2013

FORECASTING METHODOLOGY INFORMATION PAPER

National Electricity Forecasting

Published by

AEMO
Australian Energy Market Operator
ABN 94 072 010 327

Disclaimer

Copyright Notice

Acknowledgements

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

[This page is left blank intentionally]

ABOUT THIS INFORMATION PAPER

The 2013 Forecasting Methodology Information Paper is a companion document to the 2013 National Electricity Forecasting Report (NEFR). It is designed to assist in interpreting the electricity demand forecasts contained in the NEFR.

This paper provides a detailed description of how the 2013 annual energy and maximum demand forecasts were developed. It outlines how AEMO sought to ensure the forecasting processes and assumptions were consistently applied and fit for purpose. It details the modelling improvements made to the forecasts compared to the 2012 report, following detailed analysis.

In addition to explaining the methodology behind the demand forecasts, this paper provides further detail on the electricity demand segments featured in the 2013 NEFR and the approaches used to develop the forecasts for each forecasting component.

Key improvements include:

- The inclusion of the short-term focus (one-to-five-years) in the annual energy models.
- The inclusion of weather adjustments and allowing for the expected use of appliances at peak times in maximum demand models.
- A direct approach to gathering operational data from large industrial customers and transmission network service providers (TNSPs) or distribution network service providers (DNSPs) in developing large industrial load forecasts.
- Inclusion of additional data for historical estimates and payback periods as the basis for installed capacity forecasts for rooftop photovoltaic (PV) uptake.
- Increased transparency of the forecast approach and results, with the inclusion of Commonwealth Government initiatives and building standards for energy efficiency offsets.
- A revised methodology for the development of forecasts for existing and possible future small non-scheduled generation plant.

The modelling and forecasting methodology processes for each component have been endorsed and approved by both AEMO's subject matter experts and external reviewers. Reviewers include AEMO's advisor Woodhall Investment Research, and independent peer reviewer, Frontier Economics.

CONTENTS

TABLES

FIGURES

EQUATIONS

[This page is left blank intentionally]

CHAPTER 1 - INTRODUCTION

1.1 National electricity forecasting

In 2012, AEMO changed the way it develops and publishes annual electricity demand forecasts for the electricity industry, by developing independent forecasts for each region in the National Electricity Market (NEM). In 2013, AEMO has made further improvements to this process.

Electricity demand forecasts are used for operational purposes, for the calculation of marginal loss factors, and as a key input into AEMO's national transmission planning role.

This requires a close understanding of how the forecasts are developed to ensure forecasting processes and assumptions are consistently applied and fit for purpose.

AEMO is leading collaboration with the industry to ensure representative and reliable forecasts are consistently produced for each region.

This report outlines the methodology used in the annual energy and maximum demand forecasting process.

Table 1-1 shows how the 2013 NEFR scenarios relate to the 2012 AEMO scenarios and the other related scenarios detailed in this paper.

Table 1-1 — 2013 NEFR scenario mapping

2013 NEFR reference	2012 AEMO scenario	Related economic scenario	Related large industrial scenario	Related rooftop PV scenario	Related energy efficiency scenario	Related small non-scheduled generation scenario
High	Scenario 2 - Fast World Recovery	HCO5[a]	High	Moderate Uptake	Moderate Uptake	High Uptake
Medium	Scenario 3 - Planning	MCO5[b]	Medium	Moderate Uptake	Moderate Uptake	Moderate Uptake
Low	Scenario 6 - Slow Growth	LCO5[c]	Low	Moderate Uptake	Moderate Uptake	Slow Uptake

[a] High economic growth scenario, assuming carbon emissions reduction of 5% by 2020.
[b] Medium economic growth scenario, assuming carbon emissions reduction of 5% by 2020.
[c] Low economic growth scenario, assuming carbon emissions reduction of 5% by 2020.

1.2 Content of paper

Chapter 1, Introduction, provides the background to AEMO's national electricity forecasts, the context for this methodology paper.

Chapter 2, Residential and commercial load, the methodology used to develop annual energy and maximum demand forecasts for residential and commercial load.

Chapter 3, Large industrial load, provides the methodology used to develop annual energy and maximum demand forecasts for large industrial load.

Chapter 4, Rooftop PV, provides the methodology used to develop annual energy and maximum demand forecasts for rooftop PV output.

Chapter 5, Energy efficiency, provides the methodology used to develop annual energy and maximum demand offset forecasts for energy efficiency measures.

Chapter 6, Small non-scheduled generation, provides the methodology used to develop annual energy and maximum demand forecasts for small non-scheduled generation.

