FORECASTING METHODOLOGY INFORMATION PAPER

2015 NATIONAL ELECTRICITY FORECASTING REPORT

Published: **July 2015**

AEMO
AUSTRALIAN ENERGY MARKET OPERATOR

IMPORTANT NOTICE

Purpose

AEMO has prepared this document to provide information about the 2015 National Electricity Forecasting Report (NEFR), as at the date of publication. It describes how the 2015 NEFR operational consumption, maximum demand and minimum demand forecasts were developed.

Disclaimer

Acknowledgement

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

ABOUT THIS INFORMATION PAPER

The 2015 Forecasting Methodology Information Paper is a companion document to the 2015 National Electricity Forecasting Report (NEFR). It is designed to help interpret the electricity consumption forecasts contained in the NEFR, by:

- Providing a detailed description of how annual operational consumption, maximum demand (MD) and minimum demand forecasts were developed.
- Outlining how AEMO sought to ensure the forecasting processes and assumptions were consistently applied and fit for purpose.
- Providing further detail on the customer segments used.
- Describing AEMO's approach to developing the forecasts for each forecasting component (residential and commercial sector, industrial sector, rooftop photovoltaic (PV), energy efficiency, and small non-scheduled generation (SNSG)).
- Detailing modelling improvements made since the 2014 NEFR.

AEMO has made these key methodology improvements for the 2015 NEFR:

- Increased the sample size of large industrial loads, from 93 in 2014 to 115 in 2015.
- Modelled residential and commercial rooftop photovoltaic (PV) separately, to reflect the different drivers in each sector.
- Incorporated industrial loads directly into the maximum demand model.
- Modified the maximum demand model to include temperature and day-of-week interactions, by modelling the demand for workdays and non-workdays separately.
- Improved the methodology for determining the impact of energy efficiency on maximum demand.

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CHAPTER 1. INTRODUCTION

Electricity demand forecasts are used for operational purposes, to calculate marginal loss factors, and as a key input into AEMO's national transmission planning role. It is important to understand how the forecasts are developed and what assumptions are applied.

In 2012, AEMO changed the way it develops and publishes annual electricity demand forecasts for the electricity industry, by developing independent forecasts for each National Electricity Market (NEM) region. AEMO collaborates with industry to ensure representative and robust forecasts are consistently produced for each region. In 2015, AEMO made further improvements to this process.

This report outlines the methodology used in the annual operational consumption, maximum demand and minimum demand forecasting process.

As part of the 2015 NEFR, AEMO produced forecasts for energy consumption, maximum demand and, for the first time, South Australian minimum demand. The forecasts were produced in components, which were then aggregated at a regional level to produce regional forecasts for energy and demand. These components were:

- Residential and commercial load.
- Large industrial load.
- Transmission losses.
- Auxiliary losses.
- Small non-scheduled generation.

Forecasts for energy efficiency and rooftop photovoltaic (PV) were also produced, and can be described as post-model adjustments to the residential and commercial forecasts.

The 2015 NEFR forecast operational consumption, maximum demand, and minimum demand under low, medium and high demand scenarios, with the medium scenario considered the most likely. Table 1 summarises how each of the three 2015 NEFR scenarios related to the component forecasts.

Table 1 2015 NEFR component scenario mapping

2015 NEFR Reference	Related economic scenario	Related large industrial scenario	Related rooftop PV scenario	Related energy efficiency scenario	Related small non-scheduled generation scenario
High	HCO5	High	Low uptake	Low uptake	High uptake
Medium	MCO5	Medium	Moderate uptake	Moderate uptake	Moderate uptake
Low	LCO5	Low	High uptake	High uptake	Low uptake

1.1 Key definitions

AEMO forecasts are reported as:

- **Annual operational consumption:** electricity used by residential, commercial, and large industrial consumers drawn from the electricity grid, including transmission losses.[1] It is measured in gigawatt hours (GWh) and the forecasts are presented on a "sent-out"[2] basis.
- **Operational maximum (minimum) demand:** the highest (lowest) level of electricity drawn from the transmission grid at any one time in a year measured on a daily basis, averaged over

[1] Supplied by scheduled, semi-scheduled and significant non-scheduled generating units. Refer to AEMO's definitions here.
[2] Measured at the connection point between the generating system and the network.

a 30 minute period. It is measured in megawatts (MW) and the forecasts are presented "as generated".[3]

Operational consumption = Residential and commercial consumption + Large industrial consumption + Transmission losses

Residential and commercial consumption = Underlying consumption − Rooftop PV − Energy efficiency adjustment

Large industrial consumption = Underlying consumption − Embedded generation

Underlying consumption refers to everything consumed on site, and may be met by localised generation from rooftop PV and embedded generators, or by the electricity grid.

Operational demand = Operational demand from all consumers + Energy used in transmission and distribution + Auxiliary loads

[3] Measured at the terminals of a generating system.

CHAPTER 2. OPERATIONAL CONSUMPTION

2.1 Residential and commercial load

Residential and commercial load is defined as the load on the network attributable to residential and commercial consumers. It includes distribution losses incurred in the provision of electricity to customers.

The general model structure for the 2015 NEFR methodology for residential and commercial load was unchanged from the 2014 NEFR. However, several aspects were refined in response to external peer review feedback, changes in the market environment, and ongoing internal improvement initiatives. The changes included:

- Exploring the consumer response to price decreases.
- Emphasising more recent consumption data, given the trend of declining electricity consumption has recently slowed.
- Incorporating the likelihood of a consumer response to the Australian Energy Regulator (AER) determination of distribution costs in New South Wales.
- Incorporating more weather stations in the weather variables.
- Reducing the size of the residential and commercial component, due to a reallocation of customers as large industrial.[4]

As it did for the 2014 NEFR, AEMO engaged Woodhall Investment Research Ltd to help develop the annual consumption models. The following sections detail the data used in modelling, the development of the model and the model specification.

2.1.1 Data sources and variable selection

The residential and commercial model used historical data to estimate a relationship between electricity consumption and four key drivers of consumption (income, price, weather, and population). It then used these estimates and forecast values for the key drivers to calculate consumption forecasts. The data sources used are listed in Table 2.

Table 2 Data sources used for the residential and commercial forecasts

Source	Data
Frontier Economics[5], the Australian Bureau of Statistics (ABS), KPMG[6]	Historical and forecast economic variables including: • Real gross state product (GSP). • Population (POP). • Real total price of electricity (TPE). • Real residential price of electricity (RPE). • Real business price of electricity (BPE).
Bureau of Meteorology	Historical weather data
Metering Settlements and Transfer Solution (MSATS)	Historical consumption data

[4] Residential and commercial load is a derived value − AEMO derives residential and commercial load by subtracting industrial consumption, auxiliary load, and transmission losses from total operational consumption − so increasing the number of industrial customers decreases the estimated residential and commercial load.
[5] Frontier Economics, Electricity market forecasts: 2015, April 2015. Available at http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/NEFR-Supplementary-Information
[6] For a summary of these, see AEMO, Economic Outlook, available at http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/NEFR-Supplementary-Information

AEMO used a combination of theory and testing when selecting which variables to include as drivers in the model. It gave consideration to the theoretical relationship between consumption and a range of drivers, so the estimated coefficients made theoretical sense. For example, the coefficients for each variable should show that energy demand is likely to:

- Increase with real state-wide income.
- Decrease with rising electricity prices.
- Reflect seasonal weather variations throughout the year.

Statistical approaches involved examining the fit and statistical significance of each variable when placed in the model, and the reasonableness of the modelling results.

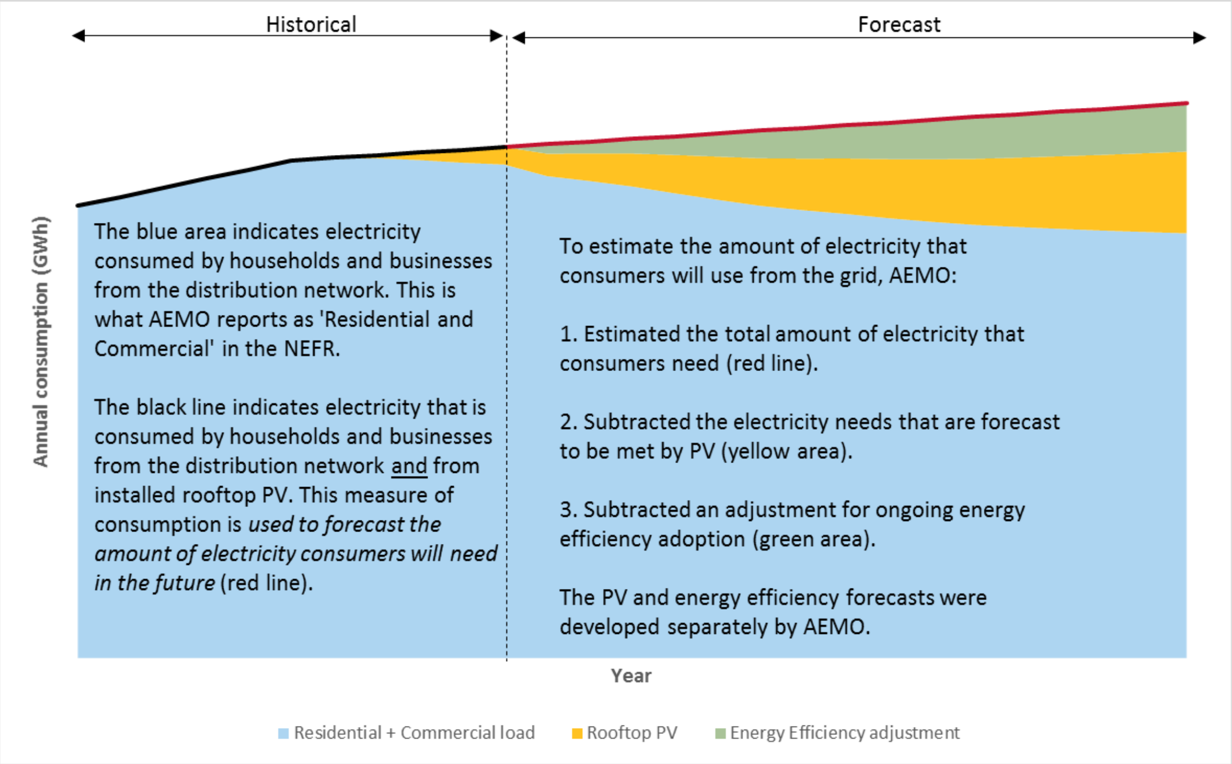
The data is region-specific, so unique models were developed for each region. AEMO used quarterly data for modelling, commencing September, December, March, and June. Results were then aggregated to financial year.

Calculating consumption data

AEMO estimated historical consumption data for the residential and commercial segment using the data it collects for market settlements. It aggregated data collected every half-hour for each NEM region since January 2000 to produce quarterly data. AEMO used a top-down approach to derive residential and commercial load, by subtracting industrial consumption, auxiliary load, and transmission losses from total operational consumption.

For modelling, estimated rooftop PV consumption was added to the calculated operational residential and commercial consumption. See Figure 1 for further explanation of how residential and commercial consumption was defined and calculated.

Figure 1 Defining and calculating residential and commercial data



As noted above, the historical residential and commercial data used in the 2015 NEFR differed to that used in the 2014 NEFR, because 22 customers were moved from the residential and commercial sector to the industrial sector. This was part of an ongoing modelling improvement, which involved increasing the number of industrial customers for which AEMO produced individual forecasts. This change resulted in reduced residential and commercial load.

Calculating income data

The 2014 NEFR used Principal Component Analysis (PCA) to create a single income variable utilising GSP and State Final Demand (SFD). PCA calculates linear weights that are used to combine the two data series to create a single variable. AEMO found that the choice of variable made very little difference to the model estimation, so only GSP was considered in the 2015 NEFR. Historical and forecast income data was provided by KPMG.

Calculating price data

Historical and forecast price data was provided by Frontier Economics. Based on coefficient and residual analysis, AEMO assessed residential price of electricity (RPE) as the most appropriate price variable for Queensland and Tasmania, and total price of electricity (TPE) as the most appropriate price variable for South Australia, New South Wales and Victoria.

The price series produced by Frontier Economics included a 30% decline in electricity prices for New South Wales in 2015–16, based on the draft determination from the Australian Energy Regulator (AER). At the time of modelling, the AER had not released its final determination on network charges for New South Wales, or draft determinations for Queensland or South Australia.

The potential for price decreases is noteworthy for two reasons:

- Prices have historically continued to rise.
- The consumer response to electricity prices is asymmetric. While consumers may reduce consumption in response to price rises, they do not necessarily revert to previous levels of consumption when prices later fall, due to permanent changes in behaviour.

AEMO sought to capture this asymmetric price response by modelling the impact of price increases and decreases differently using different price variables. At the time of modelling, sufficient historical data for this approach was only available for South Australia and Tasmania. For the other regions, AEMO used the approach used in the 2014 NEFR to address the potential impact of the carbon price repeal, by assuming that rather than responding to a price decrease, consumers continue to respond to the higher prices they have experienced in recent years.

In South Australia and Tasmania, AEMO used two price variables, one to capture the response to price increases and one to capture the response to price decreases. The price variables were developed by defining two dummy variables (equation 1) and then defining two price variables using these dummy variables (equation 2).

Equation 1 **Dummy variables for changes in electricity price**

$$d_- = \begin{cases} 1, & \Delta \log(price) < 0 \\ 0, & \Delta \log(price) > 0 \end{cases} \qquad d_+ = \begin{cases} 0, & \Delta \log(price) < 0 \\ 1, & \Delta \log(price) > 0 \end{cases}$$

Equation 2 **Asymmetric price variables**

$$P_- = \sum d_- \Delta \log(price), \qquad P_+ = \sum d_+ \Delta \log(price),$$

Calculating population data

Historical and forecast population data were determined by ABS projections. Consumption and income data were converted to per capita parameters before modelling. This allowed the underlying trends in consumption to be modelled.

Calculating weather data

Historical average daily temperature data was provided by the Bureau of Meteorology. AEMO used this data to estimate historical heating degree days (HDD) and cooling degree days (CDD)[7] for each region. In the 2015 NEFR, AEMO used a weighted average of several weather stations in each region. The weather stations and weights used are shown in Table 3.

Table 3 Weather stations and weights used to calculate HDD and CDD[8]

NSW			QLD			SA		
Station ID	Station name	Station weighting	Station ID	Station name	Station weighting	Station ID	Station name	Station weighting
72150	Wagga Wagga	0.3%	40717	Coolangatta	15%	23083	Edinburgh RAAF	58%
66137	Bankstown Airport	17.2%	40211	Archerfield	12%	23090	Adelaide	42%
66037	Sydney Airport	11%	39083	Rockhampton	12%			
67113	Penrith	12%	32040	Townsville	11%			
63303	Orange Airport	7%	39128	Bundaberg Airport	12%			
66062	Sydney (Observatory Hill)	12%	39326	Gladstone Airport	12%			
67105	Richmond RAAF	10%	40842	Brisbane Airport	12%			
70014	Canberra Airport	7%	40913	Brisbane	13%			
60139	Port Macquarie	10%						
61390	Newcastle University	4%						
69139	Bega	9%						
VIC			**TAS**					
86071	Melbourne	27%	94008	Hobart Airport	18%			
81123	Bendigo	34%	91126	Devonport	18%			
86282	Melbourne Airport	14%	91237	Launceston	26%			
86371	Frankston AWS	18%	94029	Hobart	19%			
87163	Geelong Airport	7%	94087	Mount Wellington	19%			

During the modelling process, HDD and CDD were found to be significant in New South Wales, Victoria, and South Australia. HDD was not significant in Queensland and CDD was not significant in Tasmania so these variables were omitted from the final models.

[7] HDD and CDD are measures of how much (in degrees) and for how long (in days) the outside air temperature is lower/higher than a threshold temperature.
[8] Numbers may not add to 100% due to rounding error.

AEMO estimated forecast HDD and CDD using the historical trend in the data. This was done on a quarterly basis to allow for differing seasonal trends. HDD were found to be decreasing and CDD to be increasing over time in all regions, except Queensland where CDD was also decreasing.

Other variables

Other variables, such as the price of substitute electricity sources (for example gas), were considered but were found to be statistically insignificant.

Table 4 Summary of final variable selection

	Electricity consumption	Income	Price	Temperature
Variable	**Y** = Electricity/population * 1000	**GSP**/population * 1000	**P** = TPE or RPE $\mathbf{P_-}$ and $\mathbf{P_+}$ (SA and Tas)	**HDD** and **CDD**
Unit	kWh/capita	$/capita	c/kWh	Degree days

2.1.2 Model development

Annual consumption forecasts were developed using econometric methods which estimated the relationship between historical electricity consumption and the key drivers that determine residential and commercial consumption (income, electricity price, weather, and population).

The estimates, also known as coefficients, were then used in conjunction with forecast values for the key drivers, to derive electricity consumption forecasts.

The model used in the 2015 NEFR is based on the 2014 NEFR model. It was developed in two stages, which allowed AEMO to produce long-run and short-run coefficients.[9] A summary of the methodology is provided below. For more details, see the 2013 and 2014 NEFR Methodology Information Papers.[10]

There were two additional changes in the 2015 NEFR methodology, compared to the 2014 NEFR:

- AEMO reviewed the use of the intercept correction applied in 2014 to correct an upward forecast bias.
- The Maximum Price Model, which was used to model the consumer response to the proposed carbon price repeal, was used to model the consumer response to an expected fall in electricity prices due to changes in network tariffs.

Estimating the long-run relationship: Dynamic Ordinary Least Squares

The long-run response estimated the relationship between electricity consumption and a number of long-run drivers (such as income and electricity prices).

