consumption is included in the High scenario.
- LGA's long term forecast reflects updated field and gas processing plant energy usage figures. LGA estimates this usage by applying actual gas usage acquired from the Queensland Department of Natural Resources and Mines and AEMO.

[3] Short-term here refers to 2 to 5 five years.

[4] The 2017 LGA report is available at https://www.aemo.com.au/Gas/National-planning-and-forecasting/Gas-Statement-of-Opportunities

[5] See page vii of 2016 LGA report, located at: https://www.aemo.com.au/-/media/Files/Gas/National_Planning_and_Forecasting/NGFR/2016/Projections-of-Gas-and-Electricity-Used-in-LNG-Public-Report-November-2016.pdf.

[6] LGA assumes that all existing east coast LNG trains continue to operate for the entire the outlook period.

3. Gas-Powered Generation (GPG) Consumption

This chapter describes the methodology and key assumptions AEMO used to forecast GPG annual gas consumption in supplying electricity to the National Electricity Market (NEM).[7]

To forecast the GPG consumption, AEMO considered three scenarios to model the NEM, with economic drivers that are consistent, in principle, to the economic drivers of the Neutral, Strong and Weak scenarios in the GSOO. The scenarios to forecast GPG consumption are consistent with three of the core scenarios produced for the ISP, and greater detail on these scenario settings is available within AEMO's ISP.

AEMO used detailed electricity market modelling of the NEM to project gas consumption for GPG. The market modelling is consistent with AEMO's ISP. The modelling was conducted in two phases. Further detail on each of the ISP market modelling stages is available, accompanying the ISP. [8]

Phase 1

The first phase determines the co-optimised generation and transmission expansion plan for the NEM via the long-term (LT) phase of the ISP. The modelling incorporates various policy, technical, financial and commercial drivers to develop the least cost NEM development path. This includes state and national renewable energy targets, national emissions abatement objectives, and technology cost reductions over the forecast period. The approach considers the variability of renewable energy resources and the transmission developments required to access potential renewable energy zones (REZs). It also considers the need to replace ageing thermal generation, and the role that energy storage technologies and flexible thermal generation technologies may have, such as GPG, given increased penetration of variable renewable energy sources at utility scale and from distributed energy resources (DER).

Phase 2

The second phase models the NEM with increased granularity using hourly, time sequential modelling incorporating the generation and transmission mix determined by the LT phase. This short-term (ST) phase is essential to validate generation and transmission plans from the LT phase. For the purposes of forecasting gas offtake for GPG, competitive behaviour of generation portfolios is captured through application of a Nash-Cournot bid optimisation model for the largest NEM portfolios. This bidding model provides a more realistic approximation of generator dispatch and unit commitment decisions than other bidding methods, such as a short run marginal cost (SRMC) approach which assumes all available generation capacities are offered in the market at the unit's SRMC.

For these ST simulations:

- Prior to optimising dispatch in any given year, the model schedules planned maintenance and randomly assigns generator outages to be simulated using a Monte Carlo simulation engine. Dispatch is then optimised on an hourly basis for each forced outage sequence, given the load characteristics, plant capacities and availabilities, fuel restrictions and take-or-pay contracts, variable operating costs including fuel costs, interconnector constraints, and any other operating restrictions that were specified.
- Expected hourly electricity prices for each NEM region, and hourly dispatch for all NEM power stations, were produced as output and were calculated by modelling strategic behaviour, based on a Nash-Cournot equilibrium gaming model. The Nash-Cournot model was benchmarked to historical market outcomes to ensure the bidding strategies employed produced market outcomes commensurate with historical observations.
- The model produces hourly forecasts of gas usage on a unit-by-unit basis, which AEMO then aggregates into daily traces by power station to be fed into the GSOO gas model.

[7] This includes the vast majority of GPG in the eastern and south-eastern gas markets. Any GPG outside this, such as in Mount Isa, is captured as Industrial (tariff D) demand.

[8] Once published, the ISP and its supporting information will be available at the following link: https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/Integrated-System-Plan

4. Tariff D (Industrial) Consumption

This chapter outlines the methodology used to develop annual gas consumption forecasts for industrial customers. Industrial consumption, also known as Tariff D consumption, is defined as consumption by network customers who are billed on a demand basis.[9] These consumers typically consume more than 10 TJ per year.

AEMO defined two categories of industrial customer for analysis purposes:

- **Large Industrial Loads (LIL):** consume more than 500 TJ annually at an individual site. Typically includes aluminium and steel producers, glass plants, paper and chemical producers, oil refineries and GPG that is not included in GPG forecasts.[10]
- **Small-to-Medium Industrial Loads (SMIL):** consume more than 10 TJ but less than 500 TJ annually at an individual site. Typically includes food manufacturing, casinos, shopping centres, hospitals, stadiums, and universities.

AEMO's industrial sector modelling uses an integrated, bottom-up sector modelling approach to industrial forecasts to capture the structural change effect in the Australian economy, which was first introduced in the 2015 NGFR.

4.1 Data sources

The industrial sector modelling relies on a combination of sources for input data, namely:

Table 1 Historic and Forecast Input Data Sources for Industrial Modelling

Data Series	Source 1	Source 2	Source 3	Source 4
Historic Consumption data by region	AEMO Database	CGI Logica	Transmission & Distribution, Industrial Surveys	Gas Bulletin Board (GBB)
Historic Consumption data by sector	Dept. of Energy and Environment			
Weather Data	BOM			
Climate Change Data	CSIRO			
Economic Data	ABS	Economic Consultancy		
Wholesale Gas Price	AEMO estimates + CORE Energy			
Retail Gas Price	AEMO Calculated			

For more details and source references please see Appendix A4.

[9] Customers are charged based on their Maximum Hourly Quantity (MHQ), measured in gigajoules (GJ) per hour.

[10] This includes GPG which is not connected to the NEM, and large co-generation.

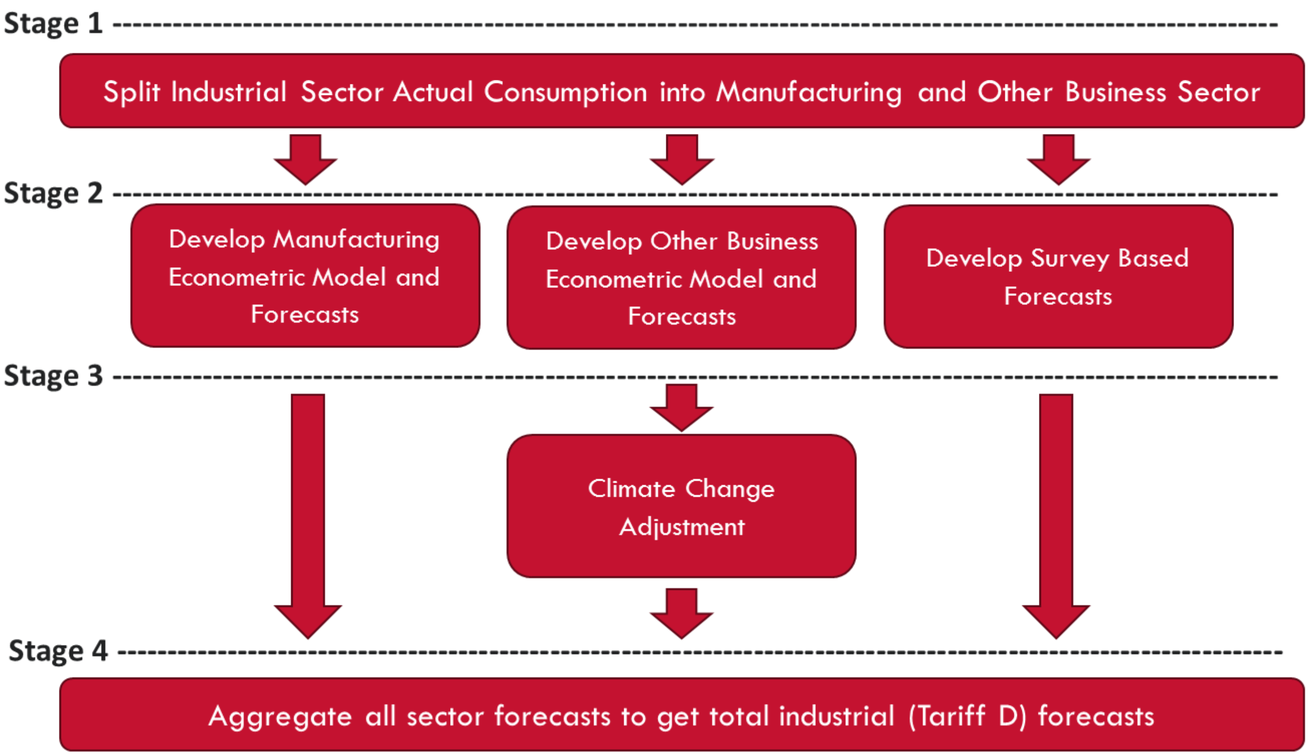
4.2 Methodology – New South Wales, Queensland, South Australia and Victoria

Industrial consumption models the energy intensive (Manufacturing) sector separately from non-energy intensive (Other Business) sector.