Chapter 7, provides the methodology used to develop the demand-side participation forecasts.

Appendix A, Input data, changes and estimated components, provides information about the systems from which AEMO extracts data used as NEFR inputs, and details any changes to historical data used.

Appendix B, Rooftop photovoltaic forecast, specifies the forecast rooftop photovoltaic (PV) uptake scenarios based on the methodology described in Chapter 4.

Appendix C, Energy efficiency forecast, specifies the forecast energy efficiency uptake scenarios based on the methodology described in Chapter 5.

Appendix D, Demand-side participation forecast, presents the forecast values for demand-side participation (DSP) based on the methodology presented in Chapter 7.

Appendix E, Generators included in the 2013 NEFR, identifies the scheduled, semi-scheduled and small non-scheduled power stations for each region that contribute to develop both operational and annual energy demand forecasts.

CHAPTER 2 - RESIDENTIAL AND COMMERCIAL LOAD

The residential and commercial annual energy load used in the 2013 NEFR forecasts is calculated by taking non-large industrial consumption[1], and subtracting rooftop photovoltaic (PV) contribution and energy efficiency savings as post-model adjustments.

This chapter provides the methodology used to develop annual energy and maximum demand forecasts for the residential and commercial sector.

To model residential and commercial maximum demand, transmission losses, auxiliary load and estimates of rooftop PV contribution are added to residential and commercial load. Similar to the annual energy forecasts, for maximum demand forecasts energy efficiency savings and future estimates of rooftop PV contribution are subtracted as post-model adjustments.

2.1 Annual energy

This section provides the methodology used to develop annual energy forecast models for residential and commercial. These are developed using econometric methods, which relate historical quarterly electricity consumption to a number of key drivers.

AEMO's models typically use real electricity prices, real state income, heating and cooling degree days, and seasonal dummy variables as inputs. The models produce quarterly electricity consumption forecasts, which are then aggregated to derive annual forecasts.

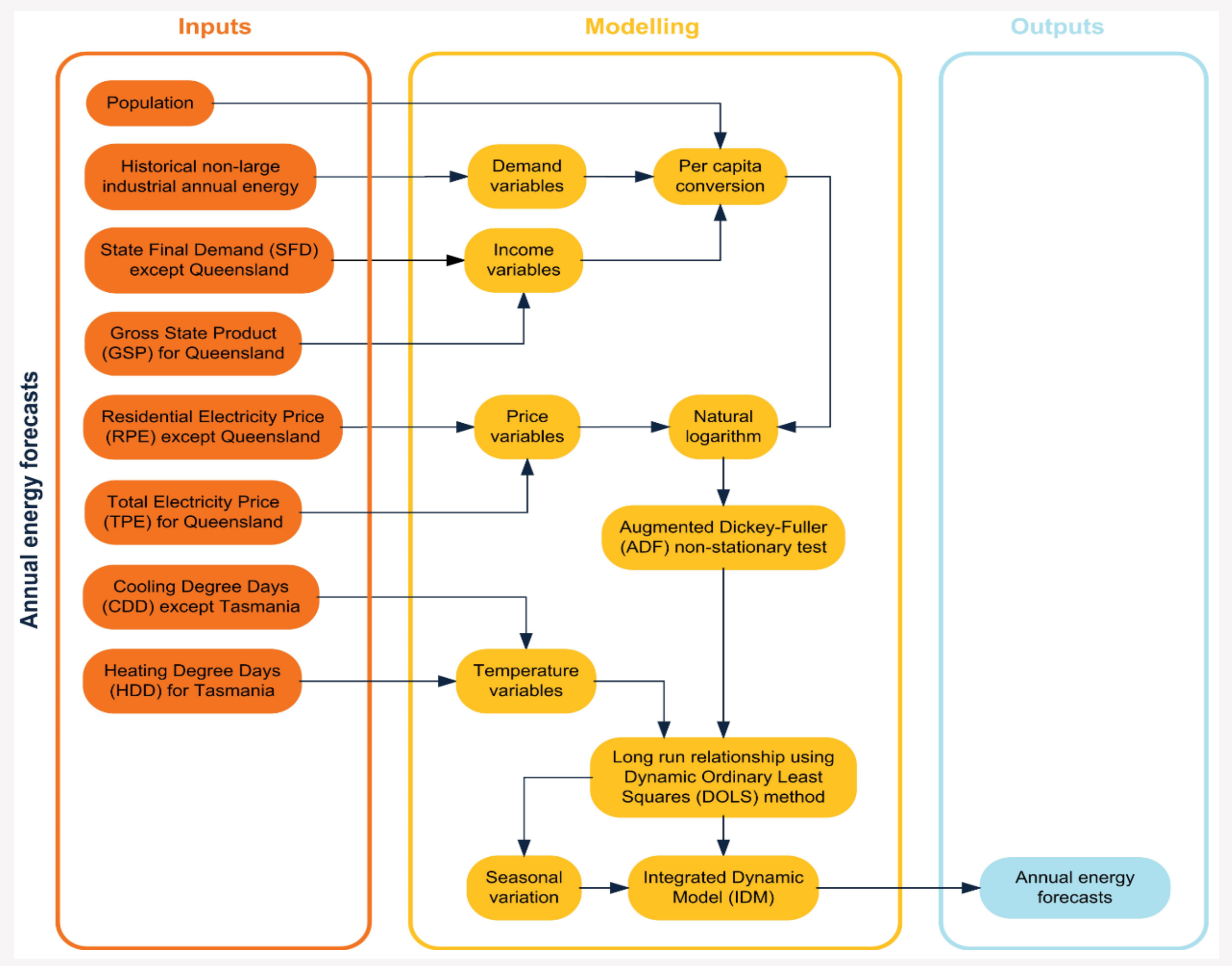
AEMO engaged Woodhall Investment Research Pty Ltd to assist in developing the annual energy models. Frontier Economics also independently peer reviewed the models and AEMO's forecasting methodology.