As it did for the 2014 NEFR, AEMO adopted the Dynamic Ordinary Least Squares (DOLS)[11] approach. This involved estimating the cointegrating[12] long-run equation and adding sufficient leads and lags[13] of

[9] Coefficients can be used to describe the change in energy that can be expected due to a change in a given variable. Estimating long-run and short-run coefficients allows AEMO to analyse the long-term and short-term impact of a change in a variable.

[10] AEMO, Forecasting Methodology Information Paper. Available at http://www.aemo.com.au/Electricity/Planning/Forecasting/NEFR-Archive/National-Electricity-Forecasting-Report-2014/NEFR-Supplementary-Information-2014 and http://www.aemo.com.au/Electricity/Planning/Forecasting/NEFR-Archive/National-Electricity-Forecasting-Report-2013/NEFR-Supplementary-Information-2013

[11] As proposed by Saikkonen (1991).

[12] Based on work undertaken for the 2013 NEFR, the variables used in the forecast models may be cointegrated, indicating a long-run relationship between price and income which can be used to forecast electricity consumption.

[13] Leads and lags are transformations of existing time series data that are added to the equation to improve the fit of the model. They are created by delaying or bringing forward the data series by a specified number of time periods. AEMO determined the appropriate number of leads and lags of the differenced variables by assessing the stability of the coefficients under different lead and lags structures in DOLS. See the 2013 NEFR Methodology for more information on the method used to select leads and lags.

the first differences[14] of the explanatory variables. The specification of the DOLS equation is shown below in Equation 3.

Equation 3 Dynamic Ordinary Least Squares

$$y_t = c_0 + c_1 x_t + \sum_{i=-n}^{n} c_{i2} \Delta x_{t+i} + u_t$$

AEMO adopted this approach because it:

- Enables a valid and consistent approach to be applied across all NEM regions.
- Provides an efficient estimator for the long-run relationship in the presence of variables with differing and higher orders of integration. Additionally, if a Newey-West[15] correction is applied, it is reasonable to apply standard tests on the coefficients.
- Is known to be effective when working with small datasets where endogeneity[16] may be present.

AEMO used the statistical package EVIEWS to estimate the DOLS equation for each region, with income and price variables entering the equation as the cointegrating regressors. All regional DOLS models also included constant temperature variables (to model the contemporaneous weather impact on consumption) and seasonal dummy variables (to account for seasonality) as deterministic regressors or covariates.

Estimating the short-run response: Integrated Dynamic Model

The short-run response estimated how much demand can deviate in the short run from the long-run demand forecast, in response to a change in a variable. As it did for the 2014 NEFR, AEMO adopted the Integrated Dynamic Model (IDM) approach.

The standard approach when estimating a short-run response within a cointegrating long-run equation is to place the lagged error correction (EC) term within a dynamic system, such as an error correction model (ECM), as shown in Equation 4 below. The ECM describes how the dependent variable and explanatory variables behave in the short-run, and the speed at which the system will adjust back to the long-run equilibrium consistent with the long-run cointegrating relationship.

Equation 4 Error Correction Model with long-run estimates

$$\Delta y_t = \delta(y_{t-1} - c_0 + c_1 x_{t-1}) + \sum_{i=1}^{n} \alpha_i \Delta y_{t-i} + \sum_{i=0}^{n} \beta_i \Delta x_{t-i} + u_t$$

However, when using AEMO's data, the contemporaneous coefficients estimated in the ECM were problematic to interpret, as they were unusually large due to seasonality in the data.

Consequently, in the 2013 and 2014 NEFR, AEMO adopted an Integrated Dynamic Model (IDM). This approach was maintained for the 2015 NEFR. The IDM integrated the long-run relationship between the variables (assuming cointegration) while allowing for short-run fluctuations consistent with the long-run

[14] Differences are a transformation of a data series, usually adopted to deal with time series data that exhibits strong increasing (or decreasing) trends, i.e. data with a non-zero means, also known as non-stationary data. This technique allows the underlying variation in the time series to become more apparent. They are created by taking the difference of data points in consecutive observations (e.g. $\text{income}_t - \text{income}_{t-1}$). When the first difference of non-stationary data achieves stationarity, as is the case for AEMO's data, then the time series is said to be integrated to order one.

[15] A Newey-West correction is used to correct autocorrelation in the standard errors of a regression model, and is generally used for time series data where the standard assumption of regression analysis does not apply.

[16] AEMO's dataset is small and endogeneity is suspected.

equilibrium. The IDM integrated the lagged EC term (the residuals estimated from the DOLS) into the model. It also included fourth lagged differences of all the main economic and temperature variables.

Equation 5 Integrated Dynamic Model

$$\Delta_4 y_t = c_0 + \sum_{i=1}^{4} c_{i1}\Delta_4 x_{t-i} + c_2\, EC(-1) + c_3 EC(-2) + c_4 EC(-3) + c_5 EC(-4) + u_t$$

where Δ_4 is the fourth-difference operator such that $\Delta_4 y = y - y(-4)$, where c is the estimate of the annual difference of x for each quarter, c_2 through c_5 are the estimates of the EC term and u is the error term.

Initially, four lags of the EC term were used, representing an equilibrium adjustment for each quarter. However, based on further analysis, AEMO found that in each region, only the fourth lagged *EC* term was statistically significant.

AEMO considered IDM as superior to a standard ECM in modelling seasonal data.[17] Advantages included:

- Similar to an ECM, the IDM imposed constant elasticities for each variable across all seasons. (By taking the fourth differences of the main variables, the IDM could account for seasonal differences so that short-run effects could be seasonally adjusted.) IDM allowed for an equilibrium adjustment to vary across seasons so that the adjustment to the long run would also be seasonally corrected.
- An integrated model that produced both short-run and long-run forecasts where a transition from short-run to long-run did not need to be specialised and could be gradual.

Intercept correction

To assess the forecasts, AEMO checked the “fit” of the model, that is, the difference between actual historical consumption and an estimate for past consumption calculated by the model. For both the 2013 and 2014 NEFR, the estimated historical values were above actual consumption for the last few years of data.

The annual operational consumption models were based on over 10 years of data, during which the dominant trend has been rising consumption. This could lead to an upwards bias in estimated values. If it appears the trend has shifted with a consumption decline or increase observed in recent years, the “overestimation” observed in the historical data could lead to over-forecasting.

In the 2014 NEFR, AEMO tested the inclusion of an intercept correction[18] around the turning point in the historical consumption data, to reduce the magnitude of the overestimation in the last few periods of historical data. The intercept correction added emphasis to recent data where a change in the consumption trend has been observed, and this starting point varied by NEM region.

A statistical assessment showed that including an intercept correction was statistically significant and added more information to the model in all regions except Tasmania. Consequently, in the 2014 NEFR AEMO applied an intercept correction to all regions except Tasmania.

In the 2015 NEFR, AEMO reassessed the intercept correction based on the performance of the 2014 forecasts over the last year. In Queensland, AEMO’s forecast had underestimated consumption, so the intercept correction was removed to give a better “fit”.

[17] Based on impulse response functions for short-run demand response to innovations in the variables.
[18] An intercept correction is a simple method that adds a dummy variable to a particular period of time.

2.1.3 Model specification

For each region, a DOLS equation was estimated to produce the long-run income and price elasticities. An IDM was then estimated and used to produce the residential and commercial forecast.

The DOLS equation used for Queensland, New South Wales and Victoria is shown in Equation 6, and the equation for South Australia and Tasmania in Equation 7. HDD and CDD were omitted for Queensland and Tasmania respectively, as they were found to not be significant.

Equation 6 Dynamic Ordinary Least Squares, model structure for Queensland, New South Wales and Victoria

$$Log(y) = c_1 + c_2 Log(I) + c_3 Log(P) + c_5 HDD + c_6 CDD + c_7 s_2 + c_8 s_3 + c_9 s_4$$

Equation 7 Dynamic Ordinary Least Squares, model structure for South Australia and Tasmania

$$\boldsymbol{Log(y) = c_1 + c_2 Log(I) + c_3 P_- + c_4 P_+ + c_5 HDD + c_6 CDD + c_7 s_2 + c_8 s_3 + c_9 s_4}$$

Table 5 shows the values for the estimated coefficients in each region.

Table 5 DOLS coefficients

	Constant c_1	Log(I) c_2	Log(P) c_3		HDD c_5	CDD c_6	s_2 c_7	s_3 c_8	s_4 c_9	T[19] C_{10}
Qld	5.92764	0.25038	-0.32311		N/A	0.00042	0.08501	0.13604	0.01203	N/A
NSW	1.46439	0.71014	-0.37243		0.00031	0.00038	0.01738	0.02449	-0.01360	N/A
Vic	4.49344	0.34837	-0.21229		0.00032	0.00039	0.01853	0.01996	-0.00241	N/A
	Constant c_1	Log(I) c_2	P_- c_3	P_+ c_4	HDD c_5	CDD c_6	s_2 c_7	s_3 c_8	s_4 c_9	
SA	1.03486	0.65829	0.01800	-0.23230	0.00037	0.00058	0.03891	0.04927	-0.00689	0.00042
Tas	-1.44733	0.95976	0.08472	-0.40337	0.00047	N/A	-0.01408	0.01424	-0.06210	N/A

The coefficients (c_2 – c_6) for the cointegrating long-run equation can be interpreted as follows:

- Per capita consumption has a long-run income elasticity of c_2. As the value for c_2 is positive for all NEM regions, the long-run response to an increase of 1% in income per capita is a c_2% increase in electricity consumption.
- Per capita consumption has a long-run price elasticity of:
  - c_3 for Queensland, New South Wales and Victoria. As the value for c_3 is negative for these regions, the long-run response to an increase of 1% in price is a c_3% decrease in electricity consumption.
  - c_3 and c_4 for South Australia and Tasmania. As the value for c_3 is positive, the long-run response to a decrease of 1% in the price differential is a c_3% increase in electricity consumption. As the value for c_4 is negative, the long-run response to an increase of 1% in the price differential is a c_4% increase in electricity consumption.
- HDDs and CDDs are significant in explaining energy consumption in the long run, but only at the time of each heating or cooling event.

[19] An intercept correction was applied in South Australia in the DOLS model.

As the forecasts were developed on a per capita basis, population has an implied elasticity of 0.01, meaning the long-run response to an increase of 1% in population is a 1% increase in electricity consumption.

Using Queensland as an example:

- A 1% increase in income per capita would lead to a 0.25% increase in electricity consumption.
- A 1% increase in price would lead to a 0.32% decrease in electricity consumption.

The long-run income and price elasticities that were estimated for each NEM region were statistically significant and, most importantly, were consistent with the general literature for income and price effects on electricity consumption. Residual plots from the model are in Appendix D.

AEMO used the IDM equation shown in Equation 8 for each NEM region, with the two price variables only relevant for South Australia and Tasmania, and the intercept correction *T* not significant for all regions.

Equation 8 Integrated Dynamic Model, regional model structure

$$\Delta_4 y = c_1 + c_2\Delta_4 I_s + c_3\Delta_4 P_s + c_4\Delta_4 P_s' + c_5\Delta_4 HDD_s + c_6\Delta_4 CDD_s + c_7 EC(-4) + c_8 T$$

Table 6 shows the values for the estimated coefficients in each region.

Table 6 IDM coefficients

	Constant c_1	$\Delta_4 I_s$ c_2	$\Delta_4 P_s$ c_3		$\Delta_4 HDD_s$ c_5	$\Delta_4 CDD_s$ c_6	$EC(-4)$ c_7	T c_8
Qld	0.00381	0.05976	-0.32534		N/A	0.00040	-0.63679	N/A
NSW	0.00962	-0.05100	-0.08387		0.00033	0.00039	-0.26102	-0.02668
Vic	-0.00023	0.27164	-0.11815		0.00031	0.00040	-0.60002	-0.01875
	Constant c_1	$\Delta_4 I_s$ c_2	$\Delta_4 P_{-s}$ c_3	$\Delta_4 P_{+s}$ c_4	$\Delta_4 HDD_s$ c_5	$\Delta_4 CDD_s$ c_6	$EC(-4)$ c_7	T c_8
SA	0.00531	0.29216	0.02856	-0.18085	0.00041	0.00057	-0.72363	N/A
Tas	-0.00101	0.73234	0.09035	-0.47625	0.00043	N/A	-1.23253	N/A

The coefficients for the IDM equation can be interpreted as follows:

- The instantaneous response to a 1% increase in income is a c_2% increase in electricity consumption.
- For Queensland, New South Wales and Victoria, the instantaneous response to a 1% increase in price is a c_3% decrease in electricity consumption.
- For South Australia and Tasmania, the instantaneous response to a 1% decrease in the price variable is a c_3% increase in electricity consumption.
- For South Australia and Tasmania, the instantaneous response to a 1% increase in the price variable is a c_4% decrease in electricity consumption.
- The adjustment to the new long-run, following a short-run response to a change in a driver, takes place at a rate of c_7*100% after four quarters.

Using Queensland as an example:

- A 1% increase in income per capita would lead to an instantaneous electricity consumption increase of 0.06%.
- A 1% increase in price would lead to an instantaneous decrease in electricity consumption of 0.33%.

- The adjustment to the long-run, following short-run disequilibria, takes place at a rate of 64% after four quarters.

2.1.4 Modelling limitations and exclusions

Residential and commercial forecasting is subject to a number of limitations:

- Separate drivers for the residential and commercial market segments cannot be considered, because the segments have been modelled together.
- A top-down economic approach has been used to model regional consumption. The impact of appliance penetration or specific retail price offers has not been assessed.
- Behavioural effects have not been explicitly considered in the 2015 NEFR.

2.2 Rooftop PV

Similar to previous editions of the NEFR, the 2015 NEFR rooftop PV forecast rested on two fundamental components:

- Installed capacity forecasts.
- Half-hourly traces of rooftop PV generation.

AEMO made some key changes to rooftop PV modelling compared to the 2014 NEFR (see Table 7). In particular:

- Residential and commercial rooftop PV uptake was modelled separately, to capture the different underlying drivers.
- Systems greater than 100 kW were included in the commercial uptake. In 2014, only systems below 100 kW were included in modelling, and all were classified as residential systems.

Note that solar farms were excluded from the forecasts. These were categorised as small non-scheduled generation and will be discussed further in Section 2.5.

Table 7 Key changes in the 2015 NEFR rooftop PV forecasts

NEFR	Forecast component	Scope	Model
2014	Residential	<= 100 kW	Payback
2015	Residential	< 10 kW	Payback
	Commercial	>= 10 kW	Net present value

2.2.1 Data sources

The rooftop PV forecasts relied on several data sources, as listed in Table 8 below.

Table 8 Main data sources used for rooftop PV forecasts

Source	Data	Use
Clean Energy Regulator (CER)	A list of all installations registered with the Clean Energy Regulator (CER) to December 2014. This included size of installations and out-of-pocket expenses (for many systems).	Historical data. Also used to estimate payback and net present values for existing systems.
ROAM Consulting	Normalised generation from rooftop PV systems in the NEM	Used to estimate annual generation from rooftop PV systems based on uptake forecasts
Bureau of Meteorology (BOM)	Solar radiation data and temperature data.	Used to extrapolate half-hourly PV traces for use in maximum demand
Australian Bureau of Statistics (ABS)	Number of dwellings and businesses, type of businesses and population data	Used to estimate saturation

Source	Data	Use
Frontier Economics	Projected residential and commercial electricity prices	Used in the payback and net present value analysis
KPMG	Projected exchange rates	Used in the payback and net present value analysis

2.2.2 Rooftop PV scenarios

Three rooftop PV uptake scenarios were developed, each one relating to the economic scenarios developed for the NEFR. A mapping of the economic scenarios and underlying drivers of the rooftop PV uptake scenarios is shown below in Table 9.

Table 9 Mapping of PV uptake scenarios and the economic scenarios

Driver	Low rooftop PV uptake	Moderate rooftop PV uptake	High rooftop PV uptake
Economic scenario	High centralised energy demand.	Medium centralised energy demand.	Low centralised energy demand.
Rooftop PV systems cost (before the STC rebate is applied)	Increases slightly up to 2018 then remains flat. By 2035, system costs range from \$2.6/Watt and \$3.0/Watt depending on region.	Continues declining. By 2035, system costs range from \$1.9/Watt to \$2.2/Watt depending on region.	Continues declining until \$1/Watt by 2035.
Government incentives	Existing feed-in tariff and SRES remain unchanged.		

AEMO assumed that some form of feed-in tariff will remain via retailers, even though governments might remove or reduce a mandated feed-in tariff in the future.

2.2.3 Residential installed capacity forecast

Consistent with the 2014 NEFR, the methodology used to develop the residential rooftop PV installed capacity forecasts in the 2015 NEFR was:

1. Estimate historical payback periods for residential rooftop PV systems in each NEM region.
2. Develop and calibrate a relationship between payback period and installed capacity uptake rate using historical data.
3. Estimate future payback periods, based on a variety of economic and demographic variables.
4. Derive the installed capacity forecast using this forecast payback period.
5. Apply saturation levels to the installed capacity forecasts.

Changes in the model parameters since 2014 are summarised in Table 10 below.

Table 10 Changes in the model parameters since 2014

Parameter	2014 NEFR	2015 NEFR
Historical data	Data from the CER up to December 2013	Data from the CER up to December 2014
Feed-in tariff	7 – 8 c/kWh depending on the NEM region	5 – 6 c/kWh depending on the NEM region
Electricity prices	Based on the 2014 forecasts from Frontier Economics	Based on the 2015 forecasts from Frontier Economics
Gross system cost (before the STC rebate is applied)	Medium scenario: System costs were forecast to continue to fall at historical rates until 2016 and then remain flat.	Medium scenario: Exchange rates now have an impact on projected system costs. System costs were forecast to fall very slightly in the short term due to falling exchange rates. After around 2018, a forecast higher exchange rate would reduce system costs further.