This uses a combination of survey and econometric modelling approaches to forecasting:

- **Other Business sector:** Uses Econometric modelling
- **Manufacturing sector Large Industrial Loads (LIL):** Survey based forecasts
- **Manufacturing sector remaining:** Econometric modelling

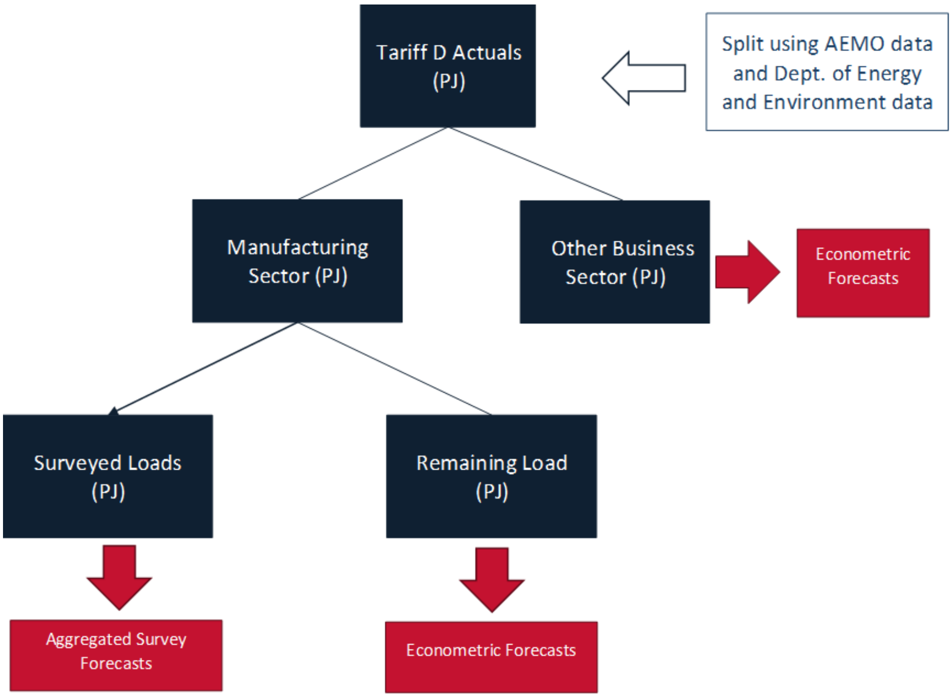
Figure 1 Industrial Sector Forecasting Process Flow Overview



4.2.1 Splitting Actual Consumption

The energy intensive Manufacturing sector is modelled separately to the Other Business sector because they have different underlying drivers. This allows the model to capture structural change in the economy. Figure 2 shows the process flow of splitting the actual consumption for the latest year of data to get the starting point for forecasts.

Figure 2 Actual Consumption Decomposition for starting point of modelling



As outlined in section 4.1, AEMO uses a combination of internally sourced meter data and the Energy Statistics table[11] published by the Department of Energy and Environment to calculate the Manufacturing vs. Other business sector split.

The split for the latest year of actual consumption is shown in Table 2.

Table 2 2017 industrial consumption sectoral split - Manufacturing versus Other Business

Region	Manufacturing (%)	Other business (%)
New South Wales	83.6%	16.4%
Queensland	97.6%	2.4%
South Australia	88.4%	11.6%
Tasmania	83.0%	17.0%
Victoria	82.1%	17.9%

[11] https://www.energy.gov.au/government-priorities/energy-data/australian-energy-statistics

4.2.2 Develop Manufacturing Econometric Model and Forecast

The long-term manufacturing sector forecast was developed using the following econometric model. The specific variables are described in Table 3 below.

$$\ln(\widehat{Man\_Cons})_i = \hat{\beta}_0 + \hat{\beta}_1 \ln(Ind.Prod)_i + \hat{\beta}_2 \ln(Gas.Price)_i + \sum_{j=0}^{n} \hat{\gamma}_j D_{j_i}$$

Table 3 New South Wales, Queensland, South Australia and Victoria – Manufacturing model variable description

Variable names	ID	Units	Description
Manufacturing Consumption	Man_Cons	PJ	Tariff D manufacturing consumption.
Industrial Production	Ind.Prod	$'Mill	Aggregate measure of mining, manufacturing and utilities industry activity.
Retail Gas Price	Gas.Price	$/GJ	Retail gas price (uses large industrial gas price).
Dummy Variables	D	{1,0}	Dummy variables are added in to stabilise the historical data for temporary shocks that may otherwise bias the coefficients, e.g. the Global Financial Crisis (GFC).

4.2.3 Develop Other Business Sector Econometrics Model and Forecast

The long term other business sector forecast was developed using the following econometric model. The specific variables are described in Table 4 below.

$$\ln(\widehat{Oth\_Cons})_i = \hat{\beta}_0 + \hat{\beta}_1 \ln(GVA.Serv)_i + \hat{\beta}_2 \ln(Gas.Price)_i + \sum_{j=0}^{n} \hat{\gamma}_j D_{j_i}$$

Table 4 New South Wales, Queensland, South Australia, and Victoria – Other Business Model Variable Description

Variable names	ID	Units	Description
Other Business Sector Consumption	Other_Cons	PJ	Tariff D other business sector consumption.
Services GVA	GVA.Serv	$'Mill	Aggregate measure of economic activity in all industries except for agriculture, construction, mining, manufacturing and utilities.
Retail Gas Price	Gas_Price	$/GJ	Retail gas price (uses small industrial gas price).
Dummy Variables	D	{1,0}	Dummy variables are added in to stabilise the historical data for temporary shocks that may otherwise bias the coefficients, e.g. the Global Financial Crisis (GFC).

4.2.4 Develop Survey Based Forecast

AEMO conducts a survey and interview process with large industrial users to derive the aggregated regional forecasts. The survey process follows 5 key steps as shown:

Identify large industrial users → Collect recent actuals and analyse → Request survey responses → Conduct interviews → Finalise Forecasts

Identify Large Industrial users

Large industrial loads are identified through several means:

1. **Distribution and Transmission Surveys:** request information on loads consuming more than 10 TJ annually; request information on new large loads.
2. **AEMO database:** in VIC and QLD markets AEMO has all the registered distribution network connected industrials. In VIC AEMO also has all the transmission connected industrials.
3. **Media search.**

Collect recent actual consumption data and analyse

Recent actual consumption data is analysed for each large industrial load site for two key reasons:

1. To understand latest trends at the site level
2. To prioritise the large industrial loads for interviews (detailed in the next section)

Request survey responses & Conduct Interviews

Step 1: Initial survey

AEMO sends out surveys to all identified LILs requesting historical and forecast gas consumption information by site. The surveys request annual gas consumption and maximum demand forecasts for three scenarios. The core economic drivers for each of the three scenarios are provided to survey recipients to ensure forecasts are internally consistent to other components:

- **Neutral scenario** – gas consumption when economy follows the most likely economic pathway.
- **Strong scenario** – gas consumption when economy follows a strong economic pathway.
- **Weak scenario** – gas consumption when economy follows a weak economic pathway.

Step 2: Detailed interviews

Following the survey, AEMO interviews large industrial loads to discuss their responses. This typically includes discussions about:

- Key gas consumption drivers, such as exchange rates, commodity pricing, availability of feedstock, current and potential plant capacity, mine life, and cogeneration.
- Currently contracted gas prices and contract expiry dates.
- Gas prices the LILs forecast over the medium and long term (per scenario), and possible impacts on profitability and operations.
- Potential drivers of major change in gas consumption (e.g., expansion, closure, cogeneration, fuel substitution) including "break-even" gas pricing[12] and timing.
- Different assumptions between the Strong, Neutral, and Weak scenarios.

Interviews of large industrial loads are prioritised based on the following criteria, based on analysis of actual consumption:

- **Volume of load (highest to lowest):** Movement in the largest volume consumers can have bigger market ramifications (e.g. impact market price).
- **Year on Year *percentage* variation:** Assesses volatility in load, those with highest volatility are harder to forecast.

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[12] This is the point of balance between profit and loss.

- **Year on Year *absolute* variation (PJ):** Even if loads are volatile, if they are relatively small, it might be captured in the uncertainty around our forecasts and not impact overall trend whereas the largest loads will have a more material impact.
- **Forecast vs actuals for historic survey responses (where available):** This measure is used to assess accuracy of forecasts. For instance, if there was high volatility in actual consumption, was it anticipated it in last year's survey forecasts? If not then it requires further investigation.

This process is also used as a benchmark for validating the survey responses.

Finalise forecasts

- The site based survey forecasts for each scenario is finalised based on interview discussion[13].
- All the survey forecasts are aggregated to regional level for each region.

4.2.5 Climate Change Adjustment

AEMO forecasts a climate change index (see Appendix A2). This adjustment is applied to the heating load[14] forecast for industrial sector consumption.

AEMO assumes all heating load is in the Other Business sector. Therefore, the climate change adjustment is only made to the Other Business sector forecasts, after the total econometric forecasts have been derived (see section 4.2.3).

Step 1: Split Other Business Sector into Heating and Non-Heating load in Base Year

Develop short term regression model using daily actual consumption data for the latest year available and regress against the Heating Degree Day (HDD) or Effective Degree Day (EDD)[15] for the same time. For more details on effective degree days please see Appendix A2.

$$Actual\ \widehat{Consumption}_{t0} = \hat{\gamma}_0 + \hat{\gamma}_1 HDD\ or\ EDD_{t0} + \sum_{j=0}^{n} \hat{\gamma}_j D_{j_{t0}}$$

Calculate the actual heating load and non-heating load components for Other Business sector consumption for the latest year of actual consumption ($\boldsymbol{t_0}$).

$$Heating\ Load_{t0} = (\beta_1 * HDD\ or\ EDD_{t0})$$

$$Non\ Heating\ Load_{t0} = Total\ Other\ Business\ Load_{t0} - Heating\ Load_{t0}$$

Step 2A: Grow the heating load for the forecast period with the climate change index[16] and econometric index[17]

$$Oth\_Heat\_Cons_t = Oth\_Heat\_Cons_{t-1} * \frac{HDD_t}{HDD_{t-1}} * \frac{Econometric_t}{Econometric_{t-1}}$$

[13] This may include override of initial survey results on the basis of AEMO's discussion with the industrial user.

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

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

[16] Climate change index refers to climate change adjusted HDD or EDD forecasts series. For more details see appendix A2.3.

[17] The econometric index refers to the forecasts developed in section 4.2.3.

Step 2B: Grow the non-heating load for the forecast period with the econometric index only

$$Oth\_NonHeat\_Cons_t = Oth\_NonHeat\_Cons_{t-1} * \frac{Econometric_t}{Econometric_{t-1}}$$

Step3: Aggregate climate adjusted heating load forecast and non-heating load forecast to get final Other Business sector forecasts.

$$Oth\_Tot\_Cons_t = Oth\_Heat\_Cons_t + Oth\_NonHeat\_Cons_t$$

4.2.6 Aggregate all sector forecasts to get total industrial (Tariff D) forecasts

4.3 Methodology - Tasmania

Tasmania's gas network commenced operations much later (2004) than the other states. Gas consumption growth since has reflected the progressive increase in connections of commercial and residential gas users.