An overview of the annual energy forecast methodology used in the 2013 NEFR is shown in Figure 2-1.

[1] Non-large industrial consumption can be derived by subtracting rooftop PV and energy efficiency values. These can be found in the regional Excel work books http://aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report-2013.

[2] This is a time series where the population mean, variance, and covariances change over time, so it is characterised by its non-constant mean and variance and not having the property of mean reversion.

Figure 2-1 — Annual energy forecasts diagram



2.1.1 Annual energy models

Long term, electricity demand is determined by the price of electricity and the price of relevant substitute sources of energy and state income. Short term seasonal demand variation is driven mainly by weather. AEMO chose to develop econometric models for each National Electricity Market (NEM) region for the following reasons:

- The key drivers of residential and commercial energy consumption are the economic and demographic variables.
- Econometric models are suitable for medium- to long-run forecasts.
- Econometric models can explain the separate contribution of each demand driver to energy consumption.

The annual energy models were constructed on a quarterly basis, commencing September, December, March and June. These were then aggregated to come up with the annual energy consumption relating to a particular financial year.

The models relate historical non-large industrial energy consumption trends to a number of independent long-run drivers (such as state income and electricity prices). This produces a long-run forecast path around which actual demand fluctuates.

However, due to the non-stationary[2] property of the time series data used in the annual energy model, traditional static models cannot be used as this can violate the assumptions of the Ordinary Least Squares (OLS) method of selecting the best linear unbiased estimates of the coefficients. But methods are available for estimating long-run relationships in non-stationary data which have been adopted by AEMO.

A solution to this problem is to transform the time series by differencing it so that it becomes stationary. If taking the first difference of a non-stationary time series can achieve stationarity, then the time series is integrated to order 1 or I(1).[3]

If two non-stationary time series of the same order are integrated and there is a linear combination of the two time series that is stationary, then the two time series are said to be cointegrated and a long-run relationship between the variables can be estimated.[4] Cointegration is especially important as AEMO's dataset is relatively short.[5]

In the 2012 NEFR, AEMO found that the economic variables used to model energy consumption were non-stationary, so forecast models based on cointegration were developed. While these models were based on well-established cointegrating methods that have been empirically used for estimating the long-run relationship between non-stationary variables, they require large data sets. As a result, AEMO moved away from this approach in the 2013 NEFR. (For information on the models developed for the 2012 NEFR, see the 2012 Forecasting Methodology Information Paper.[6])

Dynamic Ordinary Least Squares

To enable a valid and consistent approach to be applied across all NEM regions, AEMO adopted the Dynamic Ordinary Least Squares (DOLS) estimator proposed by Saikkonen (1991) across all NEM regions.

The DOLS method is known to be effective when working with small datasets and where endogeneity may be present. (These were two issues evident in the 2012 NEFR methodology).The DOLS method provides an efficient estimator for the long-run relationship in the presence of variables with differing and higher orders of integration. And if a Newey-West correction[7] is applied, it is reasonable to apply standard tests on the coefficients.