Parameter	2014 NEFR	2015 NEFR
Saturation	Dwellings available for rooftop PV installations included separate houses, semi-detached row or terrace houses, townhouses, blocks of flats, units and blocks of apartments, structures attached to a building and caravans. Average residential system size for saturation was 3.5 kW.	Dwellings available for rooftop PV installations included only separate houses, semi-detached row or terrace houses and townhouses. Average residential system size for saturation was assumed to be 4 kW.

For more details, see the 2014 Forecasting Methodology Information Paper.

2.2.4 Commercial installed capacity forecast

Commercial rooftop PV forecasts were developed for the first time in the 2015 NEFR. These forecasts were produced based using the following methodology:

1. Segmented the commercial rooftop PV market
2. Estimated net present values for existing commercial rooftop PV systems in each NEM region.
3. Developed and calibrated a relationship between net present values and installed capacity uptake rate using historical data.
4. Estimated net present values for future commercial rooftop PV installations, based on a variety of economic and demographic variables.
5. Forecast installed capacity using results from Step 3, assuming the historical relationship between uptake and net present values (from Step 2) applies to future installations.
6. Applied saturation levels to the installed capacity forecasts.

Details of each step are discussed below.

Step 1: Segmented the commercial rooftop PV market

Historical data indicates that commercial rooftop PV installations, particularly those below 100 kW, were concentrated in specific sizes, and therefore could be categorised by the different segments in Table 11.

The installed capacity for each segment was forecast separately, to reflect the likely different underlying drivers and economics.

Table 11 Categorisation of commercial PV installations

Segment	Size range
Small	10 – 25 kW
Medium	25 – 90 kW
Large	90 – 100 kW
Very large	> 100 kW

Step 2: Estimated historical net present values

Where information about out-of-pocket expenses was available from historical data, the net present values for existing commercial PV systems were estimated, assuming the following:

Table 12 Assumptions for net present value estimation

Parameter	Assumption
Finance	Upfront purchase

Parameter	Assumption
Discount rate	7%
System lifetime	25 years
PV exports	No exports
Electricity prices	Average prices for business customers (provided by Frontier Economics)
System degradation	1% per annum
STC rebate	Applicable to systems below 100 kW

Step 3: Developed a relationship between historical uptake and net present values

AEMO derived a linear relationship from historical monthly uptake (in MW), and the median net present values estimated from Step 2. This analysis only included commercial systems that were installed since 2012, as many earlier installations may have been driven by government incentives and green marketing. Importantly, analysis showed that historical uptake and net present values are positively correlated.

Historical uptake of systems above 100 kW was excluded from this analysis, due to a lack of information about the costs of these systems.

Step 4: Estimated net present values for future installations

The net present values for future installations of commercial rooftop PV were estimated. Similar assumptions to those in Step 2 were used (see Table 12), although the STC rebate would be reduced depending on the year of installation as a result of the decreasing deeming period.

Step 5: Forecast installed capacity

Future uptake of different segments (i.e. small, medium and large) of commercial rooftop PV systems was modelled based on their estimated net present values. This assumes the linear relationship between historical uptake and net present values derived in Step 3 would hold for future installations.

As discussed previously, there is insufficient information about commercial systems above 100 kW to perform a net present value analysis. As such, future uptake of these systems was assumed to be identical to the average historical uptake rate observed in 2014.

Step 6: Estimated and applied saturation levels

Saturation levels place an upper limit on installed capacity. They primarily reflect the amount of suitable commercial roof space available for rooftop PV installations.

Saturation levels were estimated based on the number and type of businesses from the ABS. First, the business type was used, to determine if a business is likely to be on a standalone site (e.g. manufacturing), or clustered with other businesses on a shared common site (e.g. retail).

Using this classification, AEMO then calculated saturation levels, using the assumptions in Table 13.

Table 13 Estimating saturation levels for commercial rooftop PV

Business site	Saturation level	Assumption
Standalone	75 % X total number of standalone businesses	Only 75% of standalone business sites are suitable for commercial PV installations, due to building restrictions, rental etc.
Clustered	10% X total number of clustered businesses	Only 10% of clustered business sites are suitable for commercial PV installations due to shared roof space and other building restrictions.

Further, the average system size installed was assumed to vary with the number of employees for a given business (see Table 14).

Table 14 Average system size assumed for commercial rooftop PV

Number of employees	Average system size
1-19	20 kW
20-199	40 kW
> 200	100 kW

Finally, the total number of businesses was assumed to grow at the same rate as population growth during the forecast period.

2.2.5 Rooftop PV energy forecasts

AEMO derived the rooftop PV forecasts using the installed capacity forecasts and average monthly rooftop PV energy distribution profiles. The average monthly energy distribution profiles were calculated using the average monthly aggregated energy data from ROAM Consulting. Further detail can be found in the 2013 and 2014 Forecasting Methodology Information papers.

The output of a rooftop PV system will reduce as the system degrades over time. There are also expected improvements in rooftop PV efficiency over the forecast period for new installations. AEMO did not explicitly model either of these effects, and assumed instead that the degeneration of existing systems over 10 years or more would be offset by efficiency gains of new systems being installed.

2.2.6 Modelling limitations and exclusions

The following items were not considered in the rooftop PV forecasts, but AEMO is monitoring the market for developments in network limitations and financing methods.

- Network limitations.
  - As the size of installed capacity continues to rise, certain portions of the network could start facing stability issues due to the high penetration rates of rooftop PV.
  - To maintain network stability, limitations or restrictions on system sizes might be introduced. This could take the form of outright limitations, or of additional costs of connection or higher network charges to support upgrades.
- Different financing methods.
  - AEMO is aware of new financing methods, such as leasing, being introduced into the market. These will reduce the upfront costs of installing a rooftop PV system. In most cases, these have targeted commercial installations, but extension to the residential sector is possible.
- Rooftop PV panel degradation and efficiency improvements.
  - AEMO did not include either system degradation or system efficiency gains in modelling energy generated from rooftop PV systems. System degradation was only considered when estimating the net present values for commercial systems.

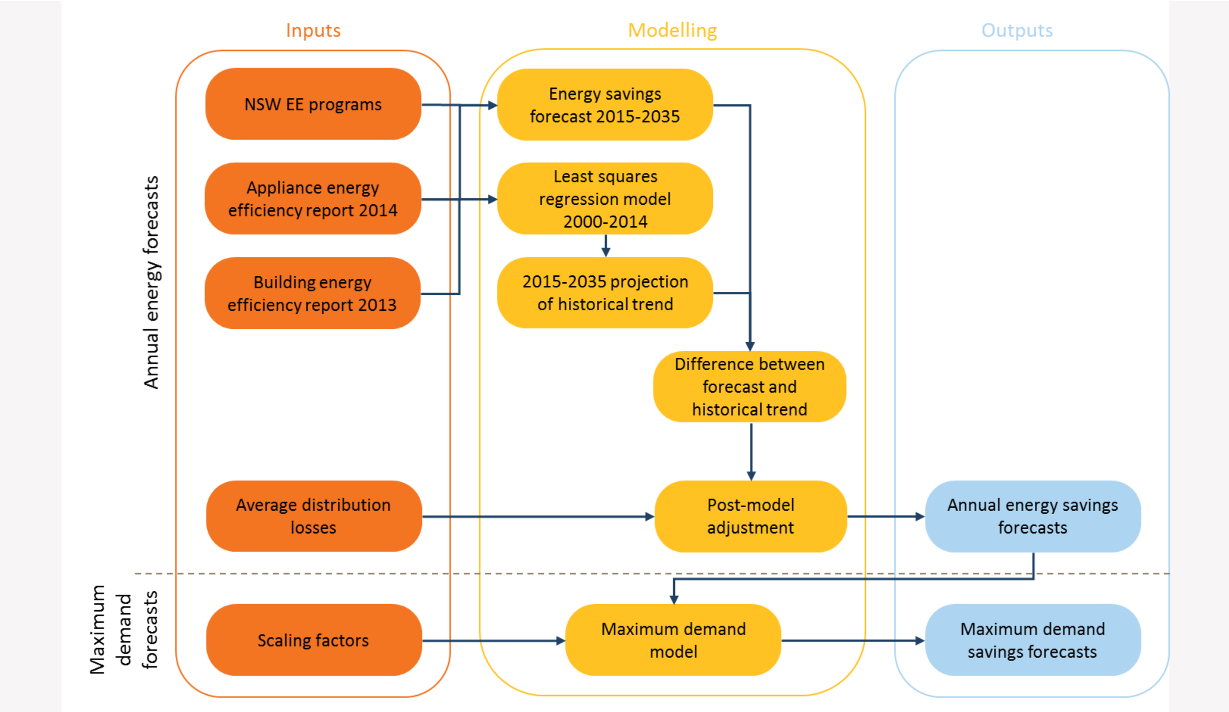
2.3 Energy efficiency

Methodology changes since the 2014 NEFR improve the transparency of the approach to energy efficiency (EE) forecasting, and the quality of the results (see Figure 2 for an overview of the methodology used).

The key change was the use of New South Wales energy efficiency programs, and updated state appliance consumption projections. The 2015 forecasts were based on two recent studies for the New

South Wales Department of Industry (DOI), providing consistent assumptions and information that specifically address the potential for EE savings for a range of EE programs. Updated appliance EE data from DOI were also incorporated.

Figure 2 Energy efficiency forecasting methodology



2.3.1 Data sources

AEMO estimated EE savings from appliances and buildings. These savings were calculated using three key data sources, summarised in Table 15.

Table 15 Data sources used to forecast energy efficiency

Source	Data	Description	Reference
George Wilkenfeld and Associates	Appliances	EE savings for five of the measures[20] were updated based on a projection performed by the consultant for the Department of Environment. Values from the projection are as at 25/02/2015.	*Review of Impact Modelling for E3 Work Program*. Published report to the Department of Climate Change and Energy Efficiency (DCCEE), March 2014.[21]
Pitt & Sherry	Buildings		*Qualitative Assessment of Energy Savings from Building Energy Efficiency Measures Final Report*. Published report prepared for DCCEE, March 2013.[22]

[20] Household Refrigerators & Freezers - Labelling 1986 to MEPS 2005, Televisions-labelling & MEPS, Lamp efficacy (Res use), Air conditioners - Res MEPS 2004-2010 and Clothes washers, dishwashers, clothes dryers (Plug loads only).
[21] Available at: http://www.energyrating.gov.au/wp-content/uploads/Energy_Rating_Documents/Library/General/Equipment_Energy_Efficiency_Program_(E3)/Impacts-of-the-E3-Program.pdf Viewed 18 March 2015.
[22] Available at: http://www.pittsh.com.au/assets/files/CE%20Showcase/Quantitative%20Assessment%20of%20Buildings%20Measures.pdf Viewed 18 March 2015.

Source	Data	Description	Reference
Jacobs	NSW EE programs[23]	NSW state government energy efficiency programs included: • Energy Savings Scheme (ESS). • Energy Saver Program (ESP). • Energy Efficiency for Small Business Program (EESBP).	*NSW energy efficiency programs – cost benefit analysis.* Unpublished report prepared for the NSW Office of Environment and Heritage, December 2014.

These sources provided recent assessments of EE savings across programs initiated by the Federal Government and New South Wales State Government. Both the George Wilkenfeld and Pitt & Sherry sources listed used information from Regulation Impact Statements (RIS) undertaken before programs are initiated.

Industrial EE savings were not explicitly included in this year's analysis, as the program AEMO relied on last year (Energy Efficiency Opportunities program) has been discontinued, and the measures were considered less likely to be implemented. Also, AEMO assumed that EE savings have been considered by some industrial loads in their forecasts provided to AEMO.

Appliance energy efficiency savings

George Wilkenfeld estimated 38 TWh of savings across the NEM by 2030 from appliance energy rating labelling and Minimum Energy Performance Standards (MEPS) – collectively referred to in some studies as E3. A further 2 TWh in savings was estimated as a result of NSW EE programs. Of the total estimated 40 TWh in savings, over 70% came from programs already in place.

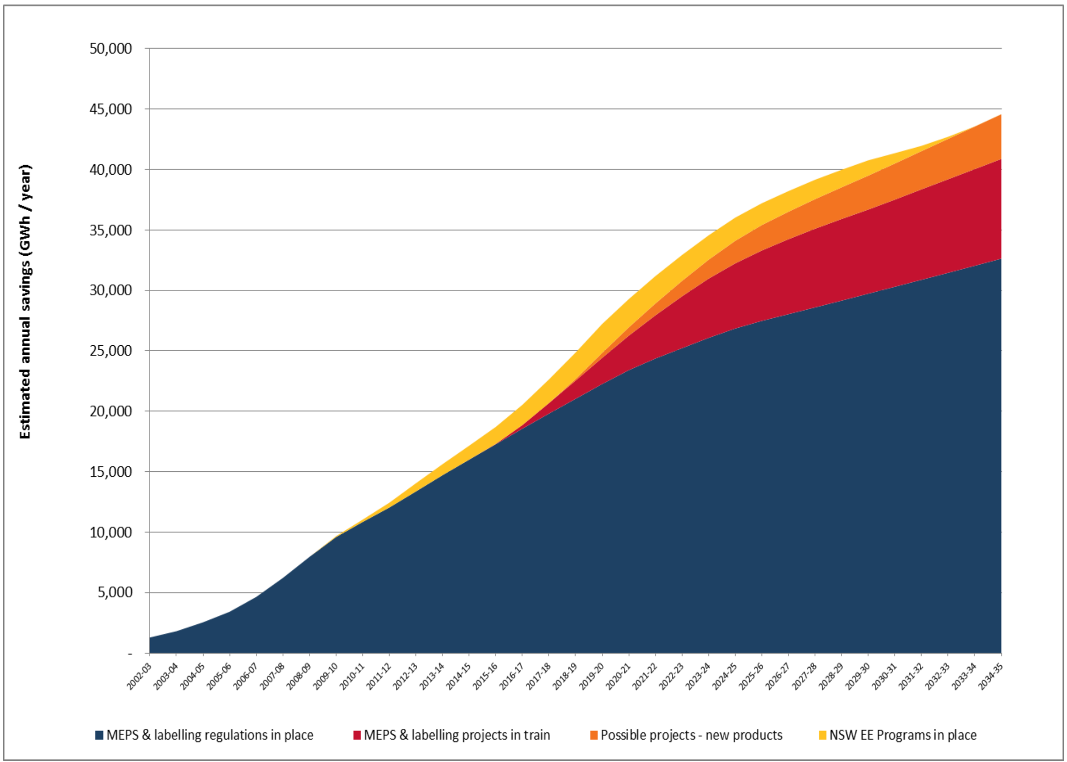
As the George Wilkenfeld report only provides national savings, AEMO determined estimated regional savings using information from the latest Federal Department of the Environment, Water, Heritage and the Arts report on residential energy use.[24] Potential savings from Western Australia and Northern Territory were excluded. The George Wilkenfeld report included forecast values to 2030, which AEMO extended to 2035 using linear extrapolation from the last five years (2026 to 2030).

Figure 3 shows the projected savings across the NEM. Stable growth between 2024−25 and 2029−30 suggests the extrapolation is a reasonable approximation of savings beyond 2030.

[23] Included NSW EE programs are Energy Savings Scheme (ESS), Energy Saver Program (ESP) and Energy Efficiency for Small Business Program (EESBP)

[24] http://www.industry.gov.au/Energy/Energy-information/Documents/energyuseaustralianresidentialsector19862020part1.pdf. Viewed 18 March 2015.
http://www.industry.gov.au/Energy/Energy-information/Documents/energyuseappendixg.pdf Viewed 18 March 2015.

Figure 3 Projected energy efficiency savings for appliances, E3 modelling categories



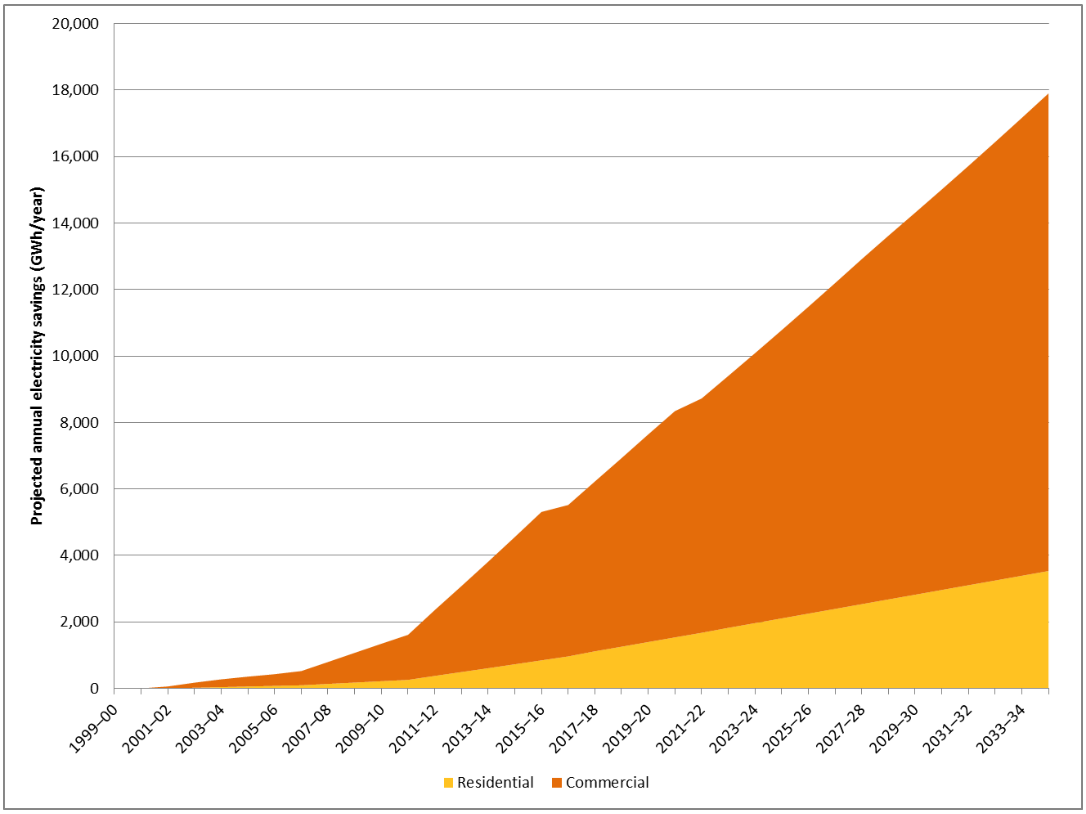
The 2009 MEPS chiller program was excluded from the appliance savings, because it was treated as an existing project in the building EE savings (as part of the baseline for the Pitt & Sherry assessment).