AEMO surveyed Tas Gas (Tasmania's largest natural gas retailer) to obtain actual consumption for 2017 for distribution-connected and transmission-connected Tariff D consumers. Applying historical data, AEMO modelled and forecasted the connections and gas consumption for the two classes of Tariff D consumers by applying the following assumptions[18]:

- **Transmission-connected consumers:** Forecasts for these consumers is assumed to remain constant, barring any step changes provided confidentially by surveys or subsequent interviews.[19] Gas prices are assumed to have no direct impact on these consumers except for curtailing future growth.
- **Distribution-connected consumers:** Forecast to grow in line with a logarithmic model, translated to match expected consumption in the latest year of actual consumption data that is available.

[18] Distinct to other States, AEMO did not apply a bottom-up approach. Tasmania's Tariff D customers were modelled in aggregate and only distinguished between distribution and transmission connected gas consumers.

[19] On the basis of surveys and interviews.

5. Tariff V (Residential and Commercial) Consumption

Residential and small commercial and industrial consumption, also known as Tariff V consumption, is defined as consumption by network customers who are billed on a volume basis. These consumers typically use less than 10 TJ/year.

AEMO has used econometric models to develop forecasts for the established networks of Victoria, South Australia, New South Wales (including Australian Capital Territory) and Queensland. For Tasmania, which only started connecting residential and commercial customers in 2004, AEMO applied a network development model.

5.1 Definitions

Tariff V customers are gas consumers of relatively small gas volumes, using less than 10 TJ of gas per annum, or customers with a basic meter.

Victoria has the highest consumption and greatest number of gas customers of all the eastern and south-eastern states. Approximately 97% of Victorian Tariff V customers are residential.

Growth in both Tariff V residential and Tariff V commercial consumption can be attributed to similar key drivers including weather, gas price, energy efficiency measures, and growth in connections.

5.2 Forecast number of connections

Tariff V gas connection forecasts are made up of two components, residential and non-residential gas connection forecasts.

Residential gas connections are determined by:

- Forecasting the total number of households for each State.
  - To forecast the number of households for each State, AEMO relies on the Housing Industry Association (HIA) dwelling completion forecasts and the Australian Bureau of Statistics (ABS) housing forecasts.
  - These growth forecasts are applied to the historical number of households from the previous year with HIA's forecasts implemented for the short-term forecast (the first 3 years) before transitioning into the ABS housing forecasts over the medium to long-term.
- Forecasting the number of residential electricity connections. The total number of electricity connections is assumed to be a single connection for each household over the outlook period. This assumption appears to be consistent with the historical number of electricity connections acquired from each system operator for each State.
- Determining the gas connections forecast by multiplying by the forecast number of residential electricity connections by an estimate of the ratio of residential gas to electricity connections. The most recent historical ratio of Meter Installation Registration Numbers (MIRNs, gas connections) to National Metering Identifiers (NMIs, electricity connections) for each state is carried forward to the end of the forecast period[20].

For non-residential Tariff V connections, the number of connections are assumed to grow at a similar rate to that experienced over the last 3 years, tempered by changes to forecast economic growth. The 3 year trend was selected to capture the stable connections growth rate exhibited over that period.

[20] Apart from Tasmania, due to the State government investment into residential gas connections, the ratio for all other States have been relatively constant and has only varied by around 1% over the last 5 years.

5.3 Forecast annual consumption methodology – New South Wales, Queensland, South Australia, and Victoria

5.3.1 Overview of the methodology

The methodology described in this section relates to all east coast regions except Tasmania. It involved the following steps:

- Analyse Tariff V daily consumption and weather relationship for each region. The regression results are used to estimate weather normalised residential and non-residential annual consumption, annual heating and base load for 2017.
- Analyse impact of gas price, appliance and home thermal efficiency, and appliance fuel switching on residential consumption using Victorian Tariff V residential meter data for 2004–14. The Victorian consumer behaviour model applies to other east coast regions.
- Forecast Tariff V residential and non-residential annual consumption using results of the above analysis and other inputs described below.

Data sources for the Tariff V forecast are listed in Appendix A4.

5.3.2 Methodology detail

Step 1: Estimate Tariff V residential and non-residential annual consumption for 2017

The objective of this step was to estimate weather-corrected 2017 Tariff V residential and non-residential annual consumption for each region, to be used as the basis for forecasting regional Tariff V annual consumption over the 20-year horizon.

The first step of the analysis was to correct the Tariff V annual consumption for standard weather conditions. This required estimating the appropriate temperature sensitivity to use by regression analysis of weekly Tariff V consumption against average weekly EDD.

The regression model took the following form:

$$Y_i = \alpha + \beta * EDD_i + \gamma * H$$

where:

Y_i = average Tariff V daily consumption for week i

i = week number

α = average Tariff V base load

β = average Tariff V temperature sensitivity (TJ/EDD)

EDD_i = average daily EDD for week i

γ = estimate daily base load reduction over the 3 weeks Christmas – New Year business close down period

H = index to flag business close down period (= 3 for last week and first week of the year, 2 for week 2, 1 for week 3 of the New Year, 0 otherwise)

The weather normalised Tariff V estimated annual consumption for year j is therefore equal to

$$Y_{WN,j} = Y_j - \beta * (EDD_j - EDD_{WS})$$

Note: EDD_{WS} is the forecast weather standard. See Appendix A2.

Historical Tariff V residential and non-residential annual consumption was provided by distributors in stakeholder surveys and was used to estimate the share of residential and non-residential annual consumption of total Tariff V. These shares were further split into heating and base load using the coefficients determined in the above regression.

Step 2: Analyse average gas appliance annual consumption in Victorian existing and new homes by suburb type

The objective of this step was to analyse historical trends in average residential annual heating and base load for existing and new homes by geographical locations (postcodes), and type of suburbs (inner, middle, outer, and regional).

New homes are defined as greenfield sites connected to the Declared Transmission System (DTS) since 2004, which are subject to the Victorian building codes for new residential homes.

Estimates of Victorian residential annual base load (gas cooker, hot water) and heating load (room and central heaters) were developed using Victorian Tariff V residential basic meter data available from AEMO's meter database.

The charts below display the trend in average annual base load and weather normalised heating for existing homes and new homes 2005–13 by suburb type:

- Inner suburbs are postcodes within 10 km of Melbourne CBD.
- Middle suburbs are postcodes between 10 km and 20 km of Melbourne CBD.
- Outer suburbs are postcodes between 20 km and 50 km of Melbourne CBD.
- Regional suburbs are all other postcodes in Victoria.

Figure 3 Average annual consumption in existing residential homes

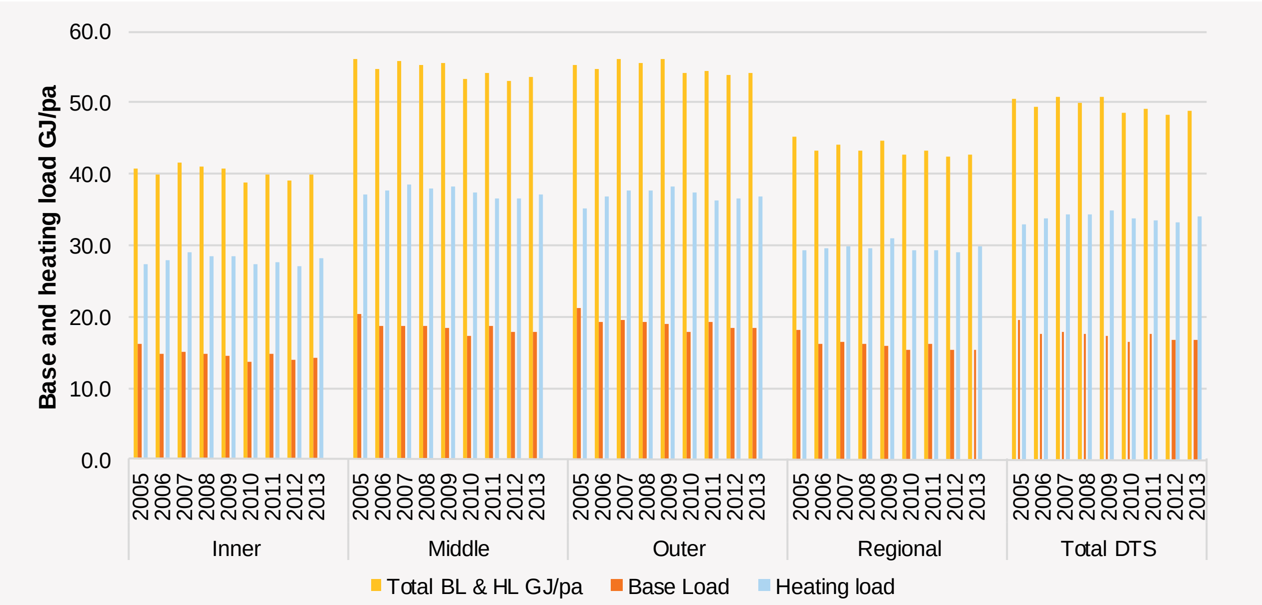
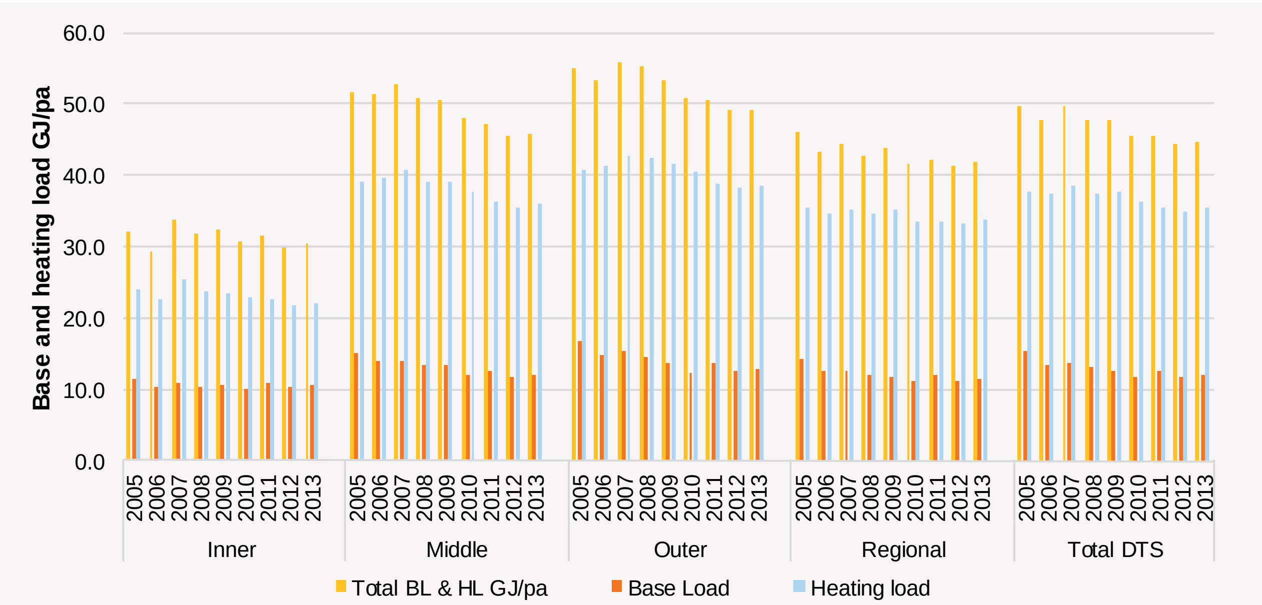