The DOLS methodology adopted by AEMO involves estimating the cointegrating long-run equation and augmenting it with sufficient leads and lags of the first differences of the explanatory variables to correct small sample bias and endogeniety. The specification of the DOLS equation is shown in Equation 2-1.

Equation 2-1 — Dynamic Ordinary Least Squares

$$y_t = \mathrm{c}_0 + c_1 x_t + \sum_{i=-n}^{n} c_{i2} \Delta x_{t+i} + u_t$$

Once this is estimated, an Error Correction (EC) term calculated from the residuals from the DOLS equation can be placed in a dynamic equation known as an Error Correction Model (ECM) along with the contemporaneous independent variables. The specification of this model is shown in Equation 2-2.

2 This is a time series where the population mean, variance, and covariances change over time, so it is characterised by its non-constant mean and variance and not having the property of mean reversion.

3 A times series that must be differenced d times to achieve stationarity is called integrated to order d or I(d).

4 If the data is cointegrated then the estimated coefficients will converge quickly towards their true values. This property of cointegration is known as super-consistency.

5 With consistent electricity data available since the first quarter of 2000 and from the first quarter of 2002 for Tasmania.

6 AEMO. Available at: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report 2012/~/media/Files/Other/forecasting/Forecasting_Methodology_Information_Paper_v2.ashx.

7 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.

Equation 2-2 — Error Correction Model with long-run estimates

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

The coefficient δ represents the speed of adjustment to the long-run path and the remaining coefficients α_i and β_i can be estimated after determining the most suitable lag structure.[8]

Data sources and variable selection

AEMO constructed an historical database of demand data at the half-hourly level for each NEM region. This includes large industrial demand, auxiliary loads, transmission losses and residential and commercial demand from January 2000 onwards for all regions. It also includes weather data at the half-hourly level for various locations across the NEM; this was sourced from a commercial weather provider.

Historical and projected demographic and economic data, including income and price data, was prepared for AEMO by the National Institute of Economic and Industry Research (NIEIR) and used as a key input in the modelling.

AEMO considered the following specific variables when constructing the annual energy models (the original data source is included in brackets):

- Energy consumption data (AEMO).
- Population (NIEIR).
- Real gross state product (GSP) per capita (NIEIR).
- Real state final demand (SFD) per capita (NIEIR).
- Real total price of electricity (TPE) c/kWh (NIEIR).
- Real residential electricity prices (RPE) c/kWh (NIEIR).
- Real business electricity price (BPE) c/kWh (NIEIR).
- Real residential gas price (RGP) index (NIEIR).
- Real business gas price (BGP) index (NIEIR).
- Real total gas price (TGP) index (NIEIR).
- Real average price of other household fuels index (NIEIR).
- Real standard variable mortgage interest rate (SVR) % per annum (NIEIR).
- Heating degree days (HDD), using region-representative weather stations (BOM).
- Cooling degree days (CDD), using regions representative weather stations (BOM).

AEMO attempted to use the same variables across all regions; however, this was ineffective as some variable combinations produced unrealistic model outputs. Accordingly, AEMO relied on a statistical approach in deciding which variables to use in each model. This involved examining the fit and statistical significance of each variable when placed in the model, and assessing the modelling output.

Selecting the best variable for each region was determined by testing the data. Consideration was also given to the theoretical relationship between energy demand and a range of drivers so that the estimated coefficients made theoretical sense. For example, the coefficients for each variable should show that energy demand is likely to:

[8] For a quarterly time series, the first difference would equal the difference between the current value and the value from the previous quarter and each successive lag would represent the value from the previous quarter.

- Increase with real state-wide income.
- Decrease with rising electricity prices relative to the general price level.
- Be highly seasonal due to varying weather throughout the year.

AEMO applied a general statistical approach by testing combinations of variables in different model specifications and selecting variables which provided the best explanation of energy consumption. Stability diagnostic assessments were also used to assess the stability of the coefficients and model specification.[9]

The final variables and model specification was determined through AEMO's assessment of the statistical significance and the intuitiveness of the coefficients estimated for each variable, and by assessing the results of the diagnostics applied for each model.

The price and income variables show positive trends, which suggest non-stationarity. The variables used are region-specific with either gross state product (GSP) or state final demand (SFD) used to represent state income, real average retail electricity prices[10], real average gas prices and other heating fuels, real standard variable mortgage rates, heating and cooling degree days, and seasonal dummies. All relevant variables were deflated by CPI with the exception of demand, which is measured in kWh.