Building energy efficiency savings

The estimated savings from building-related EE measures were based on the Pitt & Sherry study. AEMO determined total savings for the NEM based on the report's savings for each state.

Figure 4 shows these projected savings. Savings across the NEM from building-related EE measures were estimated to be 18 TWh by 2035.

Figure 4 Projected energy efficiency savings for buildings



Source: Pitt and Sherry (2013)

2.3.2 Energy efficiency uptake scenarios

The three EE uptake scenarios used for the 2015 NEFR forecasts represented uncertainties about the number of new EE programs to be implemented in the long-term forecast period.

Scenario	Energy Efficiency Scenario	Definition
High consumption	Slow uptake	The slow uptake scenario assumes no additional EE programs beyond those already implemented. It assumes no additional EE savings above the existing long-term trend.
Medium consumption	Moderate uptake	The moderate uptake scenario assumes that all EE programs already implemented and those currently being implemented remain. This incorporates assumed implementation delays for some programs (such as phasing out carbon-intensive water heaters) and uncertainty about whether some programs will be implemented (such as Residential Mandatory Disclosure).
Low consumption	Rapid uptake	The rapid uptake scenario assumes implementation of additional EE programs beyond those already approved and assumes all potential savings are realised.

2.3.3 Calculating energy efficiency impact

AEMO estimated EE savings, and incorporated this as a post model adjustment (PMA) to annual energy and maximum demand. To determine residential and commercial consumption, AEMO applied a PMA to the non-industrial consumption for appliances and building EE.

Calculation for appliances and building savings

AEMO developed forecasts for the three EE uptake scenarios (rapid, moderate, and slow) defined in Section 2.3.2, using a three step approach:

1. Estimated the expected EE savings for annual energy using EE policy measures identified for the period 2000 to 2035.
2. Calculated the long-term efficiency trend observed in the regression period (2003–14) for all NEM regions (aggregated), and projected this trend to 2035. The difference between this projected trend (grey line in Figure 5 and Figure 6) and the expected savings over the forecast period (2015–35) is the EE PMA for annual energy.
3. Disaggregated into forecasts for each region, based on region-specific savings identified in 2.3.1 and accounted for distribution losses (detailed below).

For example, EE forecasts for measures that target appliances and buildings in Queensland are shown in Figure 5 and Figure 6 respectively.

Figure 5 Energy efficiency forecasts for appliances in Queensland

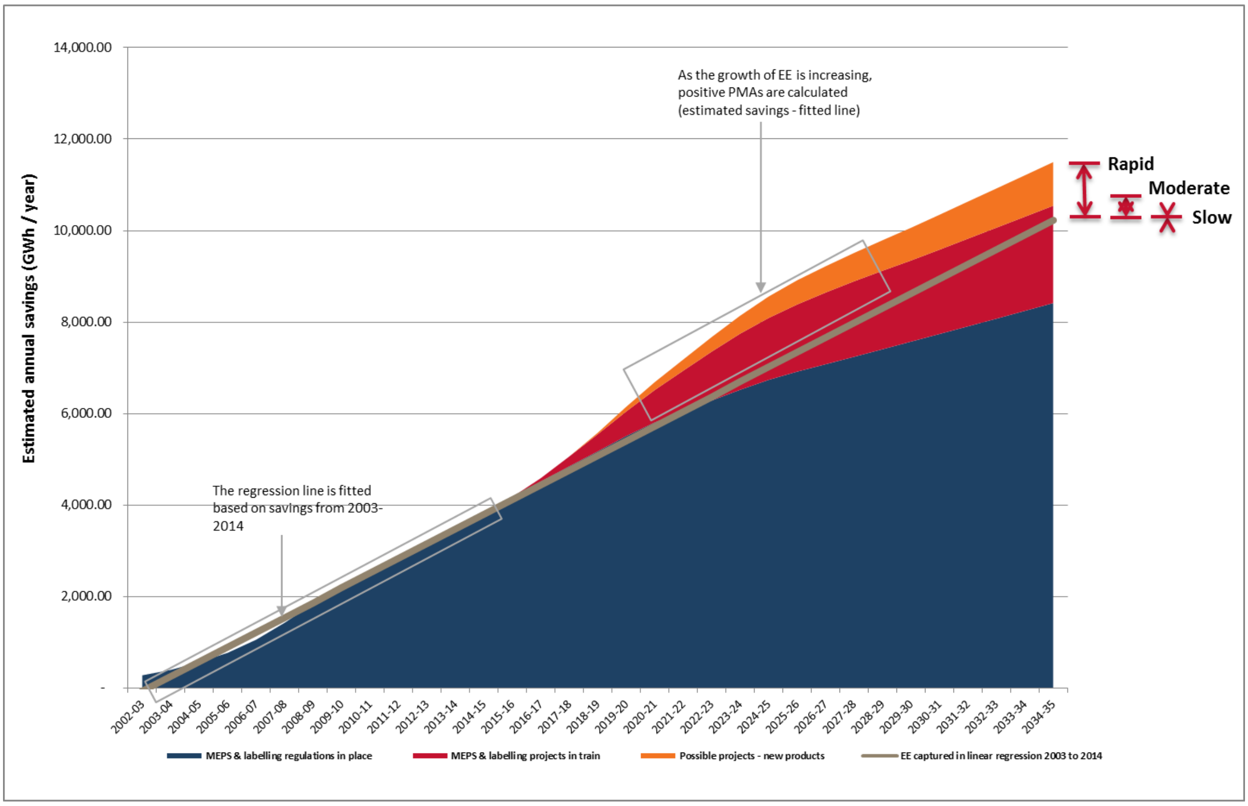
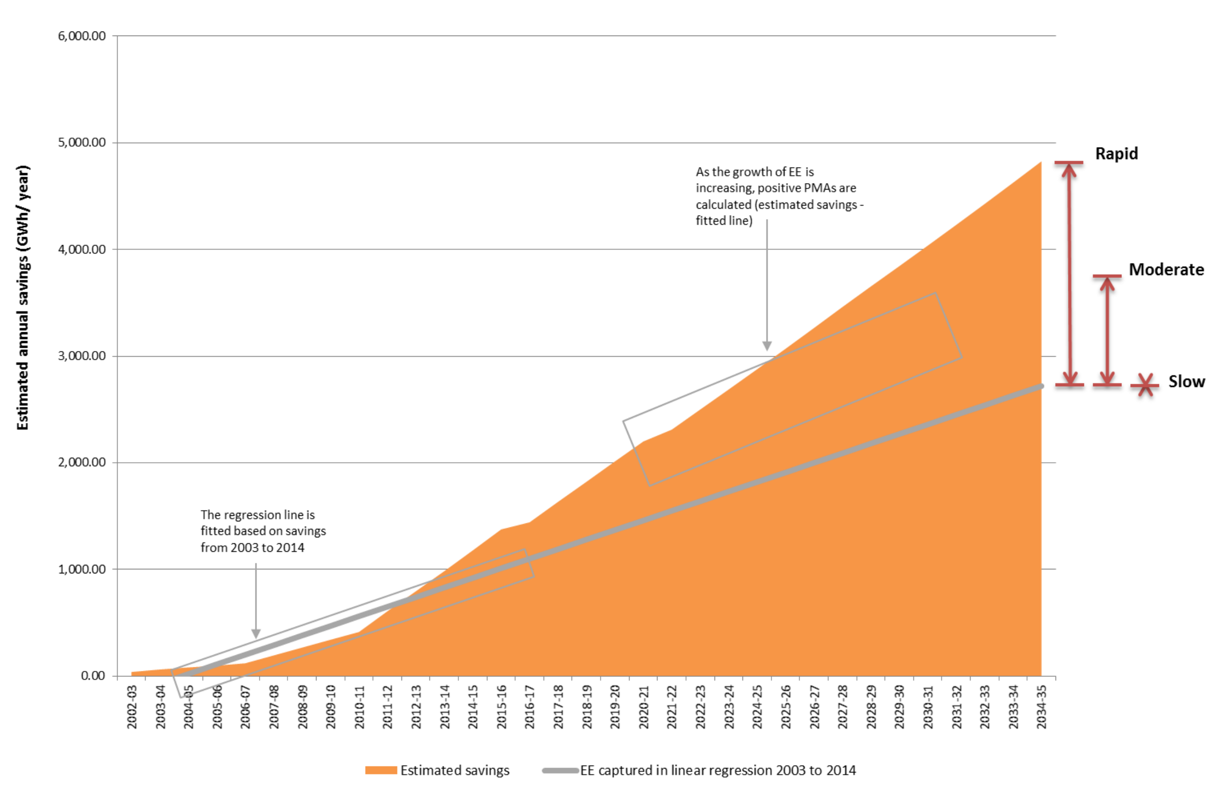


Figure 6 Energy efficiency forecasts for buildings in Queensland



Source: Pitt and Sherry (2013)

The savings in the previous two figures identify electricity that is not needed due to EE savings at the end-user premises. In other words, if there was no EE implemented, this electricity would be required. Since the PMA is modelled on transmission-delivered consumption, distribution network losses that would have occurred when transmitting the electricity need to be accounted for.

$$Annual\ Energy\ PMA\ for\ EE = Distribution\ losses + EE\ savings\ at\ end\ user.$$

The distribution losses used in this analysis are shown in Table 16. These are generally from recent losses reported to the Australian Energy Regulator (AER) by distribution companies as part of the distribution loss factor approvals process.

Table 16 Estimated distribution losses in Australia (% of transmitted energy)

NSW	Qld	SA	Tas	Vic
4.8%	5.4%	6.1%	5.4%	5.2%

2.3.4 Modelling limitations and exclusions

The EE forecasts were based on existing and planned policies and measures, and included consideration of currently identified future programs. Pitt & Sherry considered there is a large potential for additional savings, some of which could be achieved by future policies. AEMO has not considered future polices that have not been identified, due to the uncertainty involved in such an approach.

The forecasts did not include rebound effects, where a portion of cost savings from EE measures are spent on additional energy services. EE savings in lighting, space conditioning (air conditioning and heating), and hot water use are likely to have rebound effects. Energy Efficient Strategies (EES)

(2011)[25] estimated rebound to be approximately 15%, meaning that for every 1 GWh of energy savings, 0.15 GWh of additional consumption would occur, leading to a net EE saving of 0.85 GWh.

AEMO has not considered the effect of any interaction between electricity price response, EE, and the uptake of distributed generation such as rooftop PV, in the annual operational consumption and maximum demand forecasts, and has not measured the potential overlap.

The forecasts considered electricity only, and did not include the gas consumption impacts considered in the George Wilkenfeld and Pitt & Sherry reports.

2.4 Large industrial load

Large industrial loads are industrial customers that account for a relatively large proportion of consumption in each NEM region. These customers include aluminium and steel producers, liquefied natural gas (LNG) export facilities, petroleum, paper and chemical manufacturers, large coal and metal ore mines and water desalination plants. AEMO classified industrial loads into industry sectors using the Australian and New Zealand Standard Industrial Classification (ANZSIC)[26] code.

The half-hourly demand for large industrial customers is not typically temperature sensitive, although desalination and water pumping loads are affected by rainfall.

Forecasts for committed Liquefied Natural Gas (LNG) export facilities were produced by Lewis Grey Associates. Details on the methodology used can be found on AEMO's website.[27]

Forecasts for all other industrial loads have been individually developed by AEMO, based on sectoral outlooks for each industry, and in consultation with individual customers and relevant Transmission Network Service Providers (TNSPs) and Distribution Network Service Providers (DNSPs). These forecasts were aggregated at the regional level for confidentiality reasons.

This year, AEMO also split the regional forecasts into two categories – 'manufacturing', as defined by Division C of the ANZSIC code, and 'other'.

Changes in the large industrial load methodology in the 2015 NEFR, compared to the approach used in 2014, included:

- Classifying loads into ANZSIC subdivisions, and using sector-based growth rates to develop the long term high, medium and low scenario forecasts.
- Net addition of 22 sites based on revised site identification method.
- High case includes identified projects that could commence within the next three years.
- Using information obtained during the NGFR process regarding gas contract position and onsite generation.

2.4.1 Data sources

AEMO forecast large industrial electricity consumption based several data sources, as listed in Table 17 below.

[25] Energy Efficient Strategies. *The Value of Ceiling Insulation*. Report to ICANZ. September 2011. Available at: http://icanz.org.au/wp-content/uploads/2013/04/ICANZ-CeilingInsulationReport-V04.pdf Viewed 23 July 2014.
[26] For more information on ANZSIC code classifications, refer to the ABS website, http://www.abs.gov.au/ausstats/abs@.nsf/0/20C5B5A4F46DF95BCA25711F00146D75?opendocument
[27] http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Electricity/Planning/Reports/NEFR/2015/Projections%20of%20Gas%20and%20Electricity%20Used%20in%20LNG%20%20Public%20Report%20%20Final.ashx

Table 17 Large industrial load data sources

Source	Data	Use
Large industrial customers	Consumption and demand forecasts	To develop customer forecasts.
Distribution network service providers (DNSPs) or transmission network service providers (TNPSs)	Information regarding existing and future customers	Used to assess customer forecast information.
News sources, annual reports, other media	Publically available information or announcements.	Used to assess customer forecasts.
Metering Settlements and Transfer Solution (MSATS)	Historical data	To develop forecasts where customers are unable to provide information
Deloitte Access Economics, KPMG, BIS Shrapnel	Industry sector growth outlooks	To develop long term industry forecasts.

2.4.2 Forecast method

Step 1: Selected large industrial customers

The industrial customers included:

- All transmission-connected loads.
- All distribution loads with MD greater than 10 MW on at least 36 days in the previous year (10% of days in a year).
- Key customers identified by TNSPs and DNSPs (including past customers and new customers with potential for significant change).

The approach used to identify customers meeting the above requirements was refined this year, and the number of industrial loads included was increased from 93 to 115. Table 18 below shows the number of large industrial customers included in the 2014 and 2015 NEFRs, and their aggregate contribution to regional energy consumption. Note that four sites were removed in the 2015 NEFR, due to their closure or project cancellation.

Table 18 Large industrial load numbers in each NEM region in the 2013 and 2014 NEFRs

Region	Number of customers			% of 2013−14 annual energy	
	2014 NEFR	2015 NEFR	Net Change	2014 NEFR	2015 NEFR
NSW	23	36	13	20%	23%
Qld	25	31	6	37%	30%
SA	16	18	2	23%	23%
Tas	14	13	-1	60%	60%
Vic	15	17	2	20%	20%
Total NEM	93	115	22	27%	26%

Step 2: Gathered information

Questionnaire

AEMO distributed a questionnaire to all large industrial customers identified in Step 1, requesting information about their historical and forecast electricity consumption. Each customer was asked to provide:

- Forecast consumption (GWh).
- Forecast demand (MW).

- Forecast demand capacity (MW).
- Forecast onsite generation (GWh).
- Current and planned onsite generation capacity (MW).

For the forecasts, each customer was asked to provide three forecasts which reflected high, medium and low consumption. Customers were asked to develop the three forecasts based on the scenario information in Table 19.

Table 19 Large industrial load scenarios

Scenario	Definition	Expected Characteristics
High consumption	Represents a realistic increase in electricity consumption and/or demand from the network following favourable economic conditions such as high GDP, low electricity prices, high commodity prices.	Increased production, increased operations/additional shifts, decreased on-site generation, increased demand for exports.
Medium consumption	Represents the most likely forecast levels of electricity consumption and maximum demand.	Current production levels maintained or higher/ lower production levels reflecting planned and committed changes to operations.
Low consumption	Represents a realistic decrease in electricity consumption from the network following non-favourable economic conditions such as low GDP, high electricity prices or low commodity prices.	Lower production levels, lower output/shift reduction, increased on-site generation, decreased demand for exports.

Consultation

After receiving the questionnaire responses, AEMO contacted each customer directly to discuss the information and further clarify any likely changes to future operations. Individual company information collected from these interviews and questionnaires is confidential.

Step 3: Developed forecasts

AEMO reviewed all information obtained to ensure consistency across responses and incorporate any additional public announcements.

Estimated 2014–15 electricity consumption

The 2014–15 electricity consumption was estimated using nine months of actual data from July 2014 to March 2015, and three months of forecast data for April to June 2014, as actual data for this period was unavailable at the time of forecast development.