Figure 4 Average annual consumption in new residential homes



The results of the analysis are summarised below.

- Average hot water consumption (base load) has been falling across all residential areas since 2005. It has fallen more rapidly in new homes than existing homes, driven by mandatory installation of solar hot water heaters in 5 and 6 star new homes. The decline was steeper between 2005 and 2008, driven by consumers' changing water usage behaviours in response to water consumption conservation measures (for example, water-efficient shower heads) at that time.
- Over the period 2005–13, average hot water consumption in existing homes was 25% lower than in new homes.
- Heating consumption increased during 2005–08 (in new homes) and 2005–2010 (in existing homes), driven by increased penetration of central heaters. Annual heating consumption fell since that time, due to improved home insulation (the Commonwealth Government pink batt scheme).
- Over the period 2005–13, heating consumption in new homes was about 9% higher compared to existing homes, despite mandatory 5 and 6 star building shells. This was due to increased building size in new homes and building design favouring full length glass windows, offsetting potential energy savings from improved home insulation.
- Comparing hot water and heating consumption by geographical locations, inner suburbs had the lowest annual hot water and heating consumption in both new and existing homes because of smaller house sizes in these suburbs. Over the period 2005–13, hot water and heating consumption in new homes in inner suburbs was 18% and 40% lower respectively, compared to the Victorian DTS average estimate.
- By contrast, existing and new homes in outer suburbs had the highest hot water and heating consumption of all suburbs (10% higher than the Victorian DTS average), due to the larger home sizes. These suburbs also showed the fastest rate of decline in appliance consumption.

Step 3: Analyse impact of gas price and appliance and building energy efficiency on Victorian residential existing and new home gas consumption

The objective of this step was to analyse the impact of retail gas prices and appliance and building energy efficiency on the annual consumption data obtained in Step 2. The analysis was conducted separately for existing and new homes gas appliance consumption.

To overcome the problem of insufficient historical data, the analysis used pooled appliance average annual consumption data to include inner, middle, outer, regional suburbs and total DTS.

Hot water annual consumption model

$$\boldsymbol{LN(BL_i) = \alpha + \beta * LN(P_{i-1}) + \gamma * LN(T_i) + \delta * I_i + \varepsilon * M_i + \epsilon * O_i + \theta * R_i}$$

where:

BL_i = average annual base load in year i

α= average annual base load for total DTS (not impacted by gas price and energy efficiency).

β= Price elasticity for base load

P_{i-1} = lagged price for year i

γ = base load energy efficiency elasticity.

T_i = time trend for year i (= 1, 2,…, 10, 1=2005 and 10 = 2014) was used to model the falling trend in historical base load driven by more energy efficiency appliances and changed hot water consumption behaviour

I_i = dummy variable for inner suburb for year i (= 1 if inner suburbs, = 0 otherwise).

M_i= dummy variable for middle suburbs for year i (= 1 if middle suburbs, = 0 otherwise).

O_i = dummy variable for outer suburbs for year i (= 1 if outer suburbs, = 0 otherwise).

R_i = dummy variable for regional suburbs for year i (= 1 if regional suburbs, = 0 otherwise).

δ = difference between inner suburb average annual base load and to DTS average annual base load

ε = difference between middle suburb average annual base load and DTS average annual base load

ϵ = difference between outer suburb average annual base load and DTS average annual base load

θ = difference between regional suburb average annual base load and DTS average annual base load

Table 5 Model parameters for average annual base load

		Intercept	Price	Time trend	Inner	Middle	Outer	Regional	R-Square
		α	β	γ	δ	ε	ϵ	θ	
Existing homes	Coefficient	0.200	-0.066	-0.034	-0.204	0.068	0.096	-0.109	97%
	Standard error	0.319	0.076	0.017	0.012	0.012	0.012	0.012	
New homes	Coefficient	0.631	-0.162	-0.085	-0.260	0.030	0.109	-0.095	92%
	Standard error	0.610	0.145	0.033	0.023	0.023	0.023	0.023	

Heater annual consumption model

$$LN(HL_i) = \alpha + * \beta * LN(P_{i-1}) + \gamma * LN(T_i) + \mu * LN(T_l) + \delta * I_i + \varepsilon * M_i + \epsilon * O_i + \theta * R_i$$

where:

HL_i = average annual base load for year i

α = average annual heating load for total DTS (not impacted by gas price and energy efficiency).

β = price elasticity for heating load

P_{i-1} = lagged price for year i

γ = heating load energy efficiency elasticity for T_i

T_i = time trend for year i (= 1, 2,…, 6, 1=2005) used to model the falling trend in historical heating load since 2005

γ = heating load energy efficiency elasticity for T_l

T_l = time trend for year l (= 1, 2, 3, 1=2011) used to model the increase in average annual heating consumption in this period driven by increased penetration of gas central heaters.

I_i = dummy variable for inner suburb for year i (= 1 if inner suburbs, = 0 otherwise).

M_i= dummy variable for middle suburbs for year i (= 1 if middle suburbs, = 0 otherwise).

O_i = dummy variable for outer suburbs for year i (= 1 if outer suburbs, = 0 otherwise).

R_i = dummy variable for regional suburbs for year i (= 1 if regional suburbs, = 0 otherwise).

δ = difference between inner suburb average annual heating load and to DTS average annual base load

ε = difference between middle suburb average annual heating load and DTS average annual base load

ϵ = difference between outer suburb average annual heating load and DTS average annual base load

θ = difference between regional suburb average annual heating load and DTS average annual base load

Table 6 Model parameters for annual heating consumption

		Intercept	Price	Time trend	Time trend 2	Inner	Middle	Outer	Regional	R-Square
		α	β	γ	μ	δ	ε	ϵ	θ	
Existing homes	Coefficient	0.89	-0.20	-0.004	0.04	-0.35	0.15	0.13	-0.18	99%
	Standard error	0.49	0.11	0.02	0.01	0.01	0.01	0.01	0.01	
New homes	Coefficient	1.47	-0.33	-0.07	0.04	-1.24	0.04	0.11	-0.09	99%
	Standard error	1.37	0.31	0.05	0.03	0.03	0.03	0.03	0.03	

Step 4: Forecast impact of appliance fuel switching in existing homes

The impact of fuel switching was estimated based on the following assumptions:

- Hot water consumption:
  - Existing home gas hot water appliances: the average lifespan of a gas hot water unit is 10–15 years. Existing hot water stock was assumed to change over within the next 10 years[21], and to be partly replaced with solar hot

[21] The average life of a gas hot water unit is between eight and 12 years.

  - water units or heat pumps, causing existing home gas consumption for hot water purposes to approach that of new homes. A quadratic model was used to model the load reduction over the next 10 years of the forecasting horizon. In the absence of new energy policies from both the Commonwealth and State governments, the impact of fuel switching was forecast to plateau after the initial period.
  - It was also assumed that a proportion of the forecast reduced gas hot water consumption in existing homes is due to conversion of gas storage hot water units to instantaneous units. As such, an estimated load reduction was reallocated from fuel switching impact to energy efficiency impact.
  - Fuel switching in new homes was not expected to be significant over the forecasting horizon
- Heating consumption:
  - Heating units in existing homes were assumed to change over within the next 20 years, and to be replaced with either smaller gas space heaters, or smaller gas space heater units combined with reverse-cycle air-conditioners (RCAC), or RCAC only.[22] This was modelled to reduce the forecast difference between existing and new home average annual gas heating consumption by 50% in the next 20 years.
  - Fuel switching for new home heating appliances is insignificant.

Step 5: Forecast compilation

Due to data availability constraints, coefficients and ratios developed for Victorian homes in steps 2 and 3 were applied to weather normalised base and heating load estimates for New South Wales, Queensland and South Australia.

The residential annual consumption forecast for each region was developed by taking the weather normalised consumption (developed in step 1) for the most recent calendar year, and applying projected impacts across the 20 year forecast horizon. For each year, the forecast equals:

- Weather normalised consumption for the region in the reference year (most recent calendar year)
- *Plus* the consumption of forecast new connections since the reference year
- *Minus* the forecast total impact of gas price increases (determined using the price elasticities obtained in step 3)
- *Minus* the forecast of cumulative impact of appliance and building energy efficiency (determined by extrapolating the time trend derived in step 3)
- *Minus* the forecast cumulative impact of gas to electric appliance switching (developed in step 4)
- *Minus* the forecast cumulative impact of climate change on total heating consumption (further detail in Appendix A2)

The non-residential forecast was compiled using the same method, however forecast estimates of energy efficiency and fuel switching were provided by an external consultant.