Table 2-1 — Final variable selection

Variable	Unit	NSW	QLD	VIC	SA	TAS
Electricity Demand	kWh/capita	Y = 1000*energy/ population	Y = 1000*energy/ population	Y = 1000*energy/ population	Y = 1000*energy/ population	Y = 1000*energy/ population
Income	$/capita	I = 1000*SFD/ population	I = 1000*GSP/ population	I = 1000*GSP/ population	I = 1000*SFD/ population	I = 1000*SFD/ population
Electricity Price	c/kWh	P = TPE	P = TPE	P = TPE	P = RPE	P = TPE
Temperature	Degree days	Cooling degree days	Cooling degree days	Cooling degree days	Cooling degree days	
		Heating degree days		Heating degree days	Heating degree days	Heating degree days

Total price of electricity (TPE) was found to best explain price effects in demand consumption for New South Wales, Queensland, Victoria and Tasmania. For South Australia, residential price of electricity (RPE) was the best explanatory variable for price in explaining the effects of electricity prices on energy consumption.

SFD was used to represent the income variable in New South Wales, South Australia and Tasmania, while GSP was found to best explain income in Victoria and Queensland.

Cooling degree and heating degree days were both found to be significant for New South Wales, Victoria and South Australia. Heating degree days were not significant for Queensland and cooling degree days were not significant for Tasmania.[11]

Variables such as the standard variable mortgage rate and the price of substitute electricity sources (such as gas) and other household fuels were considered; however, these were found to be statistically insignificant in explaining

9 Typical stability diagnostic assessments used by AEMO include CUSUM tests, recursive coefficients estimates and assessment of the residuals produced from each equation. All tests were conducted in Eviews statistical software package.

10 Total electricity price is a weighted average of residential and business electricity prices. It does not include the prices for large industrial users as these are negotiated privately between the user and the service provider.

11 This is because there are few heating degree days for Queensland and few cooling degree days for Tasmania.

energy consumption or their estimated long run coefficients were unrealistic once entered into the long-run equation.

Electricity demand, income, and price variables were all entered into the model in natural logarithms; this made interpreting the model coefficients simpler and reduced the statistical influence of outlying data points.

2.1.2 Modelling approach

The main variables (energy demand, income and price) were first tested for non-stationarity using the Augmented Dickey-Fuller (ADF) test with the null hypothesis that the variable has a unit root or is non-stationary.[12]

Given that there is a possible trend in the data, an ADF test with a constant trend was developed using the Eviews statistical software package. Table 2-2 shows the results for each NEM region.

Table 2-2 — ADF tests, constant with linear trend

Variable	NSW		QLD		VIC		SA		TAS	
	Test Statistic	P-value	Test Statistic	P-value	Test Statistic	P-value	Test Statistic	P-value	Test Statistic	P-value
ln(y)[a]	0.29	1.00	-1.45	0.83	0.46	1.00	-3.00	0.14	-1.83	0.67
ln(i)[b]	-1.45	0.84	-2.71	0.24	-2.43	0.42	-2.94	0.15	-3.21	0.09
ln(p)[c]	-2.79	0.20	-3.25	0.08	-2.50	0.33	-1.28	0.89	-1.97	0.61

a: Natural logarithm of energy consumption.
b: Natural logarithm of income.
c: Natural logarithm of electricity price.

The results from Table 2-2 confirm that the main variables are all non-stationary at the 10% level of significance for each region. There are limitations with traditional unit root tests on small samples, as one or two abnormal observations could make it difficult to determine the correct order of integration. However, these results do provide some assurance that the data is non-stationary.

AEMO used formal tests to check for cointegration and estimate a long-run equation[13]; however, as these are not overly reliable (especially for small samples), AEMO also used alternative methods to validate that the variables were non-stationary, and that the residuals estimated from the cointegrating equation were stationary. This was done by considering the variables and the resulting residuals estimated from the DOLS.

The inspection showed that the two variables (price and income) are time trending, indicating a strong positive trend for each of the variables in all NEM regions. This suggests that the variables used for each region are most likely non-stationary. On this basis, AEMO assessed that 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 energy consumption.

To establish the existence of a long-run relationship between the variables, AEMO adopted the following approach:

1. Estimate a DOLS equation and estimate the residuals from the equation.
2. Visually inspect the residuals to determine if they are stationary. A long-run relationship can only exist if the residuals are stationary.

12 All variables were tested in natural logarithm form.
13 An Engle-Granger Single Equation Cointegration Test and a Johansen System Cointegration Test can be performed in Eviews to test for cointegrating relationships.

Long-run estimator

AEMO applied a cointegrating equation similar to Equation 2-1 to determine the long-run relationship of energy consumption for each NEM region.