Where customers were unable to provide information, AEMO estimated consumption for April to June based on historical data.

Short-term forecasts

In most cases, the questionnaire responses provided enough information to construct forecasts that directly reflected the customers' views over the next five years. Where customers were unable to provide information, AEMO used responses to the 2014 NEFR where available, or assumed that consumption remained at 2013–14 levels in the medium scenario, and that consumption in the high and low scenarios reflected historical maximum and minimum consumption.

Long-term forecasts

Long-term forecasts are more uncertain than short-term forecasts, because there is less certainty around future business operations. Consequently, AEMO forecast most customers' long-term consumption based on industry sector outlooks, to capture broader sectoral trends.

Industrial loads, as noted above, were classified into industry subdivisions using the ANZSIC code. The growth rates used to capture trends in each industry sector were based on economic information developed by BIS Shrapnel, Deloitte Access Economics and information provided to AEMO by KPMG.[28] The long-term growth rates applied to each sector to develop the high, medium and low consumption scenario forecasts are shown in Table 20.

Table 20 Large industrial load long-term industry growth rates

Industry Sector	ANZSIC Division and Subdivision	High Scenario	Medium Scenario	Low Scenario
Manufacturing				
Food product	C - 11	1.6%	0.1%	0.0%
Wood product	C - 14	1.6%	1.3%	-1.3%
Pulp, paper and converted paper product	C - 15	1.3%	-1.3%	-4.1%
Petroleum product	C - 17	1.2%	0.5%	-2.7%
Basic chemical product	C - 18	1.2%	0.5%	-2.7%
Non-metallic mineral product	C - 20	2.0%	1.8%	1.4%
Cement:				
New South Wales	C - 20	2.9%	2.8%	2.7%
Queensland	C - 20	3.3%	3.2%	3.1%
South Australia	C - 20	2.2%	1.2%	0.3%
Victoria	C - 20	2.4%	2.3%	2.2%
Tasmania	C - 20	1.6%	1.4%	1.2%
Primary metal product	C - 21	2.7%	2.0%	1.8%
Fabricated metal product	C - 22	2.7%	2.0%	1.8%
Transport Equipment	C - 23	#N/A	#N/A	#N/A
Other				
Mining:				
Coal	B - 06	2.4%	1.8%	1.2%
Gold	B - 08	0.4%	0.3%	0.3%
Iron Ore	B - 08	3.3%	2.5%	1.7%
Base Metals	B - 08	2.1%	1.6%	1.1%
Defence services	O - 76	2.5%	2.3%	2.0%

Source: KPMG, Deloitte Access Economics, BIS Shrapnel, AEMO

Very large customers and desalination plants have not been modelled based on sectoral growth rates, because incremental growth is not a realistic approach for these customers. Large customers, such as metal smelters or refineries and some metal ore mines, do not typically make changes to their level of consumption due to the high level of investment required to upgrade their facilities. They are also unique businesses, or one of a small number of similar businesses, where sector-based growth is not an appropriate forecast technique. For these customers, AEMO assumed that consumption would remain flat over the long-term period in the medium scenario. In the high and low scenarios, AEMO

[28] Information from BIS Shrapnel and Deloitte Access Economics was accessed through a subscription. The reports referenced are: BIS Shrapnel, *Long Term Forecasts 2014-2029*, 40th edition, accessed February 2015. Deloitte Access Economics, *Business Outlook: Energy prices take a dive*, December quarter 2014, accessed February 2015.

used the historical maximum or minimum consumption values, held constant over the long-term period. Some closures were assumed in the low scenario. These were based on public information regarding electricity contract expiry dates.

Desalination and water-supply pumping loads vary due to rainfall rather than economic conditions. AEMO forecast long-term electricity consumption based on information received from customers.

2.4.3 Modelling limitations and exclusions

Individual customer forecasting is subject to a number of limitations, including:

- Information provided from non-public sources is sensitive and cannot be made publicly available, so AEMO's public forecasts were aggregated for each NEM region.
- AEMO depends on DNSPs' and TNSPs' proactive advice of new projects. Because some projects may be speculative and not eventuate, there is inherent uncertainty in estimating the timing and magnitude of future consumption.

Longer-term forecasts (20 years) are particularly difficult to obtain, given the uncertainty some industries face in terms of commercial pressures (such as exchange rates and changes in taxation). Changes to commercial operations are also difficult to predict and can be abrupt (especially with regard to plant closures) and are often highly confidential.

Sectoral-based long-term forecasting does not consider changes in energy intensity over time.

Non-industrial large loads (such as casinos, shopping centres, hospitals, rail networks, stadiums, and universities) were excluded from this segment, and were incorporated into the commercial and residential forecast.

2.5 Small non-scheduled generation

Forecasts included existing small non-scheduled generation (SNSG) projects, as well as potential future SNSG projects. Forecasts for existing, operational SNSG projects were based on characteristics such as generation capacity and historical data. Forecasts for future SNSG projects (committed, advanced, and prospective) were developed based on characteristics of similar, existing SNSGs, such as location and generator class (fuel source). Small non-scheduled generation includes solar farms.

The number of generators included in the SNSG forecasts has increased since the 2014 NEFR. Refer to Appendix C for the full list of generators in each region.

2.5.1 Data sources

AEMO forecast SNSG generation based on the following data sources:

- AEMO's generation information pages.
- Publicly available information.
- Historical data.

2.5.2 SNSG scenarios

SNSG forecasts were developed for three scenarios that corresponded to the 2015 NEFR high, medium, and low scenarios.

AEMO used the data outlined in 2.5.1 and categorised all SNSG projects according to the criteria below:

- Category A (operational) – SNSG has previously generated, and is currently generating.
- Category B (committed) – A final investment decision has been made and the project is moving to, or is currently in, construction phase.
- Category C (advanced) – A final investment decision has not been made, but the project is in the later stages of the development approval process.
- Category D (prospective) – A final investment decision has not been made, and the project is in the intermediate stages of the approval process.

The project status relates to each 2015 NEFR scenario, as shown in Table 21 below.

Table 21 SNSG project status and 2015 NEFR scenarios

2015 NEFR scenario	Related SNSG scenario	Categories included
High	High uptake	A, B, C and D
Medium	Moderate uptake	A, B and C
Low	Slow uptake	A and B

2.5.3 Calculating SNSG forecasts

SNSG installed capacity and future capacity factors were calculated using up to five years of historical data, ending December 2014. AEMO assumed that the installed capacity of existing projects would remain unchanged over the 20-year outlook period, unless a site has been decommissioned.

All new projects were assumed to start operation at the mid-point of the calendar 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 calculated using actual historical generation data and installed capacity information. Future output across the forecast period was then estimated using a weighted average of the historical capacity factors for each project, based on the past five years of data. Capacity factors in the low scenario were calculated using the lowest three historical capacity factors over the past five years, and capacity factors in the high scenario were calculated using the highest three.

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

- Where similar projects already exist, in terms of NEM region and generator class (fuel source), AEMO used the total historical output from all similar, existing projects, divided by their combined rated capacity.
- Where no similar projects exist – typically a new generator class in a particular NEM region – AEMO either used the 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.

2.5.4 Modelling limitations and exclusions

AEMO constructed SNSG forecasts based on publicly available information on potential project development.

The information on projects planned during the first five years of the forecast period is sufficient. However, towards the end of the forecast period, there is no reliable information regarding SNSG project development. As such, no new projects were assumed, and contribution factors and capacity factors remain constant. While this may underestimate future SNSG generation levels, a similar lack of reliable information on SNSG retirement rates means possible overestimation of future generation from existing projects.

For these reasons, AEMO effectively assumed that the installation rate over the second half of the forecast period would equal the retirement rate, resulting in generation profiles that do not vary beyond the initial five years of the outlook period.

CHAPTER 3. MAXIMUM DEMAND

3.1 Introduction

This chapter should be read in parallel with the operational consumption chapter, which provides more information on each segment.

3.2 Residential and commercial load

This section outlines the methodology used to develop maximum demand forecasts for residential and commercial consumption. These forecasts were prepared by Monash University's Business and Economic Forecasting Unit. Monash University prepared maximum demand reports for each NEM region and an overarching technical report.[29]

Maximum demand is the single highest demand that occurs in any half-hour period over an entire season. As this is the most extreme event that occurs in a season, and is highly dependent on weather, there is substantial uncertainty inherent in maximum demand forecasts. For this reason a probabilistic distribution of maximum demand was forecast, and 10%, 50%, and 90% Probability of Exceedance (POE) levels provided.

For any given season:

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

For each NEM region, maximum demand forecasts were developed using separate models for summer (October to March) and winter (April to September). A semi-parametric model of half-hourly demand was developed as a series of 48 models relating to each period of the day.[30] These models included calendar-dependent effects (e.g., day of week, public holiday) and weather effects, as well as half-yearly (for each season) demographic and economic effects, based on AEMO's annual consumption forecasts.

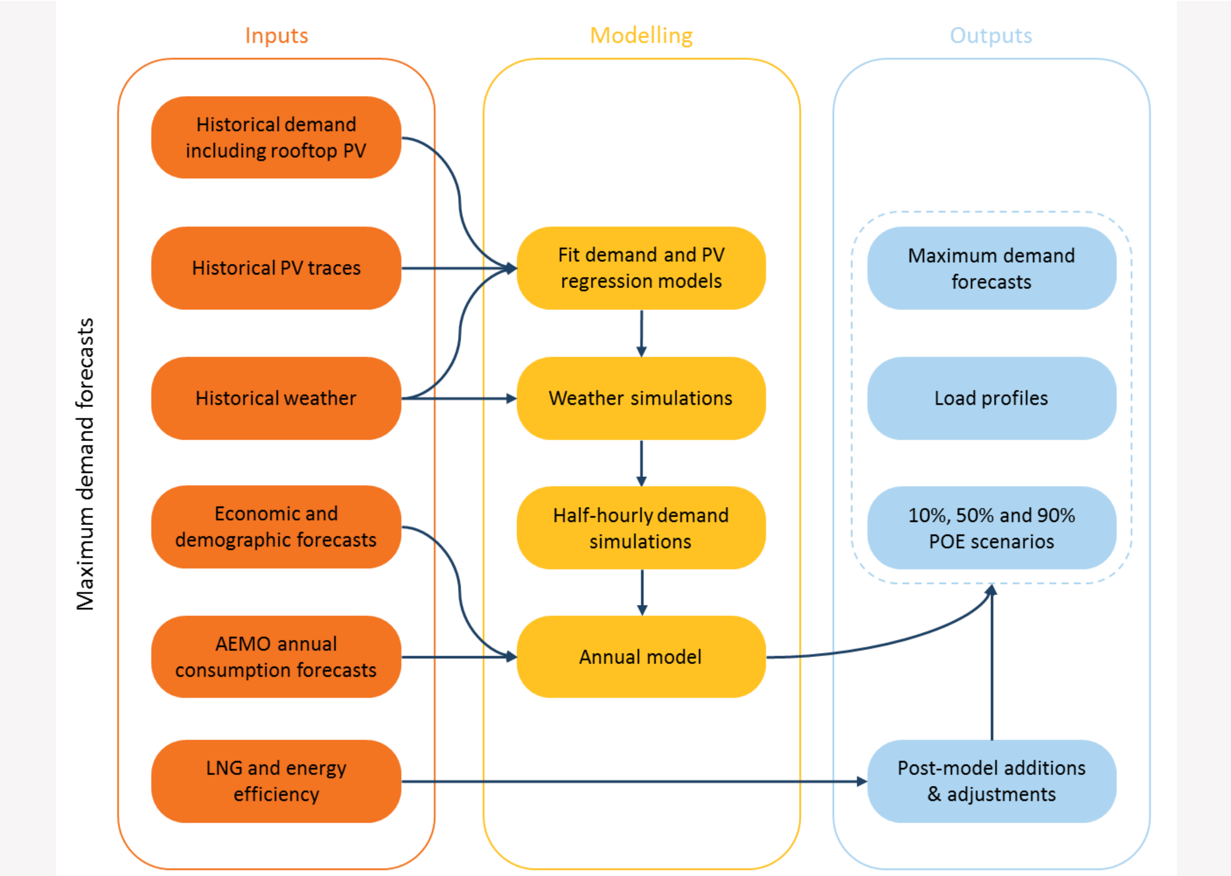
The models were used, together with simulated half-hourly temperature data and residual re-sampling, to develop POE forecasts of maximum demand. Residual re-sampling accounts for any serial correlation in the residuals.

Figure 7 gives an overview of the maximum demand forecast methodology used in the 2015 NEFR.

For the non-industrial component of the maximum demand forecasts, each summer and winter period had 48 separate models fitted (one for each half-hourly period). The historical data used to build the models was half-hourly non-industrial demand.[31] This demand is equivalent to residential and commercial consumption plus transmission network losses and generator auxiliary loads.

[29] Available at http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/NEFR-Supplementary-Information
[30] See Rob J Hyndman & Shu Fan, 2008. *Density forecasting for long-term peak electricity demand*, Monash Econometrics and Business Statistics Working Papers 6/08, Monash University, Department of Econometrics and Business Statistics.
[31] Operational as-generated demand with large industrial loads subtracted. Industrial loads are forecast using a different methodology within the Monash model.

Figure 7 Maximum demand forecast methodology diagram



The estimated historical PV generation was also added back to the non-industrial demand, to allow for modelling on the “underlying” non-industrial demand. A separate rooftop PV generation model was used to simulate future rooftop PV generation. This simulated rooftop PV generation was later subtracted from the simulated "underlying" non-industrial demand, to obtain the non-industrial demand supplied from the grid.

Equation 9 shows the semi-parametric model developed by Monash University to model demand. It is split into two separate models, one that uses demographic, economic and cooling/heating degree day variables and another that uses the remaining half-hourly variables.

Equation 9 Short- and long-run demand model

$$\log(y_{t,p}) = \log(y^*_{t,p}) + \log(\bar{y}_i).$$

Here, $\bar{y}_i$ is the average demand for season i (in which time period t falls) and $y^*_{t,p}$ is the half-hourly normalised demand for day t and period p. These two components can be expressed as:

$$\log(y^*_{t,p}) \;=\; h_p(\mathrm{t}) + \mathrm{f}_p(\boldsymbol{w}_{1,t}, \boldsymbol{w}_{2,t}) + e_t$$

$$\text{and} \qquad \bar{y}_i^{pc} = \sum_{j=1}^{J} c_j z_{j,i} + \epsilon_i,$$

where:

- $\bar{y}_i^{pc} = \bar{y}_i / P_i$ is the per capita seasonal average demand.
- P_i is the population in season i.

- $h_p(t)$ models calendar effects.
- $f_p(\boldsymbol{w}_{1,t}, \boldsymbol{w}_{2,t})$ models all temperature effects using two locations within each region to represent geographical weather diversity (except for Queensland, which uses three locations).
- $\boldsymbol{w}_{1,t}$, and $\boldsymbol{w}_{2,t}$ are vectors of current and past temperatures at each location.
- $z_{j,i}$ is a variable in season i that accounts for seasonal demographic, economic and degree days effects. Its impact on demand is measured by the magnitude of coefficient c_j.
- e_t and ϵ_i denotes the demand that is left unexplained by the model at day t.

The model above separates out the seasonal average demand.

The half-hourly demand across different years was normalised by dividing the half-hourly demand values by the seasonal average demand. Equation 10 represents the normalisation of half-hourly demand.

Equation 10 Normalisation of half-hourly demand

$$\mathbf{y}^*_{\mathbf{t,p}} = \mathbf{y}_{\mathbf{t,p}} / \bar{\mathbf{y}}_{\mathbf{i}}$$

where:

- $\mathrm{y}^*_{\mathrm{t,p}}$ is the normalised demand for day t and period p.
- $\bar{\mathrm{y}}_{\mathrm{i}}$ is the seasonal average demand for season i in MW (equal to energy in GWh multiplied by $1{,}000/h$ where h is the number of hours in season i).

For half-hourly demand $\mathrm{y}^*_{\mathrm{t,p}}$, the data were modelled in natural logarithms, as this resulted in the best fit to the available data. The model is also easier to interpret, as the temperature and calendar variables have a multiplicative effect on demand.

Some specific features of the model were:

- Calendar effects were modelled using variables that account for day-of-week, time-of-year, and public holidays, including days immediately before and after public holidays.
- Temperature effects were modelled using additive regression splines. A regression spline is a combination of several polynomial curves joined at points known as “knots”. They are used to account for non-linear relationships between driver and predictor variables, in this case, the relationship between temperature and demand.
- Temperatures from the last three hours and the same period from the last six days were included, as were the maximum and minimum temperature in the last 24 hours and the average temperature over the last seven days.
- Warming trends based on Commonwealth Scientific and Industrial Research Organisation (CSIRO) modelling were applied to simulated future temperatures to allow for climate-change impacts.
- A separate rooftop PV model was used to simulate future rooftop PV generation and its effects on demand. The rooftop PV model was a nonlinear, nonparametric function that has daily solar radiation, maximum temperature and day-of-season as driver variables.
- Industrial demand was incorporated into the Monash model. Section 3.5 discusses this change in more detail.

3.2.1 Simulation of maximum demand distribution

Producing forecasts using the half-hourly demand model requires future values for the temperature variables and the calendar-dependent effects. Average seasonal demand forecasts are also required, to convert the normalised demand forecasts back to a megawatt figure. Temperature is not random, but cannot be predicted on a daily basis more than a few days into the future.