5.4 Forecast annual consumption methodology – Tasmania

As outlined, gas consumption in Tasmania reflects the progressive increases in distribution connections to the Tasmanian gas network.

The 2018 GSOO applies the following methodology to forecast total Tariff V consumption for Tasmania:

- Total residential and commercial gas distribution consumption is forecast separately using historical data for each year.
- AEMO multiplies the number of connections by the average consumption per connection for both residential and commercial distribution consumers are then sum to form the total Tariff V gas consumption forecast for each year.
- The methodology applied in estimating the total number of Tariff V connections for Tasmania is consistent with the methodology applied for other States in Eastern Australia, discussed further in section 5.2.
- AEMO assumes the average gas usage per residential and per commercial consumer will reduce under all scenarios. This is in line with projected price increases, with elasticities of -0.2, -0.1 and -0.3 for the Natural, Strong and Weak scenarios respectively.
- For residential consumers, under the Neutral scenario, AEMO expects the average usage per residential consumer will remain roughly the same from the beginning to the end of the outlook period which is about 29 GJ/consumer per annum. For commercial consumers under the Neutral scenario, AEMO estimates the average usage per consumer reduces from about 405 GJ/consumer per annum to about 401 GJ/consumer per annum by the end of the forecast.

[22] The average life of a gas heating unit is between 18 and 22 years.

6. Maximum Demand

This chapter outlines the methodology used to develop forecasts of maximum daily demand for each year in the 20 year forecast horizon.

AEMO has updated its forecasting methodology for the 2018 GSOO using Monte Carlo simulation techniques similar to those employed by the electricity demand forecasts. The Monte Carlo simulation weather normalised demand to produce a full demand distribution related to weather and other demand drivers. The demand forecasts were then driven by population growth, fuel switching, energy efficiency, and price response for Tariff V and Tariff D.

Gas maximum demand modelling can be broken into three steps:

- Capture the relationship between demand and the underlying demand drivers.
- Simulate demand (weather normalised) based on the relationship between demand and the demand drivers.
- Forecast demand using long term demand drivers.

Forecasts of daily maximum demand are used by government and industry to assess the adequacy of infrastructure supply capacity. They also inform commercial and operational decisions that are dependent on the potential consumption range of demand over time. Variations in domestic gas consumption are mostly driven by heating demand and GPG. For all states except Queensland, this means maximum daily demand occurs during the winter heating season.

In Queensland, due to the low penetration of gas for residential use and the warm climate, maximum demand may occur in either summer or winter driven by GPG, large industrial load consumption and LNG exports.

Forecasts of maximum daily demand for each region are estimated as the sum of the following:

- Residential, commercial, and industrial maximum demand on day of system peak.
- GPG on day of system peak.
- LNG on day of system peak.

Step 1: capture the relation between demand and demand drivers

Step 1 developed short-term econometric forecast models for Tariff V (residential and commercial) and Tariff D (industrial) gas consumption using daily data. These models describe the relationship between demand and explanatory variables including calendar effects such as public holidays, day of the week and month in the year and weather effects.

The models represent a snapshot of consumer behaviour as at the base forecast year, de-trended to remove the impact of population growth, price response, fuel switching and other growth drivers. The demand models were trained on the most recent three years of daily data. The Tariff V and Tariff D models are outlined below:

Equation 1[23]

$$Tariff\ V\ Consumption = f(HDD/EDD, Weekend\_Dummy, Public\_Holiday\_Dummy, Trend\ Variable)$$

Equation 2

$$Tariff\ D\ Consumption = f(HDD/EDD, Weekend\_Dummy, Public\_Holiday\_Dummy, Trend\ Variable\ , summer\_shutdown)$$

Step 1 also found the most appropriate model to capture the relationship between demand and the demand drivers for Tariff V and Tariff D. This Step specified an array of models for Tariff V and Tariff D using the variables available, and explored a range of model specifications. Step 1 then used an algorithm to cull any models that had:

- Variance Inflation Factor[24] greater than 4.
- Nonsensical coefficient signs – all the coefficients must have reasonable signs. Heating degree variables should be positively correlated with demand, and weekend and public holidays should be negatively correlated with demand (unless in the case of a tourist economy).

[23] See Appendix A2 for the description of EDD and HDD

[24] The variance inflation factor is a measure of multicollinearity between the explanatory variables in the model

- Insignificant coefficients.

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

- Goodness-of-fit – R-Squared, Akaike Information Criterion, and Bayesian information criterion.
- Out-of-sample goodness-of-fit – for each model based on 10-fold cross validation[25] to calculate the out-of-sample forecast accuracy.
- Histogram of the residuals, quantile-quantile (Q-Q) plot, and residual plots.

Stage 2: Simulate demand to normalize weather and other explanatory variables

Once the most appropriate model was selected, stage 2 then used the linear demand models from stage 1 to simulate and normalise demand for weather effects and other explanatory variables. The simulation process randomly draws from a pool of historical weather values from 1 January 2001 to the most recent weather data available, by bootstrapping historical fortnights. The bootstrapping method sampled actual historical weather blocks, preserving the natural relationship between time-of-year and temperature.

Equations 1 and 2 can be represented in their general form as equation 3. Equation 4 represents the generalised model used for predicting prediction intervals of demand.

Equation 3 $$TJ_t = f(x_t) + \varepsilon_t$$

Equation 4 $$\widehat{TJ}_t = f(x_t) + \sigma_\varepsilon z_t$$

Where:

- $f(x_t)$ is the relationship between demand and the demand drivers (such as weather and calendar effects) at time t
- ε_t represents the random, normally distributed[26] residual at time t ($\sim N(0, \sigma_\varepsilon{}^2)$)
- z_t follows a standard normal distribution ($\sim N(0,1)$)

Equation 4 was used to calculate daily demand for the synthetic weather year, consisting of 365 days randomly selected from history (using the $f(x_t)$ component). The prediction interval of the model was simulated (using the distribution of ε_t in Equation 4).

The simulation process created 1000 synthetic weather years with random prediction intervals for each day of each weather year following a $N(0, \sigma_\varepsilon{}^2)$ distribution.

From each iteration demand for Tariff V and Tariff D was calculated individually for each day in the year. The daily regional demand was calculated as Tariff V + Tariff D. The maximum daily regional demand was found for each iteration as the single day with the highest demand in both summer and winter (1000 maxima for summer and winter). The 50% POE was calculated taking the median of the statistical distribution of the simulated maxima for each season. In a similar fashion, the 5% POE was computed by identifying the 5% percentile of the simulated distribution.

Step 3: Forecast demand using long term demand drivers

The demand values produced by the previous process reflect the relationship between demand and weather conditions as at the base year. The forecast process then grew the demand values by economic, demographic and technical conditions.

The long-term growth drivers affecting annual consumption were applied to maximum demand within the simulation process, for each of the key drivers discussed in Chapters 4 and 5. The annual growth drivers were applied to demand as indexed growth from the base year. The annual growth indices were found by considering the forecast year-on-year growth. The year-on-year growth in Tariff V and Tariff D was applied to each daily demand value to grow demand for each day in the relevant forecast year.

LNG peak day forecast was produced by an external consultant and can be found on AEMO's website[27].

GPG peak day demand was simulated using electricity market modelling and identified for each generator. From each simulation the top 10 days for Tariff V and Tariff D were found for each season. The median GPG fuel offtake for the top 10 regional demand days was calculated. The median GPG fuel offtake represents coincident GPG peak at time of regional demand peak.

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

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

[27] The 2017 LGA report is available at https://www.aemo.com.au/Gas/National-planning-and-forecasting/Gas-Statement-of-Opportunities

A1. Gas retail pricing

Price data was a key input in forecast models across multiple sectors. AEMO calculates the retail price forecasts sourcing a combination of consultant forecasts and publicly available information.

Separate prices have been prepared for four market segments:

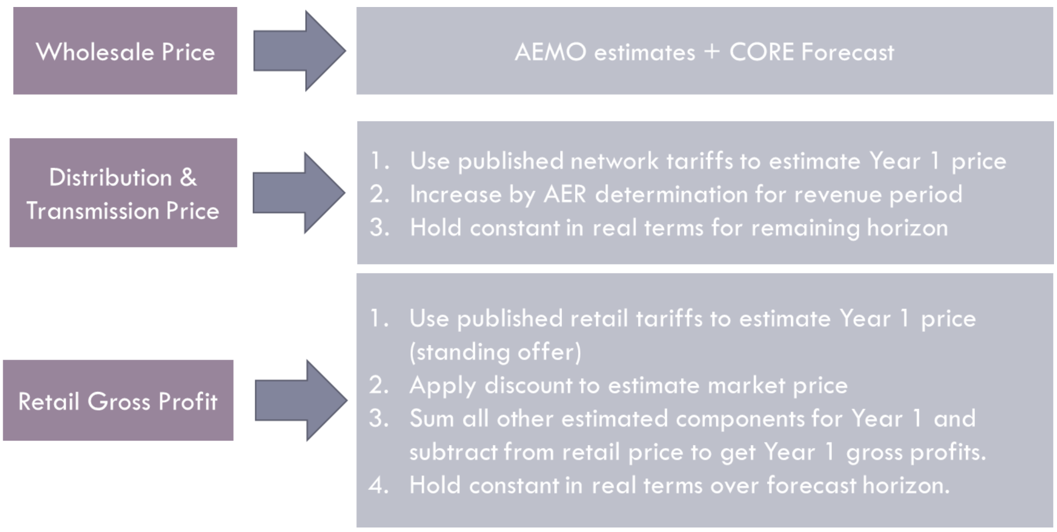
1. Residential prices
2. Small Business prices
3. Small Industrial prices
4. Large Industrial prices

A1.1 Retail Pricing Methodology

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

Figure 5 gives a general outline of how the retail prices are produced[28]. Retail Gross Profit captures both retail costs and retail margins. For details on data sources please see Appendix A4.

Figure 5 Building blocks of Retail Gas Prices



[28] Tasmania's network prices are not publicly available. For this reason, these components are estimated using Victoria as a benchmark.