Eviews was used to estimate the DOLS equation with income and price variables entering the equation as the cointegrating regressors. A constant was also included while the temperature and seasonal dummy variables were entered into the equation as deterministic regressors or covariates.

AEMO determined the order of leads and lags of the differenced variables by assessing the stability of the coefficients under different leads and lags structures in the DOLS. The inclusion of sufficient leads and lags was required to alleviate small sample bias and endogeneity. This meant a trade-off also had to be made, as including leads and lags necessitates truncating the existing data, which reduces the degrees of freedom. As such, AEMO considered a maximum of two leads and two lags as acceptable given the small sample.[14]

While there was no formal method to choose the order of leads and lags in DOLS, AEMO's preferred approach was to apply a fixed rule choosing a maximum number of leads and lags, and observe the change in the coefficients by progressively changing the number of leads and lags in the equation. The aim is to find an order where the coefficients remained stable when the leads and lags are changed.

AEMO applied the following procedure:

1. Start with one lag in the DOLS.
2. Progressively add leads and lags to the specification and assess the stability of the coefficients.
3. Where the coefficients fluctuate by changing the leads and lags, continue to progressively add leads and lags to the equation until the coefficients remain stable.

Where the coefficients remained relatively stable by changing from one lag to two lags (or one lead) then having one lag was sufficient to achieve stable coefficients. Stability diagnostic tests such as CUSUM tests, recursive coefficients estimates and assessment of the residuals produced from each DOLS equation were also used to assess the stability of the long-run coefficients once a specification for the DOLS was chosen.

In most cases, one lag or one lag and one lead was found to be sufficient in providing stable coefficients in most regions.

All regional DOLS models include contemporaneous weather impacts on consumption as well as quarterly seasonal dummy variables to account for seasonality. Table 2-3 shows the long-run elasticities for income and price estimated using DOLS.

Table 2-3 — Estimated long-run income and price elasticities

	NSW	QLD	VIC	SA	TAS
Income	0.37	0.23	0.31	0.31	0.71
(Standard Error)	-0.06	-0.08	0.03	0.05	0.12
Price	-0.21	-0.16	-0.13	-0.20	-0.44
(Standard Error)	-0.03	0.03	0.01	0.04	0.11

[14] For a DOLS with one lag and one lead, AEMO's estimation period is 2000 Q1 to 2012 Q3. Historical data up to 1999 Q3 was required to incorporate one lag.

The long-run income and price elasticities for each region are all statistically significant and, most importantly, are consistent with the general literature for income and price effects on electricity demand. While the income and price response is fairly similar across NEM regions, with the exception of Tasmania, there are some slight variations. Possible reasons for this are as follows:

- The modelled consumption for each region captures different proportions of residential versus commercial customer loads.
- Residential customer heating (or cooling) load requirements vary, resulting in larger average electricity bills influencing a greater response to income and/or price shocks. This may be the case in Tasmania.
-

Once a DOLS was estimated, the residuals from the DOLS were calculated (shown in Figure 2-2 to Figure 2-6). The reason for doing this is to assess whether a linear combination of the variables will produce stationary residuals. If the residuals are stationary, this indicates that the variables are cointegrated.