Monash University addressed this problem by simulating 1,000 seasons of synthetic half-hourly temperature data for each season to be forecast. The simulation process used a “seasonal block re-sampling approach” which simulated numerous temperature patterns based on historical data.[32]

Each of the 1,000 seasons of simulated temperature data allowed Monash University to obtain a single simulated value of maximum demand. This was done by using the half-hourly demand models to predict demand at every half-hour period in the season, and taking the maximum of all predicted half-hourly demands over the simulated season. This procedure resulted in 1,000 values of simulated maximum demand, which were used to forecast the distribution of maximum demand.

As well as temperature variations, the half-hourly model itself involves a random element (the residual e_t). To capture this random element, Monash University also re-sampled the historical model residuals to simulate numerous small adjustments to the predicted half-hourly demand in each of the simulations.

For each season, each of the 1,000 simulated maximum demands was scaled by the underlying seasonal average demand (as in Equation 10). The seasonal average demand, which is based on the annual energy models, has a random element added by simulating future temperatures and residuals.

To account for the impact of rooftop PV generation, the same 1,000 weather simulations were input into the non-parametric PV generation model. This allowed for rooftop PV generation to be subtracted from each of the demand simulations. The amount of rooftop PV generation was scaled annually according to the rooftop PV installed capacity forecasts that AEMO produces.

The 10%, 50% and 90% POE MD forecasts were obtained by taking the appropriate percentile of the 1,000 simulated maximum demands for each season.

3.2.2 Methodology improvements since 2014

AEMO and Monash University implemented the following improvements for the 2015 NEFR:

- Separate models for working and non-working days. This is known as hierarchical modelling and allowed the demand model to better account for temperature and day-of-week interactions. Hierarchical modelling typically results in more accurate fitting and prediction than single-level approaches.
- Variable selection allowed to vary for morning, afternoon and evening periods. This produced a more accurate model fit across the whole day, thereby allowing the model to handle both maximum and minimum demand forecasts.
- Industrial demand incorporated into the Monash model. Previously, the Monash model only produced forecasts for non-industrial demand. This year, the industrial component has been included directly in the Monash model to improve the accuracy of the POE distributions for operational demand.

A more detailed description of these changes is available in the Monash University technical papers.[33]

[32] For more information about this re-sampling process, see Hyndman, R. J. and S. Fan (2008). *Variations on seasonal bootstrapping for temperature simulation*. Report for Electricity Supply Industry Planning Council (SA) and Victorian Energy Corporation (VenCorp). Monash University Business and Economic Forecasting Unit.

[33] Monash University maximum demand technical reports 2015. Available at http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/NEFR-Supplementary-Information.

3.3 Rooftop PV

Similar to the 2014 NEFR, rooftop PV was incorporated directly into the MD modelling developed by Monash University. More information on incorporating rooftop PV into the MD forecasts is also provided in the supplementary reports written by Monash University and published on AEMO's website.

3.4 Energy efficiency

The 2015 MD savings were calculated based on different methodology to the 2014 NEFR, to calculate EE at different POE levels. A sensitivity analysis of the impact of energy efficiency measures at different temperatures and demands allowed for a more accurate estimate of savings at different POE levels.

AEMO calculated the regional EE impacts on summer and winter maximum demand, using annual operational consumption EE adjustments and appliance scaling factors. Appliance scaling factors were used to represent how appliance energy efficiency may vary at different temperature and demand levels. For example, a 10% POE demand which is likely to occur on high temperature days will have different EE savings compared to a 90% POE demand event which occurs on milder temperature days.

To calculate POE scaling factors, a sensitivity analysis was conducted to assess each appliance category with new or in-train MEPS standards. Each category was assessed as having either low, medium, high or no impact on a given POE level for both summer and winter. Low impact appliances had a scaling factor of 0.5 applied, medium impact had 1 assigned and high impact appliances had 1.25 assigned. The assessed impact for each appliance group is given in Appendix E.

Appliance scaling factors were then aggregated using a weighted average based on the total EE savings from each appliance group. The annual energy appliance EE adjustment was then converted to an hourly average, and multiplied by the appliance scaling factor, to obtain the appliance EE savings for maximum demand.

As it is difficult to assess how building standards affect energy efficiency savings at different temperature and demand levels, AEMO took a conservative approach when estimating these savings. Building EE savings for maximum demand were calculated by converting the annual energy building EE adjustment to an hourly average.

The building and appliance EE savings for maximum demand were then aggregated to produce the EE adjustment for maximum demand.

3.5 Large industrial load

Forecast maximum demand and capacity values were requested in the large industrial load questionnaire. Where maximum demand values were not provided or determined to be reasonable, AEMO estimated the forecast industrial site maximum demand.

Annual operational consumption values obtained from the questionnaire and historical maximum demand values were used to estimate missing maximum demand forecasts. Maximum demand was grown in line with annual consumption, using the below formula:

$$MD_{IND,y,s} = \frac{AE_{IND,y,s} - AE_{IND,y-1,s}}{8760} + MD_{IND,y-1,s}$$

where $MD_{IND,y,s}$ is the estimated maximum demand for the industrial site *IND*, in the year *y*, season *s*.

Diversity factors needed to be calculated to find the coincident peak of each of the industrial sites. Historical daily data for large industrial loads was used to estimate diversity factors.

Diversity factors for each industrial site, year and season were calculated using the top system peaks from a particular year and season. This was undertaken for two POE levels:

$$DF_{IND,y,s} = \frac{1}{n}\sum_{i=1}^{n} \frac{Industrial\ demand\ during\ i^{th}\ highest\ system\ peak\ in\ season\ s, year\ y}{Maximum\ industrial\ demand\ in\ season\ s, year\ y}$$

where $DF_{IND,y,s}$ is the diversity factor for the industrial site *IND*, in the year *y*, season *s,* and *n* is the number of system peaks.

Separate diversity factors were calculated for the 10% and 50% POEs. Three and ten system peaks were chosen for the 10% POE and 50% POE, respectively, as they appeared to provide the best reconciliation of forecasts with historical data.

The diversity factor for each year was then weighted to allow for a greater contribution from more recent years:

$$DF^{*}_{IND,s} = \frac{\sum_{y\in\{Years\}} DF_{IND,y,s} \times w_{y,s}}{\sum_{y\in\{Years\}} w_{y,s}}$$

where $DF^{*}_{IND,s}$ is the weighted diversity factor for the industrial site *IND* and season *s*.

The coincident maximum demand[34] for each industrial site was then calculated using the maximum demand forecasts and weighted diversity factors:

$$MD^{*}_{IND,y,s} = MD_{IND,y,s} \times DF^{*}_{IND,s}$$

where $MD^{*}_{IND,y,s}$ is the coincident maximum demand for the industrial site *IND*, in the year *y*, season *s*.

Individual industrial forecasts were then aggregated to give regional forecasts for industrial maximum demand.

These aggregated 10% and 50% POE forecasts were incorporated into Monash University's demand model. Monash University's model calculated an industrial maximum demand distribution using a bootstrapping methodology. This demand distribution was forecast forward by scaling to AEMO's 10% and 50% POE forecasts. For more information on how AEMO's forecasts were incorporated into the Monash model, see the Monash Technical papers in the 2015 NEFR supplementary documentation.[35]

3.6 Small non-scheduled generation

SNSG maximum demand forecasts represent the forecast contribution to demand of SNSG at the time of operational maximum demand.

The forecast contribution of SNSG to operational maximum demand was calculated using historical operational demand, generation data and installed capacity information. Each existing SNSG's output during the top 10 highest operational demand intervals for both summer and winter over the past five years was compared with its installed capacity, to calculate summer and winter peak demand contribution factors.

Contribution factors for existing projects were calculated using actual historical data and installed capacity information. Future output across the forecast period was then estimated, using the average of the historical contribution factors for each project, based on the past five years of data. Contribution factors in the low scenario were calculated using the lowest three historical contribution factors over the past five years, and the contribution factors in the high scenario were calculated using the highest three.

[34] Coincident maximum demand is the demand of a particular site at the time of the operational demand. In other words, it is the contribution of a particular site to operational maximum demand. The sum of the coincident maximum demands for each site is the contribution of the large industrial load segment to operational maximum demand.

[35] Monash University MD technical reports 2015. Available at http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/NEFR-Supplementary-Information.

The summer and winter contribution factors were assumed to be constant over the 20-year outlook period, and were applied to each individual SNSG to develop summer and winter SNSG maximum demand forecasts.

For new SNSG projects, AEMO estimated the contribution to maximum demand factors by averaging all generators from the same NEM region and generator class (fuel source), as it did for annual operational consumption.

CHAPTER 4. MINIMUM DEMAND

This chapter should be read in parallel with the operational consumption and maximum demand chapters, which provide more information on each segment.

4.1 Introduction

AEMO published minimum demand forecasts for the first time in the 2015 NEFR, for South Australia. The methodology for each component was similar to the maximum demand modelling approach, but with some key differences.

4.2 Residential and commercial load

The residential and commercial component of the minimum demand forecasts was produced using the Monash University demand model. Monash University implemented several changes to allow for minimum demand forecasts to be calculated.

In the 2014 NEFR demand forecasts, the Monash University maximum demand model was tuned to best fit demand during the afternoon, when maximum demand is expected to occur. As minimum demand occurs at different times to maximum demand, the model was recalibrated to fit demand across all times of the day. To achieve this, the data was grouped into morning, afternoon and evening periods and different variable selection was used for each time period. This improved the fit of the model, especially during low demand periods.

To produce minimum demand forecasts instead of maximum demand forecasts, each of the 1,000 seasonal demand simulations had the minimum value recorded instead of the maximum. This gave 1,000 minimum demand values from which a minimum demand distribution could be produced. The 10%, 50% and 90% POEs could then be produced from this minimum demand distribution.

As with maximum demand, the 1,000 simulated minimum demands were scaled by the underlying seasonal average demand forecasts for each year.

4.3 Rooftop PV

Similar to maximum demand, rooftop PV was incorporated directly into the minimum demand modelling developed by Monash University. More information on incorporating rooftop PV into the minimum demand forecasts is also provided in the supplementary reports written by Monash University and published on AEMO's website.

4.4 Energy efficiency

The energy efficiency post-model adjustment (PMA) for minimum demand was calculated from the annual consumption post-model adjustment to get the average hourly energy savings. This is shown in Equation 11.

Equation 11 Energy efficiency post-model adjustment for minimum demand

$$EE_{Minimum\ Demand\ PMA} = \frac{EE_{Annual\ consumption\ PMA}}{365 \times 24}$$

AEMO intends to further investigate how the impact of energy efficiency may vary during minimum demand days.

4.5 Large industrial load

Minimum demand was not requested by AEMO during the questionnaire process with large industrial customers, so minimum demand for industrial loads was calculated in aggregate. Minimum demand forecasts for industrial load were produced using a similar method as for the industrial load maximum demand forecasts.

Combined regional annual consumption values and historical, coincident industrial minimum demand values were used to estimate the minimum demand forecasts. Minimum demand was grown in line with annual consumption using the below formula:

$$MinD_{IND,y,s} = \frac{AE_{IND,y,s} - AE_{IND,y-1,s}}{8760} + MinD_{IND,y-1,s}$$

where $MinD_{IND,y,s}$ is the estimated minimum demand for the industrials *IND*, in the year *y*, season *s*.

To estimate diversity factors, aggregated historical half-hourly data for large industrial loads and the system were used. Diversity factors for industrial loads, by year and season were calculated using the lowest system consumption from a particular year and season. This was undertaken for two POE levels:

$$DF_{IND,y,s} = \frac{1}{n}\sum_{i=1}^{n} \frac{Industrial\ demand\ during\ i^{th}\ lowest\ system\ trough\ in\ season\ s, year\ y}{Minimum\ industrial\ demand\ in\ season\ s, year\ y}$$

where $DF_{IND,y,s}$ is the diversity factor for industrials *IND*, in the year *y*, season *s,* and *n* is the number of system troughs.

Ten and three system troughs were chosen for the 50% POE and 90% POE, respectively, as they appeared to provide the best reconciliation of forecasts with historical data.

A weighted diversity factor was then calculated to allow recent years to provide a stronger contribution:

$$DF^*_{IND,s} = \frac{\sum_{y\in\{Years\}} DF_{IND,y,s} \times w_{y,s}}{\sum_{y\in\{Years\}} w_{y,s}}$$

where $w_{y,s}$ are the weights for each year and season and $DF^*_{IND,s}$ is the adjusted diversity factor for the industrial *IND* and season *s*.

The coincident minimum demand[36] for industrial load was then calculated using the forecasted minimum demand and weighted diversity factor, as demonstrated in the formula below:

$$MinD^*_{IND,y,s} = MinD_{IND,y,s} \times DF^*_{IND,s}$$

where $MinD^*_{IND,y,s}$ is the diversified minimum demand for the industrial *IND*, in the year *y*, season *s*.

Individual industrial forecasts were then aggregated to give regional forecasts for industrial minimum demand.

These aggregated 50% and 90% POE forecasts for industrial minimum demand were used to scale the Monash model's industrial demand distribution. Further information on the Monash forecasting methodology is available from the Monash technical papers.

[36] The coincident minimum demand is the demand of a particular site at the time of the operational minimum demand. In other words, it is the contribution of a particular site to operational minimum demand. The sum of the coincident minimum demands for each site is the contribution of the large industrial load segment to operational minimum demand.

4.6 Small non-scheduled generation

The forecast contribution of SNSG to operational minimum demand was calculated using historical operational demand, generation data and installed capacity information. Each existing SNSG's output during the 10 lowest operational demand intervals for both summer and winter over the past five years was compared with its installed capacity to calculate summer and winter peak demand contribution factors.

Contribution factors for existing projects were calculated using actual historical data and installed capacity information. Future output across the forecast period was then estimated using the average of the historical contribution factors for each project, based on the past five years of data. Contribution factors in the low scenario were calculated using the lowest three historical contribution factors over the past five years, and the contribution factors in the high scenario were calculated using the highest three.

The summer and winter contribution factors were assumed to be constant over the 20-year outlook period, and were applied to each individual SNSG to develop summer and winter SNSG minimum demand forecasts.

APPENDIX A. AEMO DATA SOURCES

Calculations for annual energy[57] and MD calculations, transmission losses and auxiliary load used in the National Electricity Forecast Report (NEFR) use data which AEMO obtains from the following systems:

System	Data used for:
Market Management System (MMS): the wholesale market system (containing the database WARE) used for operating the NEM, including dispatch, determining the regional spot price, and ancillary services.	• Operational data for annual energy and MD calculations • Transmission losses • Auxiliary loads
Metering Settlements and Transfer Solution (MSATS): the retail market system (containing the database MDM) used for financial settlement of the NEM.	• Individual SNSG for annual energy and MD calculations • Industrial loads

APPENDIX B. TRANSMISSION LOSSES AND AUXILIARY LOAD FORECASTS

B.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

Similar to the 2014 NEFR, AEMO forecast annual transmission losses (Table 22) 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 23) 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 (SA only)

AEMO forecast transmission losses during minimum demand (Table 23) 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.

Changes since 2014 NEFR

Methodology for transmission loss forecasts during maximum demand has been revised. In 2014, transmission losses during maximum demand were forecast by averaging the losses during the highest operational demand interval in each of the previous five years. This year the analysis was extended to include the 10 highest operational demand intervals for both summer and winter in each year. A weighting factor was also applied to better reflect more recent trends.

Further, transmission losses during minimum demand were forecast for the first time for South Australia.

Table 22 Historical normalised transmission losses (annual energy)

Financial Year	NSW	QLD	VIC	SA	TAS
2000–01	2.15%	3.79%	3.16%	2.30%	-
2001–02	2.28%	4.34%	3.00%	2.01%	-
2002–03	2.23%	3.92%	3.70%	2.31%	2.22%
2003–04	2.51%	3.78%	3.51%	2.44%	2.35%
2004–05	2.59%	3.56%	3.19%	2.32%	2.39%
2005–06	2.77%	3.36%	2.99%	2.34%	2.86%
2006–07	2.75%	3.45%	2.71%	2.10%	2.34%
2007–08	2.92%	3.39%	2.43%	1.88%	2.44%
2008–09	2.68%	3.19%	2.68%	2.21%	2.61%
2009–10	2.78%	3.24%	2.88%	2.35%	3.01%
2010–11	2.47%	3.08%	2.90%	2.32%	3.00%
2011–12	2.42%	3.11%	3.00%	2.37%	2.73%
2012–13	2.14%	3.24%	2.72%	2.40%	3.21%
2013–14	1.99%	2.90%	2.97%	2.67%	4.48%
5-year average	**2.36%**	**3.11%**	**2.89%**	**2.42%**	**3.29%**

Table 23 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)	2015–16 to 2034–35	3.27%	3.60%	1.73%	3.14%	2.76%
Maximum Demand (Winter)	2015 to 2034	2.24%	3.10%	2.28%	3.66%	2.41%
Minimum Demand (Summer)	2015–16 to 2034–35	-	-	3.05%	-	-
Minimum Demand (Winter)	2015 to 2034	-	-	2.99%	-	-

B.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 2014 NEFR, the annual auxiliary factor in each region was forecast based on historical data and the anticipated changes in the future generation mix[37] (Table 24). 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 25) 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 (SA only)

Auxiliary load forecasts during minimum demand (Table 25) were based on the average auxiliary factor. This factor was calculated by first determining the average of the historical auxiliary loads during the 10 lowest 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.

Changes since 2014 NEFR

The methodology for auxiliary load forecasts during maximum demand has been revised since last year. In 2014, auxiliary loads during maximum demand were forecast by averaging the auxiliary factor during the highest operational demand interval in each of the previous five years. This year the analysis was extended to include the 10 highest operational demand intervals for both summer and winter in each year. The weighting factor to better reflect more recent trends is also new in 2015.