A2. Weather standards

A2.1 Heating Degree Days (HDD)

To help determine heating demand levels, an HDD parameter is used as an indicator of outside temperature levels below what is considered a comfortable temperature. If the average daily temperature falls below comfort levels, heating is required, with many heaters set to switch on if the temperature falls below this mark.

HDDs are determined by the difference between the average daily temperature and the base comfort level temperature (denoted as T_{base}). The HDD formula was used in forecasting Tariff D and V annual consumption and daily maximum demand for New South Wales, Queensland, South Australia, and Tasmania.

To obtain the best correlation with gas consumption, high resolution (three-hourly) temperature averages (denoted as T_{312}) were calculated for multiple weather stations in each region, then the averages were weighted according to population centres with high winter gas consumption (denoted as T_{avg312}). T_{base} was determined by examining historical gas consumption patterns with temperature in each region to find the optimal base comfort level temperature for each region.

T_{312} was calculated using eight three-hourly temperature readings for each Bureau of Meteorology weather station between 3.00 am of the current calendar day and 12.00 am of the following calendar day, as denoted by the following formula:

$$T_{312} = (T3AM + T6AM + T9AM + T12PM + T3PM + T6PM + T9PM + T12AM)/8$$

A weighted average taken across the relevant weather stations in the region to obtain a regional average daily temperature (T_{reg312}). The station weightings and T_{base} are shown in Table 7. Finally, the Degree Day (DD312) was calculated for each region, applying the standard HDD formula to the weighted T_{avg312} for each region:

$$HDD = DD_{312} = max(T_{reg312} - T_{base}, 0)$$

Table 7 Station name and ID along with weighting and base temperature used for the 2018 GSOO, excluding VIC

Region	Station name	Station ID	Tariff D Weight	Tariff V Weight	T_{base} (°C)
New South Wales	Sydney (Observatory Hill)	66062	0.74	0.00	19.57
New South Wales	Bankstown Airport	66137	0.16	1.00	19.57
New South Wales	Wagga Wagga	72150	0.10	0.00	19.57
Queensland	Archerfield	40211	0.34	1.00	19.30
Queensland	Rockhampton	39083	0.33	0.00	19.30
Queensland	Townsville	32040	0.33	0.00	19.30
South Australia	Edinburgh RAAF	23083	0.94	1.00	17.94
South Australia	Adelaide (Kent Town)	23090	0.06	0.00	17.94
Tasmania	Hobart (Ellerslie Road)	94029	1.00	1.00	17.72

A2.2 Effective Degree Days (EDD)

In Victoria, an EDD is used to quantify the impact of a range of meteorological variables on gas consumption and maximum demand. This is due to Victoria showing a high sensitivity to seasonality, wind speed, and the hours of sunshine with its heating load.

There are several EDD formulations, AEMO applies the EDD312 (2012) for modelling Victorian medium- to long-term gas demand.[29] In this GSOO the EDD312 (2012) standard was applied with an adjustment for the Melbourne

[29] EDD312 refers to the specific start time and end time of the daily inputs that are used to calculate the EDD. This start time is 3am and end time is 12am the next day.

Olympic Park weather station that commenced operation in 2015. The EDD312 standard is a function of temperature, wind chill, seasonality and solar insolation with the formulation given as:

$$EDD_{312} = \max(DD_{312} + Windchill - Insolation + Seasonality, 0)$$

The following sections outline how each of the components were calculated.

Temperature (T_{312}) and Degree Days (DD_{312})

Similar to the calculation of DD_{312} as used for the HDD calculation for the other regions, the average of the eight three-hourly Melbourne temperature readings from 3.00 am to 12.00 am the following day inclusive was taken. The Melbourne Regional Office weather station data was used until its closure on 6 January 2015, with the new Melbourne Olympic Park weather station data used afterwards. To align the Melbourne Olympic Park weather station with historic data, an adjustment factor was applied such that:

$$T_{312}(OlympicPark) = 1.028 * (T3AM + T6AM + T9AM + T12PM + T3PM + T6PM + T9PM + T12AM)/8$$

Table 8 Weather stations used for the temperature component of the Victorian EDD

Region	Station name	Station ID	Weight	T_{base} (°C)
Victoria	Melbourne Regional Office (until 5 Jan 2015)	86071	1.00	18.00
Victoria	Melbourne Olympic Park (from 6 Jan 2015)	86338	1.00	18.00

Wind chill

To calculate the wind chill function, first an average daily wind speed was calculated, again using the average of the eight three-hourly Melbourne wind observations (measured in knots) from 3.00 am to 12.00 am the following day, inclusive. The average wind speed was defined as:

$$W_{312} = (W3AM + W6AM + W9AM + W12PM + W3PM + W6PM + W9PM + W12AM)/8$$

This was calculated at the weather station level, and a weighted average of the stations in the region was taken to produce a regional wind speed. The wind speed data was sourced from the Bureau of Meteorology, and the stations used and weighting applied are given below.

Table 9 Weather stations used for the wind speed component of the Victorian EDD

Region	Station name	Station ID	Weight
Victoria	Laverton RAAF	87031	0.50
Victoria	Moorabbin Airport	86077	0.50

The wind chill formula is a product of both the average temperature and the average wind speed, with a constant (0.037) applied to account for the perceived effect of wind on temperature. A localisation factor (0.604) was also applied, to account for the shift from the Melbourne wind station (closed in 1999) to the average of Laverton and Moorabbin wind stations, to align them with the Melbourne wind station reading.

$$Windchill = 0.037 \times DD_{312} \times 0.604 \times W_{312}$$

Solar insolation

Solar insolation is the power received on Earth per unit area on a horizontal surface, and depends on the height of the Sun above the horizon. Insolation factor provides a small negative adjustment to the EDD when included, as a higher insolation indicates more sunlight in a day, a factor that can decrease the likelihood of space heating along with a higher output from solar hot water systems (reducing gas from gas hot water systems).

An average daily solar insolation was estimated by the amount of sunlight hours as measured by the Bureau of Meteorology at Melbourne Airport using the following calibration:

$$Insolation = 0.144 \times Sunshine\ Hours$$

Table 10 Weather station used for the solar insolation component of the Victorian EDD

Region	Station name	Station ID	Weight
Victoria	Melbourne Airport	86282	1.00

Seasonal factor (COSINE function)

This factor modelled seasonality in consumer response to different weather. Data show that Victorian consumers have different energy habits in winter than outside of winter despite days with the same temperature (or DD_{312}). This may indicate that residential consumers more readily turn on heaters, adjust heaters higher, or leave heaters on longer in winter than in shoulder seasons for the same weather or change in weather conditions. For example, central heaters are often programmed once cold weather sets in, resulting in more regular use.

This seasonal specific behaviour is captured by the Cosine term in the EDD formula, which implies that for the same weather conditions, heating demand is higher in the winter periods than the shoulder seasons or in summer, and is defined as:

$$Seasonality = 2 \times cos(2\pi \times (day.of.year - 190)/365)$$

Determining HDD and EDD standards

A median of HDD/EDD weather data from 2000 to the current year was used to derive a standard weather year.

A2.3 Climate change impact

In order to apply weather standards for the 20-year forecast horizon AEMO has estimated the impact that recent changes in climate have had on HDDs (and therefore also EDDs) and adjusted the forecast to account for expected increases in temperatures as result of further climate change.

Approach

To consider how to incorporate the climate change impact on forecast energy demand, AEMO sought both advice and data from the Bureau of Meteorology and the CSIRO, then analysed historical and forecast temperature changes for the different weather regions across Australia.

In this process, AEMO obtained the median forecast increase in annual average temperatures for more than 40 different climate models. This median was used as a "consensus" forecast. The climate models simulate future states of the Earth's climate using Representative Concentration Pathways (RCPs) that span a range of global warming scenarios.

There are several future RCP trajectories available. AEMO chose the RCP4.5 as it has an emissions scenario consistent with current policy assumptions, noting that the difference between emissions scenarios tend to be small in the first 20 years regardless, as most of the forecast temperature increase is already locked in. This RCP4.5 scenario results in an estimated increase in average temperatures by approximately 0.5 °C over the next 20 years across all regions in Australia compared to current temperatures.

Validation against historical weather

To include the effect of a climate change signal on the heating demand of energy consumers, an adjustment to be made on the HDD forecasts was proposed. Analysis of historical temperature records show that climate change effect since 1980 has been at least a 0.5 °C increase in average temperatures across Australia.[30] This increase is significant enough to have potentially affected the number of HDDs, as the variable is derived from average temperatures. AEMO sought to first observe and quantify changes in the HDD variable over time to provide historical validation, before applying a climate change trend to the HDD forecast.

In addition, investigation was required to quantify the impact of the so-called Urban Heat Island Effect (UHI). Some of the recent warming in capital cities can be attributed to the increase in urbanisation in capital cities with higher overnight temperatures as buildings and other concrete structures can absorb and retain heat much more when compared to surrounding rural environments.

To quantify this effect, AEMO compared temperature measurements in rural and city-based weather stations in the same climate region. For example, a comparison of the average winter temperatures from 1995 until 2015 for the city-based station (Melbourne Regional Office) and in a regional area (Melbourne Airport) showed an increase in the average daily winter temperatures of 0.42 °C and 0.24 °C respectively. This finding, of the city station showing twice the warming of the rural station, is consistent with other work that has estimated that approximately half the warming in Melbourne city can be attributed to the UHI.[31] Figure 6 below shows how the application of the climate change trend in Melbourne Airport's temperature data (on an annual basis) can account for a large part in the observed reduction of HDDs over the last 20 years. Investigation of the other main weather stations (see Table 7) used for

30 http://www.bom.gov.au/climate/change/index.shtml#tabs=Tracker&tracker=timeseries.