Figure 2-2 — Long-run residuals for Queensland

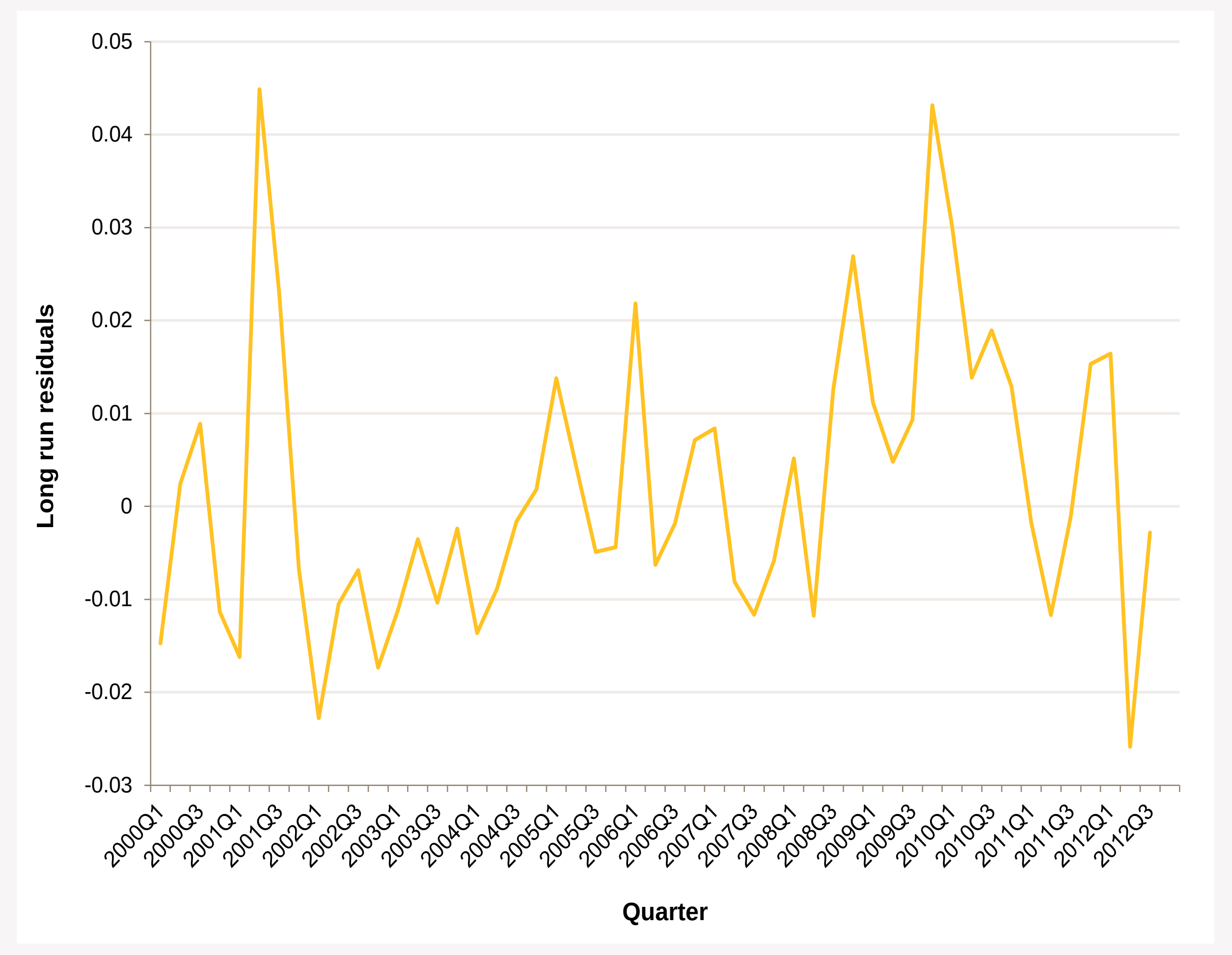


Figure 2-3 — Long-run residuals for New South Wales