Further, auxiliary loads during minimum demand were forecast for the first time for South Australia.

[37] Forecasts of the future generation mix were obtained from the 2014 National Transmission Network Development Plan (NTNDP).

Table 24 Forecasts of the auxiliary factor for each NEM region (annual energy)

Financial Year	NSW	QLD	SA	TAS	VIC
2015–16	4.36%	6.73%	4.34%	2.00%	8.93%
2016–17	4.39%	6.73%	4.46%	2.00%	8.93%
2017–18	4.33%	6.72%	2.09%	2.00%	8.87%
2018–19	3.98%	6.55%	1.47%	2.00%	8.83%
2019–20	3.95%	6.55%	1.39%	2.00%	8.82%
2020–21	3.97%	6.53%	1.47%	2.00%	8.82%
2021–22	3.88%	6.53%	1.46%	2.00%	8.82%
2022–23	3.88%	6.53%	1.49%	2.00%	8.82%
2023–24	3.89%	6.53%	1.56%	2.00%	8.82%
2024–25	3.90%	6.52%	1.64%	2.00%	8.82%
2025–26	3.92%	6.52%	1.72%	2.00%	8.79%
2026–27	3.93%	6.52%	1.39%	2.00%	8.79%
2027–28	3.93%	6.51%	1.39%	2.00%	8.78%
2028–29	3.95%	6.51%	1.40%	2.00%	8.79%
2029–30	3.97%	6.51%	1.40%	2.00%	8.79%
2030–31	3.97%	6.49%	0.96%	2.00%	8.78%
2031–32	3.97%	6.49%	0.95%	2.00%	8.78%
2032–33	3.98%	6.49%	0.95%	2.00%	8.78%
2033–34	3.98%	6.49%	0.96%	2.00%	8.78%
2034–35	3.99%	6.48%	0.96%	2.00%	8.78%

Table 25 Forecasts of the auxiliary factor for each NEM region during maximum and minimum 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%
Minimum Demand (Summer)	2015-16 to 2034-35	-	-	5.36%	-	-
Minimum Demand (Winter)	2015 to 2034	-	-	4.1%	-	-

APPENDIX C. 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 contribute to these 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.

C.1 Queensland

C.1.1 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
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[38]	154	CCGT	Natural Gas Pipeline	Scheduled

[38] The NEM registration classification of Yarwun Power Station Unit 1 (dispatchable unit ID: YARWUN_1) is market non-scheduled generating unites. However, it is a condition of the registration of this unit that the Registered Participant complies with some of the obligations of a

C.1.2 Power stations (existing, SNSG) used for native consumption forecasts for Queensland – in addition to those in Table C.1.1.

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Browns Plains Power Station	2.0	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non-scheduled
Callide A4	30.0	Steam Sub Critical	Black Coal	Non-scheduled
Daandine	33.0	Compression Reciprocating Engine	Coal Seam Methane	Non-scheduled
Roghan Road	2.0	Steam Sub Critical	Bagasse	Non-scheduled
German Creek	45.0	Spark Ignition Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
ISIS Central Sugar Mill	25.0	Steam Sub Critical	Bagasse	Non-scheduled
Kareeya Power Station	7.0	Run of River	Water	Non-scheduled
KRC Cogen	5.0	Steam Sub Critical	Natural Gas Pipeline	Non-scheduled
Moranbah North	63.0	Spark Ignition Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
Moranbah	13.0	Compression Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
Oaky Creek	20.0	Compression Reciprocating Engine	Coal Seam Methane	Non-scheduled
Rochedale Renewable Energy	4.0	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non-scheduled
Rocky Point	30.0	Steam Sub Critical	Green and air dried wood	Non-scheduled
Southbank Institute of Tech	1.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Suncoast Gold Macadameias	1.0	Steam Sub Critical	Macadamia Nut Shells	Non-scheduled
Veoilia Ti Tree Bioreactor	2.0	Compression Reciprocating Engine	Landfill Methane/Landfill Gas	Non-scheduled
Windy Hill	12.0	Wind Onshore	Wind	Non-scheduled
Whitwood Road Renewable Energy Facility	1.0	Compression Reciprocating Engine	Landfill Methane/Landfill Gas	Non-scheduled
Wivenhoe Small Hydro	5.0	Run of River	Water	Non-scheduled
Invicta	50.0	Steam Sub Critical	Bagasse	Non-scheduled
Pioneer	68.0	Steam Sub Critical	Bagasse	Non-scheduled
Victoria Mill	24.0	Steam Sub Critical	Bagasse	Non-scheduled
Tully Sugar Mill	10.0	Steam Sub Critical	Bagasse	Non-scheduled
South Johnstone Sugar Mill	12.0	Steam Sub Critical	Bagasse	Non-scheduled
Cloncurry Solar Farm	2.1	Solar	Solar	Non-scheduled
Fraser Coast Community Solar system	0.4	Solar	Solar	Non-scheduled
Windorah Solar Farm	0.1	Solar	Solar	Non-scheduled

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.

C.2 New South Wales

C.2.1 Power stations used for operational consumption forecasts for New South Wales

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Bayswater	2640	Steam Sub Critical	Black Coal	Scheduled
Boco Rock Wind Farm	113	Wind - Onshore	Wind	Semi-Scheduled
Blowering	70	Hydro - Gravity	Water	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
Mt Piper	1400	Steam Sub Critical	Black Coal	Scheduled
Nyngan Solar Farm		Solar	Solar	Semi-Scheduled
Redbank	143.8	Steam Sub Critical	Black Coal	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
Wallerawang C	1000	Steam Sub Critical	Black Coal	Scheduled
Woodlawn Wind Farm	48.3	Wind - Onshore	Wind	Semi-Scheduled

C.2.2 Power stations (existing, SNSG) used for native consumption forecasts for New South Wales – in addition to those in Table C.2.1.

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
West Nowra Landfill Gas Power Generation Facility	1.0	Compression Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Awaba PS	1.1	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Bankstown Sports Club	2.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Burrendong Hydro	18.0	Hydro - Gravity	Water	Non-scheduled
Brown Mountain	5.4	Hydro - Gravity	Water	Non-scheduled
Broken Hill GT	50.0	Diesel	OCGT	Non-scheduled
Burrinjuck	27.2	Hydro - Gravity	Water	Non-scheduled
Broadwater Power Station	38.0	Steam Sub Critical	Bagasse	Non-scheduled
Capital East Solar Farm	1.0	Solar	Solar	Non-scheduled
Condong PS	30.0	Steam Sub Critical	Bagasse	Non-scheduled
Copeton Hydro	20.0	Hydro - Gravity	Water	Non-scheduled
Cullerin Range Wind Farm	30.0	Wind - Onshore	Wind	Non-scheduled
Eastern Creek PS	5.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Glenbawn Hydro	6.0	Hydro - Gravity	Water	Non-scheduled
Grange Avenue	2.0	Compression Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Hunter Economic Zone	29.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Jacks Gully	2.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Jindabyne	1.0	Hydro - Gravity	Water	Non-scheduled
Jounama	14.0	Hydro - Gravity	Water	Non-scheduled
Keepit	6.0	Hydro - Gravity	Water	Non-scheduled
Kincumber	1.0	Landfill gas	Landfill gas	Non-scheduled
Lucas Heights I	5.0	Compression Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Lucas Heights II	13.0	Compression Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Nine Network Willoughby	3.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Pindari Hydro	6.0	Hydro - Gravity	Water	Non-scheduled
Royalla Solar Farm	20.0	Solar PV	Solar	Non-scheduled
St Georges League Club	1.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Teralba	3.0	Compression Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
The Drop Hydro	3.0	Run of river	Water	Non-scheduled
Woodlawn Bioreactor Energy	7.0	Compression Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Western Suburbs League	1.0	Compression Reciprocating Engine	Diesel	Non-scheduled
West Illawarra Leagues Club	1.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Wilga Park B	6.0	Spark Ignition Reciprocating Engine	Natural Gas - Unprocessed	Non-scheduled
Woy Woy	1.1	Compression Reciprocating Engine	Landfill / Biogas	Non-scheduled
Wyangala A	20.0	Hydro - Gravity	Water	Non-scheduled
Wyangala B	4.0	Hydro - Gravity	Water	Non-scheduled
Ledday's Creek Rd	0.3	Hydro - Gravity	Other renewable	Non-scheduled
Lostock	2.0	Hydro - Gravity	Hydro	Non-scheduled
Oaky River Dam Hydro	5.0	Hydro - Gravity	Hydro	Non-scheduled
Nymbodia	5.0	Run of river	Hydro	Non-scheduled
Dubbo	0.3	Solar PV	Solar	Non-scheduled
Yass Rd	0.1	Other renewable	Other renewable	Non-scheduled
Crookwell Wind Farm	4.8	Wind - Onshore	Wind	Non-scheduled
Lake Cargelligo	3.0	Solar Thermal	Solar	Non-scheduled
Renewable Energy Facility - Albury Landfill	1.1	Renewable	Landfill Methane / Landfill Gas	Non-scheduled
Teralba Power Station	3.0	Renewable	Landfill Methane / Landfill Gas	Non-scheduled
Kooragang Island Wind Farm	0.6	Wind - Onshore	Wind	Non-scheduled
Singleton Solar Generator 1	0.2	Solar PV	Solar	Non-scheduled
Summerhill Generator	2.2	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Sydney Water North Head WWTP	1.4	Other renewable	Other renewable	Non-scheduled
Newcastle Foreshore Park PV	0.0	Solar PV	Solar	Non-scheduled
Singleton Solar Generator 2	0.2	Solar PV	Solar	Non-scheduled
ButtonDerry Waste Facility	2.3	Other renewable	Landfill Methane / Landfill Gas	Non-scheduled
Earth Power Grand Av	3.8	Spark Ignition Reciprocating Engine	Biomass recycled municipal and industrial material	Non-scheduled
Eastern Creek 2	10.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Toonumbar Dam	0.0	Hydro	Hydro	Non-scheduled
Short St Dungog	0.1	Hydro	Hydro	Non-scheduled
Stromlo Mini Hydro	0.8	Hydro	Hydro	Non-scheduled
EDL Belconnen Tip	1.0	Other renewable	Other renewable	Non-scheduled
EDL Mugga Tip	3.0	Other renewable	Other renewable	Non-scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Appin	55.0	Spark Ignition Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
Tower	41.0	Spark Ignition Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
Chichester Dam	0.1	Hydro	Hydro	Non-scheduled
Wilga Park	10.0	Spark Ignition Reciprocating Engine	Natural Gas - Unprocessed	Non-scheduled

C.3 South Australia

C.3.1 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	Non-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
Mintaro Gas Turbine Station	90	OCGT	Natural Gas Pipeline	Scheduled
Mt Millar Wind Farm	70	Wind - Onshore	Wind	Non-scheduled
Northern Power Station	530	Steam Sub Critical	Brown Coal	Scheduled
Osborne Power Station	180	CCGT	Natural Gas Pipeline	Scheduled
Pelican Point Power Station	478	CCGT	Natural Gas Pipeline	Scheduled
Playford B Power Station	240	Steam Sub Critical	Brown Coal	Scheduled
Port Lincoln Gas Turbine	73.5	OCGT	Diesel	Scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Pt. Stanvac	57.6	Compression Reciprocating Engine	Diesel	
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

C.3.2 Power stations (existing, SNSG) used for native consumption forecasts for South Australia – in addition to those in Table C.3.1.

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Amcor Glass	4.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Blue Lake Milling Power Plant	1.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Highbury	2.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Lonsdale	20.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Pedler Creek	3.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Tatiara	1.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Tea Tree	1.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Terminal Storage Mini Hydro	2.0	Hydro - Gravity	Water	Non-scheduled
Wingfield 1	5.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Wingfield 2	5.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Seacliff	1.4	Hydro - Gravity	Water	Non-scheduled

C.4 Victoria

C.4.1 Power stations used for operational consumption forecasts for Victoria

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Anglesea	150	Steam Sub Critical	Brown Coal	Non-scheduled
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
Energy Brix Complex (Morwell)	189	Steam Sub Critical	Brown Coal	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

C.4.2 Power stations (existing, SNSG) used for native consumption forecasts for Victoria – in addition to those in Table C.4.1.

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Banimboola Power Station	13.0	Hydro - gravity	Water	Non-scheduled
Ballarat Base hospital	3.0	Spark Ignition Reciprocating Engine	Natural Gas Pipeline	Non-scheduled
Brooklyn Landfill	3.0	Spark Ignition	Landfill Gas	Non-scheduled
Clayton	11.0	Spark Ignition	Landfill Gas	Non-scheduled
Codrington Wind Farm	18.0	Wind - Onshore	Wind	Non-scheduled
Corio	1.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Eildon	5.0	Hydro - Gravity	Water	Non-scheduled
Glenmaggie	4.0	Run of river	Water	Non-scheduled
Hallam Road	9.0	Spark Ignition Reciprocating Engine	Water	Landfill Methane / Landfill Gas
Hepburn Wind Farm	4.0	Wind - Onshore	Wind	Non-scheduled
South East Water - Hallam Plant	0.3	Hydro - gravity	Water	Non-scheduled
Longford	31.0	OCGT	Natural Gas Pipeline	Non-scheduled
Mornington Waste Disposal	1.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Shepparton	1.0	Spark Ignition Reciprocating Engine	Non-biomass recycled municipal and industrial mate	Non-scheduled
Springvale Landfill Gas Power Station	5.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Tatura Biogas	1.0	Spark Ignition Reciprocating Engine	Sewerage / Waste Water	Non-scheduled
Traralgon Network Support Station	10.0	Spark Ignition Reciprocating Engine	Natural Gas Pipeline	Non-scheduled
Toora Wind Farm	21.0	Wind - Onshore	Wind	Non-scheduled
William Hovell Hydro Power Station	2.0	Run of river	Water	Non-scheduled
Wollert Renewable Energy Facility	7.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Wonthaggi	12.0	Wind - Onshore	Wind	Non-scheduled
Wyndham Renewable Energy Facility	1.9	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Yarrawonga Hydro	9.0	Hydro - Gravity	Water	Non-scheduled
Clover	29	Hydro - Gravity	Water	Non-scheduled
Rubicon	11.6	Hydro - Gravity	Water	Non-scheduled
Broadmeadows Landfill	5.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Olinda Mini Hydro	0.9	Hydro - gravity	Water	Non-scheduled
Melbourne Water Number 2	6.5	Other renewable	Other renewable	Non-scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Dandenong Hospital	5.8	Other renewable	Other renewable	Non-scheduled
Dandenong PEP	2.0	Other renewable	Other renewable	Non-scheduled
Pacific Hydro Eildon Pondage	4.5	Hydro	Hydro	Non-scheduled
Cardinia Hydro Power Station	3.2	Hydro	Hydro	Non-scheduled
Berwick Landfill	6.8	Other renewable	Other renewable	Non-scheduled
Mt Beauty 1	15.0	Hydro	Hydro	Non-scheduled
Mt Beauty 2	15.0	Hydro	Hydro	Non-scheduled
Ballarat Solar Farm	0.3	Solar	Solar	Non-scheduled
Bendigo Solar Farm	0.3	Solar	Solar	Non-scheduled
Bridgewater	0.1	Solar	Solar	Non-scheduled

C.5 Tasmania

C.5.1 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
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

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
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

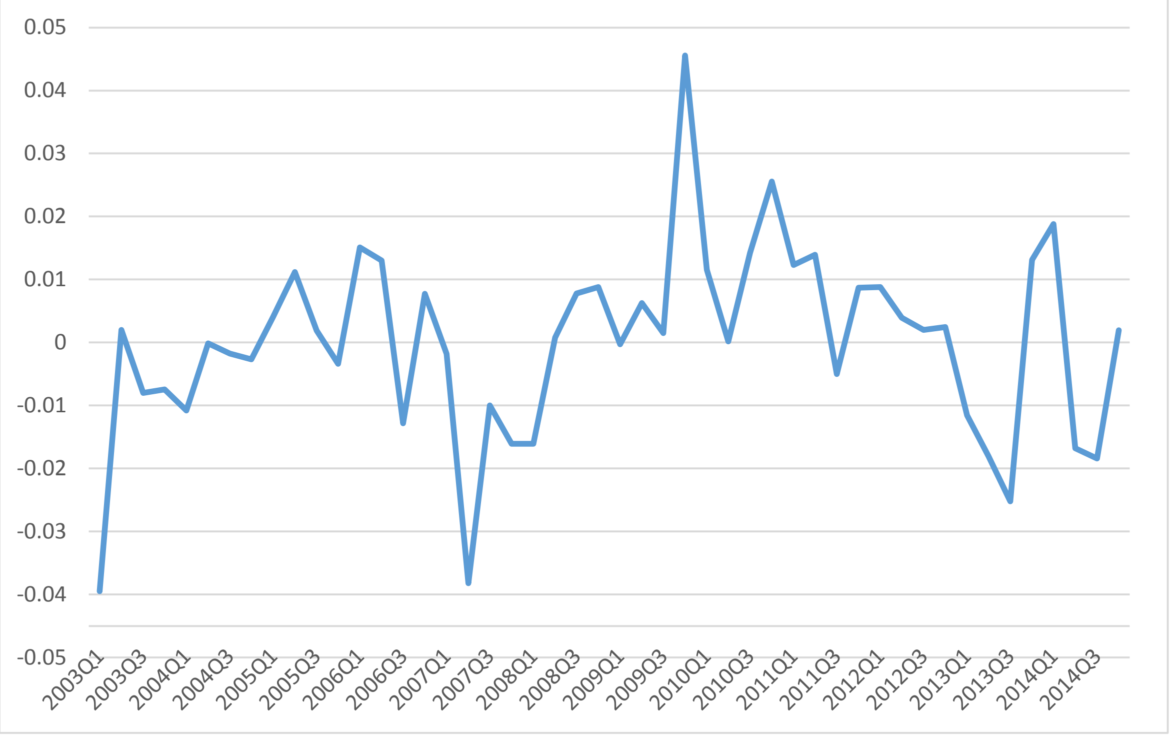
C.5.2 Power stations (existing, SNSG) used for native consumption forecasts for Tasmania – in addition to those in Table C.5.1.