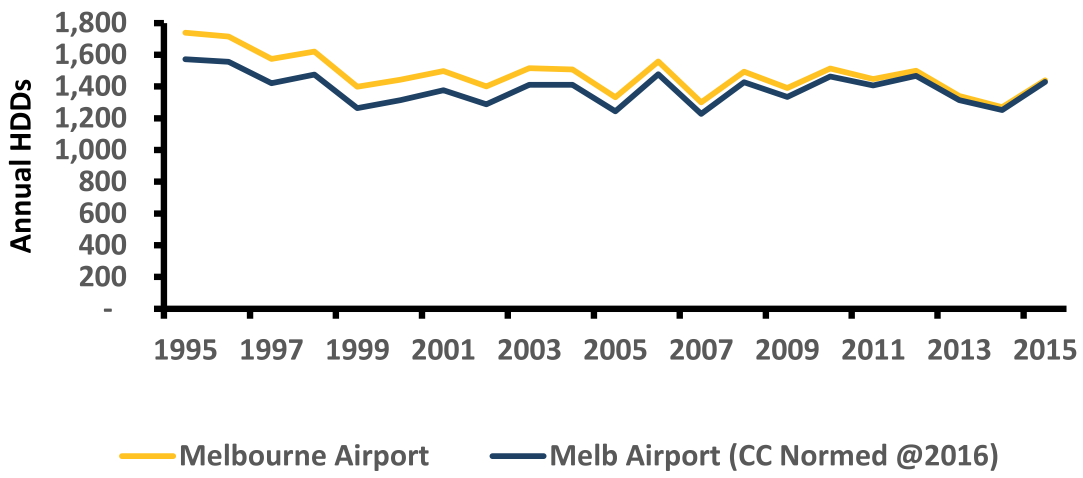
31 Suppiah. R and Whetton, P.H., "Projected changes in temperature and heating degree-days for Melbourne and Victoria, 2008-2012", March 2007. Available at: http://www.ccma.vic.gov.au/soilhealth/climate_change_literature_review/documents/organisations/csiro/MelbourneEDD2008_2012.pdf

calculating HDDs identified only small effects of UHI, likely due to these stations being situated in less urban or open aired environments.

Using historical temperature anomaly data from the Bureau of Meteorology, AEMO adjusted the daily average temperature data against the climate change average temperature anomaly to re-baseline the last 20 years of HDDs (approximately compounding + 0.025°C per annum).

This adjustment was applied to all the weather stations as described in Table 7. The ability to quantify the historical component of climate change in HDD changes over time provided a strong validation to apply a climate change signal to the HDD forecast.

Figure 6 Comparison of HDD historical models for Melbourne Airport with and without a climate change adjustment

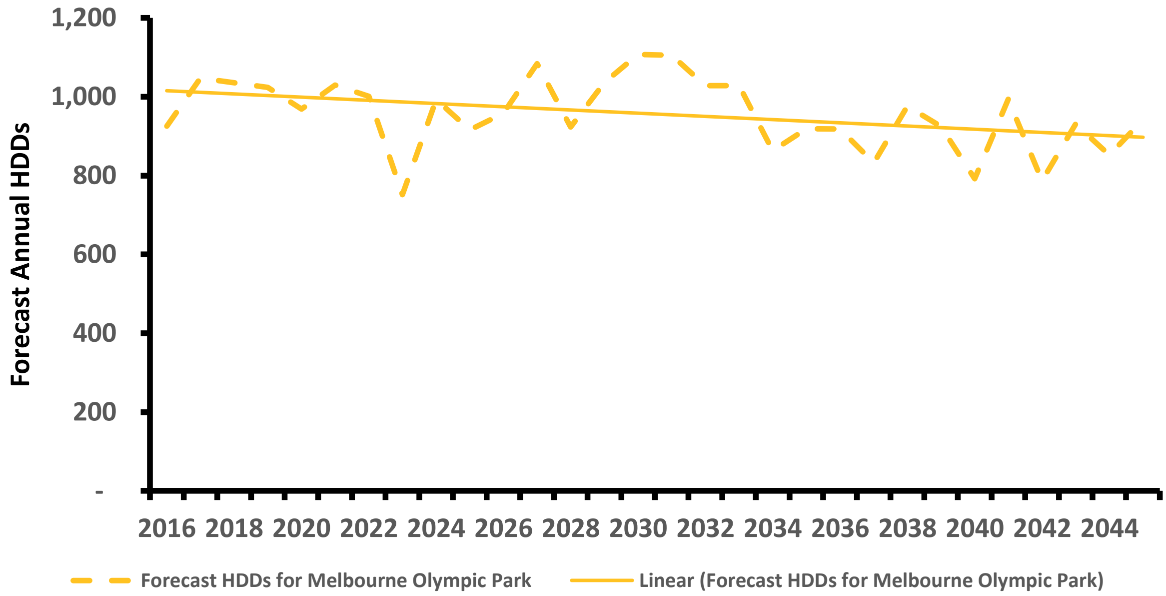


Inclusion in forecast data

The median trace of the 40 RCP4.5 models predicts a 0.5 °C increase in average temperatures from 2018–38 across Australia. AEMO used this data to adjust the forecast weather standard used in each region over the forecast period, and calculate the annual HDDs.

Climate models also simulate natural year-to-year natural weather volatility. Applying the climate change trend to the HDD will contains this year-to-year volatility. As the GSOO uses a single reference weather year across the 20 year forecast horizon, this variability was removed but the average annual reduction in HDDs was preserved by extracting the linear trend (refer to Figure 8 for an example on Melbourne's Olympic Park forecast HDDs). This linear trend was then applied against the reference HDD (or HDD component of the EDD) forecast. The annual reductions for HDDs calculated for each state were 7.7 in New South Wales, -1.7 in Queensland, and - 5.6 in South Australia, and the annual reduction in EDDs for Victoria was - 6.8.

Figure 7 A climate change adjusted HDD showing annual weather variability with a linear trend for Melbourne Olympic Park



To model gas maximum demand, high resolution historical half hourly temperature data was used to observe distributions of weather scenarios. As it is optimal to have large sample sizes for distribution analysis but also consider weather that is reflective of current climatic conditions, the temperature data was restricted to more recent historical weather data (1995–2015). This data was re-baselined to the reference year, by applying an adjustment using the Bureau of Meteorology's historical temperature anomaly data from climate change impacts since 1995. This followed a similar method to what was performed to baseline the HDDs, but at a finer (half-hourly) granularity, preserving historical volatility from an individual historical weather year but a data set more reflective of the climate in the reference year.

A limitation of this approach is that it takes an average effect of the climate change impact only on HDDs. Temperature events such as heatwaves, which potentially show an increase in intensity faster than the average change in temperatures, have been examined.[32] As such, AEMO will be working towards utilising higher resolution temperature forecast data, and will undertake further collaboration with climate scientists, to quantify changes in maximum demand from where maximum/minimum daily temperature variations show greater volatility compared to the daily average.

[32] Perkins, S. E., and L. V. Alexander. "On the measurement of heat waves." Journal of Climate 26.13 (2013): 4500-4517. http://journals.ametsoc.org/doi/abs/10.1175/JCLI-D-12-00383.1 Viewed: 24 January 2017.

A3. Distribution and transmission losses

Gas is transported from high-pressure transmission pipelines to lower-pressure distribution networks before it is used. During this process, some gas is unaccounted for and some are used for operational purposes. This quantity of gas is collectively referred to as "total losses".

In the distribution networks, losses typically result from gas pipe leakages, metering recording errors, gate station losses and other uncertainties. These gas losses are commonly known as UAFG.

Transmission pipeline losses mostly relate to gas used by in pipeline compressors and heaters in normal gas pipeline operations. While UAFG also occurs along high-pressure pipelines, due to the volumes transmission pipelines ship, these pipeline losses are addressed more rapidly than distribution losses and tend to be lower.

Due to AEMO's management of the Victorian gas Declared Transmission System, operational gas used to fuel compressor stations in Victoria is forecast separately. Operational gas has been increasing rapidly in recent years due to increasing inter-state exports from Victoria to New South Wales (via the Interconnect) and South Australia.

A3.1 Annual consumption

AEMO obtained historical losses from the sources listed in Table 11.

Historical data was normalised before being used to estimate forecasts. Transmission losses are expressed as a percentage of total gas consumption by residential and commercial consumers, industrial consumers, GPG, and distribution losses. Distribution losses are expressed as a percentage of total gas consumed by residential, commercial and industrial consumers within the distribution-connected areas.

AEMO forecasts transmission and distribution losses separately as they are driven by different underlying factors, these are then aggregated to form the final forecasts.

Transmission losses are primarily driven by operational losses, while distribution losses are driven by UAFG. Regional transmission losses are forecast to range from 0.6% to 1.6% of total consumption, while distribution losses vary between 0.1% and 6.3% for each State. These variations arise from differences in the number, size, type of users, and age of assets, network upgrades, and total gas demand for each state.

A3.2 Maximum demand

Losses during times of maximum demand were forecast by finding the highest demand days by season by tariff type. From the highest demand days the average percentage of losses relative to demand on those days was calculated. These normalised losses (transmission and distribution) during times of maximum demand in history were then applied to maximum demand days in the forecast horizon.

A4. Data Sources

Table 11 Historical data sources

Demand component	Data source for all regions except for Victoria	Data source for Victoria
Residential and commercial	Distribution businesses	AEMO's internal database
Industrial	1. Distribution businesses (for all Tariff D customers, aggregated on a network basis) 2. Transmission businesses (for all Tariff D customers, aggregated on a network basis) 3. Direct surveys (for specific large industrial customers)	AEMO's internal database
Transmission losses	Transmission businesses	AEMO's internal database
Distribution losses	Distribution businesses	1. Distribution businesses 2. AEMO's internal database
GPG	1. Transmission businesses where permission has been granted 2. AEMO's internal database	AEMO's internal database

Table 12 ANZSIC code mapping for industrial sector disaggregation

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

Table 13 Historic and Forecast Input Data Sources for Industrial Sector

Data Series	Data Sources	Reference	Notes
Historic Consumption data by region	AEMO Database	http://forecasting.aemo.com.au/	This is metered data. Actuals derived from aggregate of these sources are reported and available on AEMO's forecasting data portal
Historic Consumption data by region	CGI Logica	http://forecasting.aemo.com.au/	
Historic Consumption data by region	Transmission & Distribution, Industrial Surveys	http://forecasting.aemo.com.au/	
Historic Consumption data by region	Gas Bulletin Board (GBB)	https://www.gasbb.com.au/	LNG exports information is available on the GBB.
Historic Consumption data by industry sector	Dept. of Energy and Environment	https://www.energy.gov.au/government-priorities/energy-data/australian-energy-statistics	Energy statistics data is used to build the long-term models for the Manufacturing and Other Business sectors.
Weather Data	BOM	http://www.bom.gov.au/	Effective Degree Days (EDD) and Heating Degree Days (HDD) require weather data sourced from BOM
Climate Change Data	CSIRO	https://www.climatechangeinaustralia.gov.au/en/climate-projections/about/	*Climate Change in Australia* is a CSIRO run website. AEMO references this for climate change projections.
Economic Data	ABS	http://www.abs.gov.au/ausstats/abs@.nsf/Latestproducts/0C2B177A0259E8FFCA257B9500133E10?opendocument	Historic values for Services sector GVA and Industrial Production can be found on the ABS website
Economic Data	Economic Consultancy	http://forecasting.aemo.com.au/	Economic consultants provide AEMO with forecasts for Services sector GVA and Industrial Production. The index of the forecasts is available on AEMO's forecasting data portal
Wholesale Gas Price	AEMO estimates + CORE Energy	http://forecasting.aemo.com.au/	Wholesale gas price is an input into the Retail gas price. The index of prices is available on AEMO's forecasting data portal.

Table 14 Data sources for input to Retail Gas Price Model

Data Series	Data Sources	Reference	Notes
Wholesale Price Forecasts	AEMO estimates + CORE energy	http://forecasting.aemo.com.au/	CORE provide wholesale price forecasts to AEMO. AEMO has adjusted these forecasts in the near term to reflect recent observations of wholesale prices. Index of wholesale prices are available on AEMO's forecasting data portal.
Revenue Determinations	AER Network Determination	https://www.aer.gov.au/networks-pipelines/determinations-access-arrangements	AEMO calculates the real term change from the AER determinations over the revenue reset period and applies to the base year network price to project prices long term.
Retail Published Prices	NSW: AGL prices SA, VIC & QLD: Origin Energy TAS: TasGas	AGL: https://www.agl.com.au/get-connected/electricity-gas-plans Origin Energy: https://www.originenergy.com.au/for-home/electricity-and-gas.html TasGas: https://www.tasgas.com.au/	For each region a reference retailer is used to obtain current year retail prices. This is based on the retailer with the most customers. This is based on the AER "*State of the market Report*."
Distribution Published Prices	NSW: Jemena SA& QLD: AGN VIC: Multinet TAS: None publicly available.	Jemena: http://jemena.com.au/about/document-centre/electricity/tariffs-and-charges AGN: https://www.australiangasnetworks.com.au/our-business/regulatory-information/tariffs-and-plans Multinet: https://www.multinetgas.com.au/tariff-pricing/	For each region a reference distribution network provider is used. This is used to derive the first-year distribution price forecast.
Transmission Published Prices	NSW, QLD & VIC: APA SA: Epic TAS: None publicly available	APA: https://www.apa.com.au/archive/indicative-transmission-tariffs/ Epic: http://www.epicenergy.com.au/index.php?id=97	For each region a reference transmission network provider is used. This is used to derive the first-year transmission price forecast.

Table 15 Input data for analysis of historical trend in Tariff V consumption

Data	Source	Purpose
Tariff V daily consumption by region and exclusive of UAFG	VIC and QLD: AEMO Settlements database. NSW and SA: Meter data agent (CGI data tables). TAS: Provided by gas distribution business in stakeholder survey.	To estimate Tariff V temperature sensitivity used to estimate weather corrected estimated actual annual consumption.
Regional daily EDD (Vic) or HDD (other regions)	BOM. Further detail provided in Appendix A2	Same as above.
Victorian residential meter data 2004–14[33]	AEMO meter database.	To estimate trend in Victorian residential base and heating load.
Victorian daily EDD 2004–14	Calculated using BOM data according to the formula described in Appendix A2.	Same as the above.
Actual residential and non-residential annual consumption	Provided by gas distributors in stakeholder surveys.	Used to split Tariff V annual consumption by residential and non-residential.
Actual Tariff V residential and non-residential connections	VIC and QLD: AEMO Settlements database. NSW and SA: Meter data agent (CGI data tables). TAS: Provided by gas distribution business in stakeholder survey.	Used to calculate average consumption per Tariff V residential and non-residential connection.
Historical residential prices	See details in Appendix A1.	Used to estimate impact of gas prices on gas Tariff V residential and non-residential consumption.

Table 16 Input data for forecasting Tariff V annual consumption

Data	Source	Purpose
Forecast residential prices[34]	See details in Appendix A1.	Used to forecast gas price impact on residential and non-residential annual consumption forecasts.
Forecast Tariff V connections	See section 5.2.	
Annual EDD/HDD standards	See Appendix A2.	Used for forecasting Tariff V heating load.
Forecast non-residential annual consumption savings due to energy efficiency and fuel switching	Core Energy	Used to forecast impact of energy efficiency and fuel switching on Tariff V non-residential forecasts.
Impact of climate change on Tariff V annual heating load	See details in Appendix A2.	Used to forecast impact of climate change on Tariff V annual heating load forecasts.

33 Second tier residential customers only.

34 Forecast residential prices are used for forecasting Tariff V residential and non-residential gas consumption because both forecast price series follow similar trends.

Glossary

Terms

Term	Definition
Annual gas consumption	Refers to gas consumed over a calendar year, and can include residential and commercial consumption, industrial consumption, GPG consumption, or transmission and distribution losses. Gas used for LNG processing and exports is considered separately. Unless otherwise specified, annual consumption data includes transmission and distribution losses.
Distribution losses	Refers to gas leakage and metering uncertainties (generally referred to as UAFG) in the distribution network. This is calculated as a percentage of total residential and commercial consumption and industrial consumption connected to the distribution networks.
Effective degree days (EDD)	A measure that combines a range of weather factors that affect energy demand.
Gas-powered generation (GPG)	Refers to generation plant producing electricity by using gas as a fuel for turbines, boilers, or engines. In the NGFR forecasts, this only includes GPG that is connected to the National Electricity Market (NEM). AEMO engaged the consultancy Jacobs to provide the GPG forecasts based on their modelling of future electricity generation in the NEM.
Industrial, also known as Tariff D	Refers to users that generally consume more than 10 terajoules (TJ) of gas per year. Industrial consumption includes gas usage by industrial and large commercial users, and some GPG that is not connected to the NEM, for example, GPG around Mt Isa.
Liquefied natural gas (LNG)	Refers to natural gas that has been converted to liquid form.
Maximum demand	Refers to the highest daily demand occurring during the year. This can include residential and commercial demand, industrial demand, GPG demand, or distribution losses. Gas used for LNG production is considered separately. Unless otherwise specified, maximum demand includes transmission and distribution losses.
Per customer connection	Refers to the average consumption per residential and commercial gas connection. Expressing consumption on this basis largely removes the impact of population growth, and allows commentary about underlying consumer behaviour patterns.
Probability of Exceedance (POE)	Refers to the likelihood that a maximum demand forecast will be met or exceeded, reflecting the sensitivity of forecasts to changes in weather patterns in any given year. The GSOO provides these forecasts: • 1-in-2 maximum demand, also known as a 50% POE, means the projection is expected to be exceeded, on average, one out of every two years (or 50% of the time). • 1-in-20 maximum demand, also known as a 5% POE, means the projection is expected to be exceeded, on average, one out of every 20 years (or 5% of the time).
Residential and commercial, also known as Tariff V	Refers to residential and small-to-medium-sized commercial users consuming less than 10 TJ of gas per year. Unless otherwise specified, historical residential and commercial data is not weather-corrected.
Transmission losses	Refers to gas that is unaccounted for or consumed for operational purposes (such as compressor fuel) when transported through high-pressure transmission pipelines to lower-pressure distribution networks. Transmission losses are calculated as a percentage of total residential and commercial, industrial, and GPG consumption, and distribution losses.
Winter	June to August
Summer	December to February.
Nash-Cournot	Nash-Cournot algorithms are used to simulate competitive behaviour in electricity markets. In a Nash-Cournot gaming environment, participants adjust the quantity of supply they allow to the market and find an equilibrium against a demand function. The demand function represents how responsive to price the load is i.e. how much consumers will adjust their demand as price increases. These dynamics enable the model to simulate, to a reasonable extent, market competition which in turn provides more accurate forecasts for gas consumption by GPG

Units of measure

Abbreviation	Unit of measure
DD	Degree days
EDD	Effective degree days
GJ	Gigajoules
GWh	Gigawatt hours
HDD	Heating degree days
TJ	Terajoules

Abbreviations

Abbreviation	Expanded name
ABS	Australian Bureau of Statistics
AER	Australian Energy Regulator
APLNG	Australia Pacific LNG
CGE	Computable General Equilibrium
CSG	Coal seam gas
DB	Distribution business
DoW	Day of Week
DSM	Demand side management
DTS	Declared Transmission System
ESD	Energy Statistics Data
GFC	Global Financial Crisis
GLNG	Gladstone Liquefied Natural Gas
GPG	Gas-powered generation
GRMS	Gas Retail Market Systems
GVA	Gross Value Added
HIA	Housing Industry Association
LGA	Lewis Grey Associates
LIL	Large industrial loads
LNG	Liquefied natural gas
LRET	Large-scale Renewable Energy Target
MHQ	Maximum Hourly Quantity
MMS	Market Management System
MPC	Market Price Cap
NEFR	National Electricity Forecasting Report
NEM	National Electricity Market
NGFR	National Gas Forecasting Report
NTNDP	National Transmission Network Development Plan
POE	Probability of exceedance
QCLNG	Queensland Curtis LNG
RCAC	Reverse-cycle Air-conditioners
RCP	Representative Concentration Pathways
SMIL	Small-to-medium industrial loads
SRES	Small-scale Renewable Energy Scheme
TGP	Tasmanian Gas Pipeline
UAFG	Unaccounted for gas
UHI	Urban Heat Island Effect
VRET	Victorian Renewable Energy Target