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Butlers Gorge	14.0	Hydro - Gravity	Water	Non-scheduled
Cluny	17.0	Hydro - Gravity	Water	Non-scheduled
Paloona	28.0	Hydro - Gravity	Water	Non-scheduled
Remount	2.0	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non-scheduled
Repulse	28.0	Hydro - Gravity	Water	Non-scheduled
Rowallan	11.0	Hydro - Gravity	Water	Non-scheduled
King Island Solar	0.1	Solar	Solar	Non-scheduled

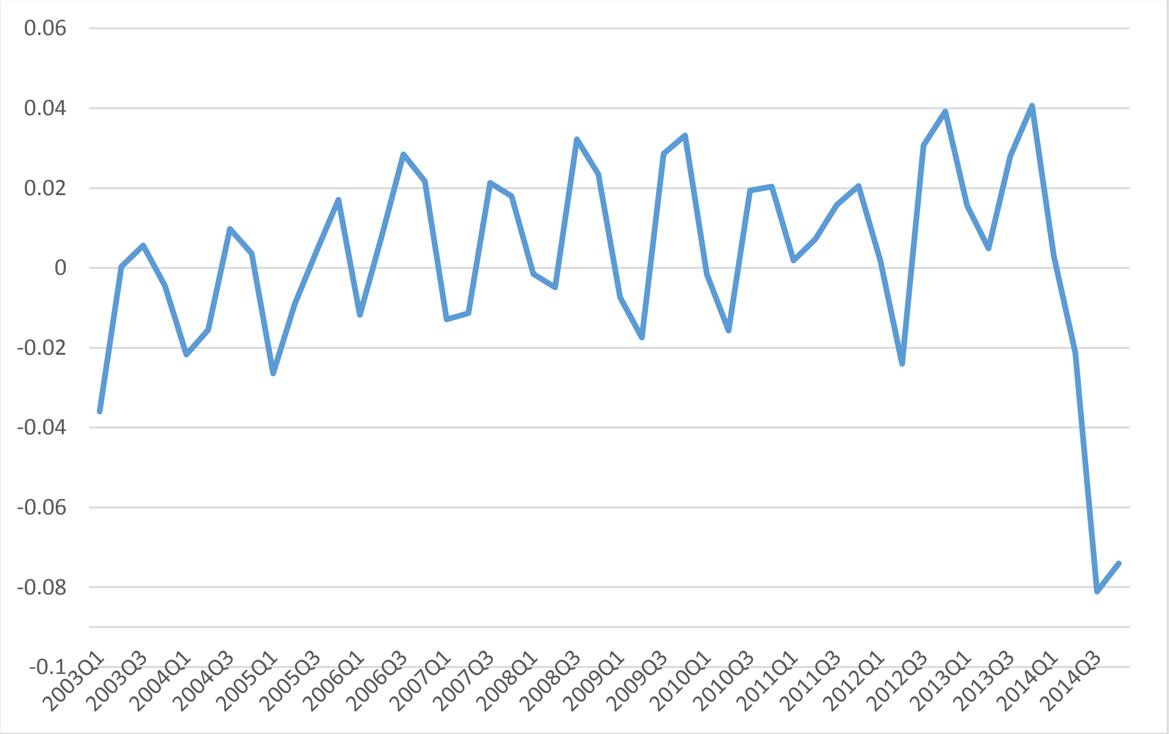
APPENDIX D. DOLS RESIDUALS

This appendix provides the residual plots for the DOLS models used to produce the residential and commercial consumption forecasts. Residual plots are commonly used to assess how well the econometric models explain historical consumption. The residual is consumption that is unexplained by the model, calculated as the difference between actual electricity consumption and historical consumption as estimated by the model. Ideally, the data in residual plots will appear random with no discernible pattern or time trend and no change in mean or variance over time.

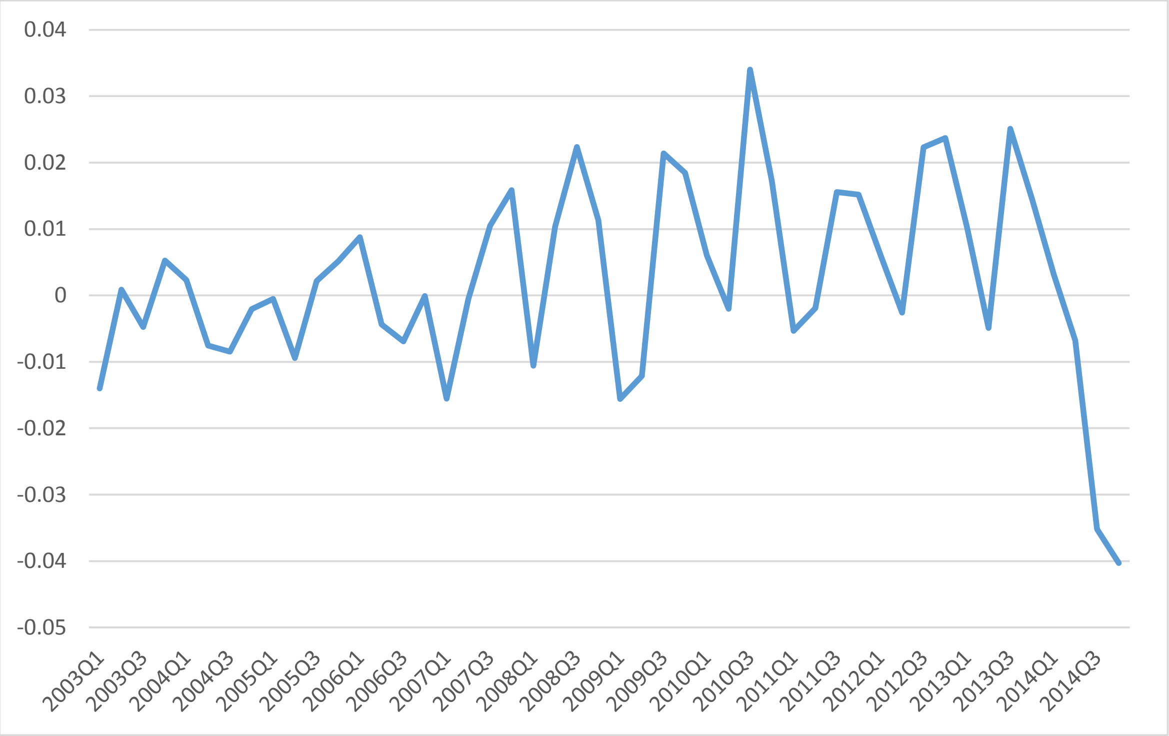
D.1 DOLS residuals for Queensland



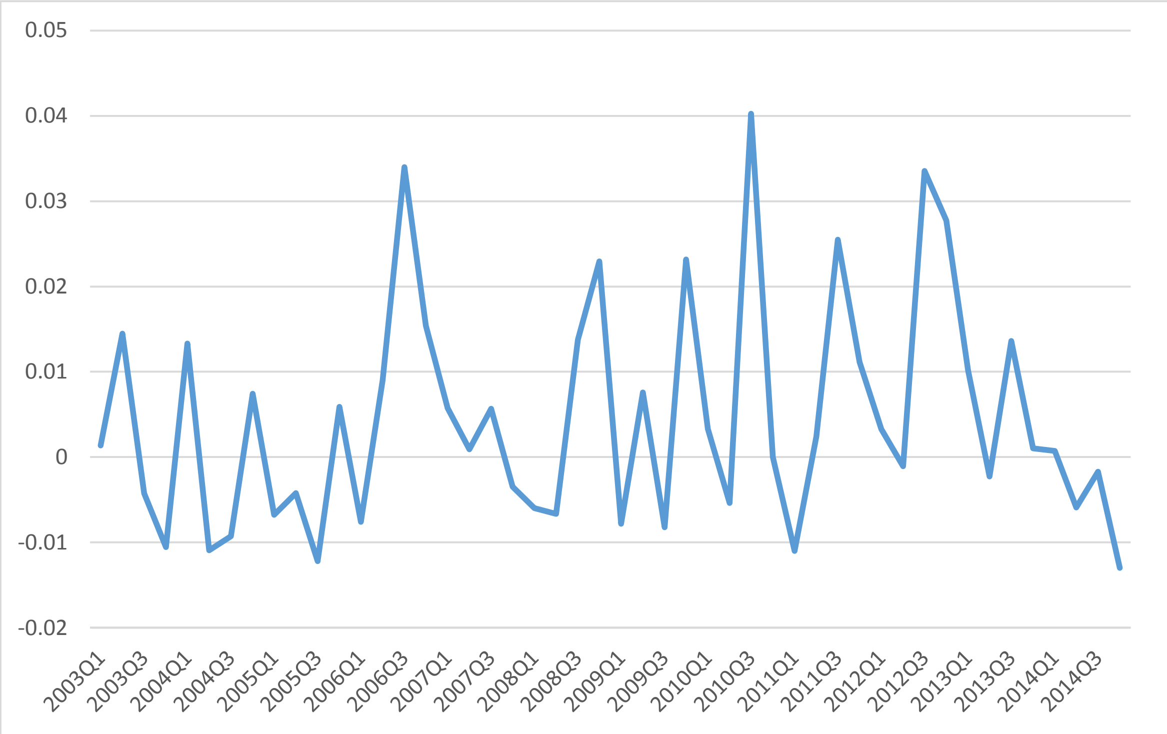
D.2 DOLS residuals for New South Wales



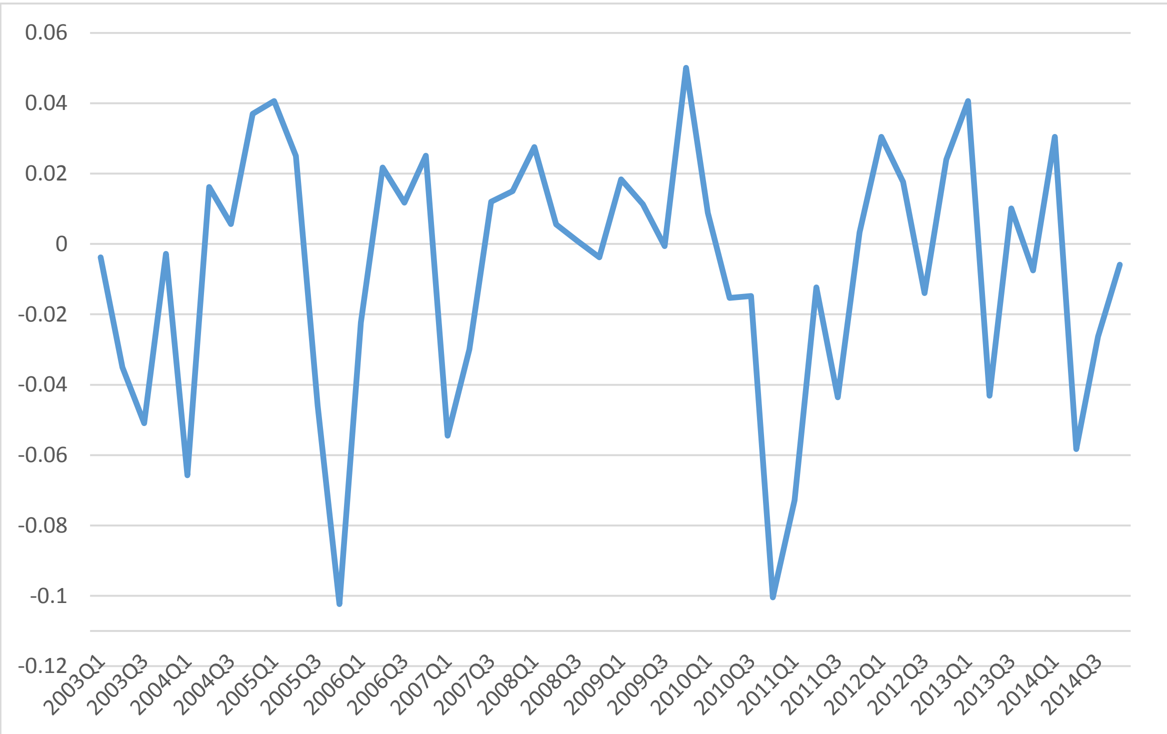
D.3 DOLS residuals for Victoria



D.4 DOLS residuals for South Australia



D.5 DOLS residuals for Tasmania



APPENDIX E. APPLIANCE ENERGY EFFICIENCY IMPACTS ON MAXIMUM DEMAND

Appliance	Season	10% POE	50% POE	90% POE
Heat pump water heaters	Summer	None	None	None
Storage water heaters	Summer	None	None	None
Solar-electric water heaters	Summer	None	None	None
Distribution transformers	Summer	High	Medium	Medium
Standby	Summer	Medium	Medium	Medium
Swimming pool pump-units	Summer	Low	Low	Low
Air conditioned chillers	Summer	Medium	Medium	Medium
Air conditioners – residential	Summer	Medium	Medium	Medium
Battery chargers	Summer	Low	Medium	Medium
Air conditioners – non-residential	Summer	Medium	Medium	Medium
Ballasts	Summer	Low	Low	Low
Linear fluorescent lamps	Summer	Low	Medium	Medium
Motors	Summer	Low	Medium	Medium
Residential refrigeration	Summer	Medium	Medium	Medium
Commercial refrigeration	Summer	Medium	Medium	Medium
Portable air conditioners	Summer	Low	Low	Low
Commercial refrigeration compressors	Summer	Low	Medium	Medium
Self-contained food-service	Summer	Low	Medium	Medium
Commercial refrigeration products	Summer	Low	Medium	Medium
Process & industry equipment	Summer	Low	Medium	Medium
Commercial catering	Summer	Low	Medium	Medium
Commercial electronics & lighting	Summer	Low	Medium	Medium
Heat pump water heaters	Winter	None	None	None
Storage water heaters	Winter	Low	None	None
Solar-electric water heaters	Winter	Low	None	None
Distribution transformers	Winter	High	Medium	Medium
Standby	Winter	Medium	Medium	Medium
Swimming pool pump-units	Winter	Low	Low	Low
Air conditioned chillers	Winter	Low	Medium	Medium
Air conditioners – residential	Winter	Low	Low	Low
Battery chargers	Winter	Low	Medium	High
Air conditioners – non-residential	Winter	Low	Medium	High
Ballasts	Winter	Medium	Medium	Medium
Linear fluorescent lamps	Winter	Medium	Medium	Medium
Motors	Winter	Low	Medium	High
Residential refrigeration	Winter	Low	Medium	High

Appliance	Season	10% POE	50% POE	90% POE
Commercial refrigeration	Winter	Low	Medium	High
Portable air conditioners	Winter	Low	Medium	Medium
Commercial refrigeration compressors	Winter	Low	Medium	Medium
Self-contained food-service	Winter	Low	Medium	Medium
Commercial refrigeration products	Winter	Low	Medium	Medium
Process and industry equipment	Winter	Low	Medium	Medium
Commercial catering	Winter	Low	Medium	Medium
Commercial electronics and lighting	Winter	Low	Medium	Medium

MEASURES AND ABBREVIATIONS

Units of measure

Abbreviation	Unit of measure
c	cents
CDD	cooling degree days
GWh	gigawatt hour
HDD	heating degree days
kW	kilowatt
kWh	kilowatt hour
MW	megawatt

Abbreviations

Abbreviation	Expanded name
ABS	Australian Bureau of Statistics
AE	Annual energy
AEMO	Australian Energy Market Operator
AER	Australian Energy Regulator
ANZSIC	Australian and New Zealand Standard Industrial Classification
BOM	Bureau of Meteorology
BPE	Business price of electricity
CCGT	Combined cycle gas turbine
CER	Clean Energy Regulator
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DCCEE	Department of Climate Change and Energy Efficiency (Commonwealth)
DF	Diversity factor
DNSP	Distribution network service provider
DOI	Department of Industry (New South Wales)
DOLS	Dynamic ordinary least squares
EC	Error correction
ECM	Error correction model
EE	Energy efficiency
EEO	Energy Efficiency Opportunities
EES	Energy Efficient Strategies
ESP	Energy Saver Program
ESS	Energy Savings Scheme
ESSBP	Energy Efficiency for Small Business Program
GDP	Gross domestic product
GSP	Gross state product
IDM	Integrated dynamic model
Ind	Industrial
LNG	Liquefied natural gas
MD	Maximum demand

Abbreviation	Expanded name
MDM	Metering Data Management
MEPS	Minimum Energy Performance Standards
MMS	Market Management System
MSATS	Metering Settlements and Transfer Solution
NEFR	National Electricity Forecasting Report
NEM	National Electricity Market
NSW	New South Wales
OCGT	Open cycle gas turbine
PCA	Principal component analysis
PMA	Post model adjustment
POE	Probability of exceedance
POP	Population
PV	Photovoltaic
Qld	Queensland
RIS	Regulation Impact Statements
RPE	Retail price of electricity
SA	South Australia
SFD	State final demand
SNSG	Small non-scheduled generation
SRES	Small-scale Renewable Energy Scheme
STC	Small-scale technology certificates
Tas	Tasmania
TNSP	Transmission network service provider
TPE	Total price of electricity
Vic	Victoria