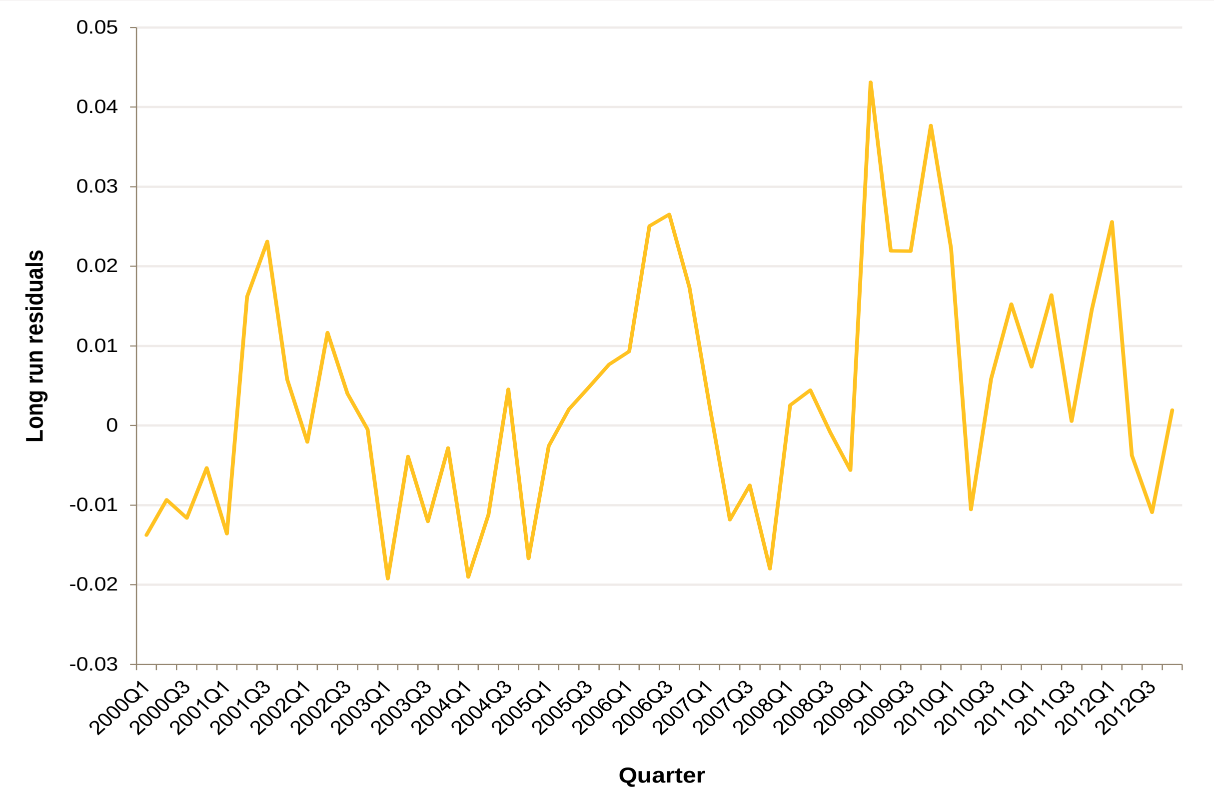


Figure 2-4 — Long-run residuals for South Australia

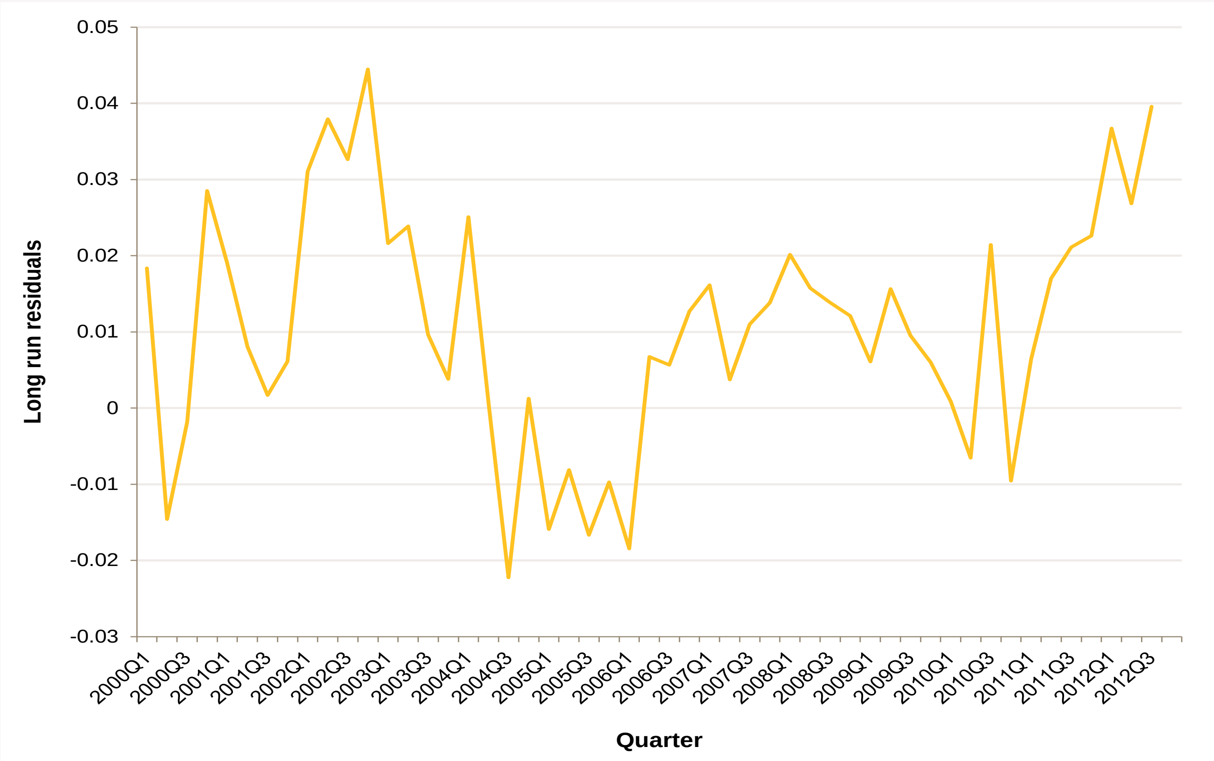


Figure 2-5 — Long-run residuals for Victoria

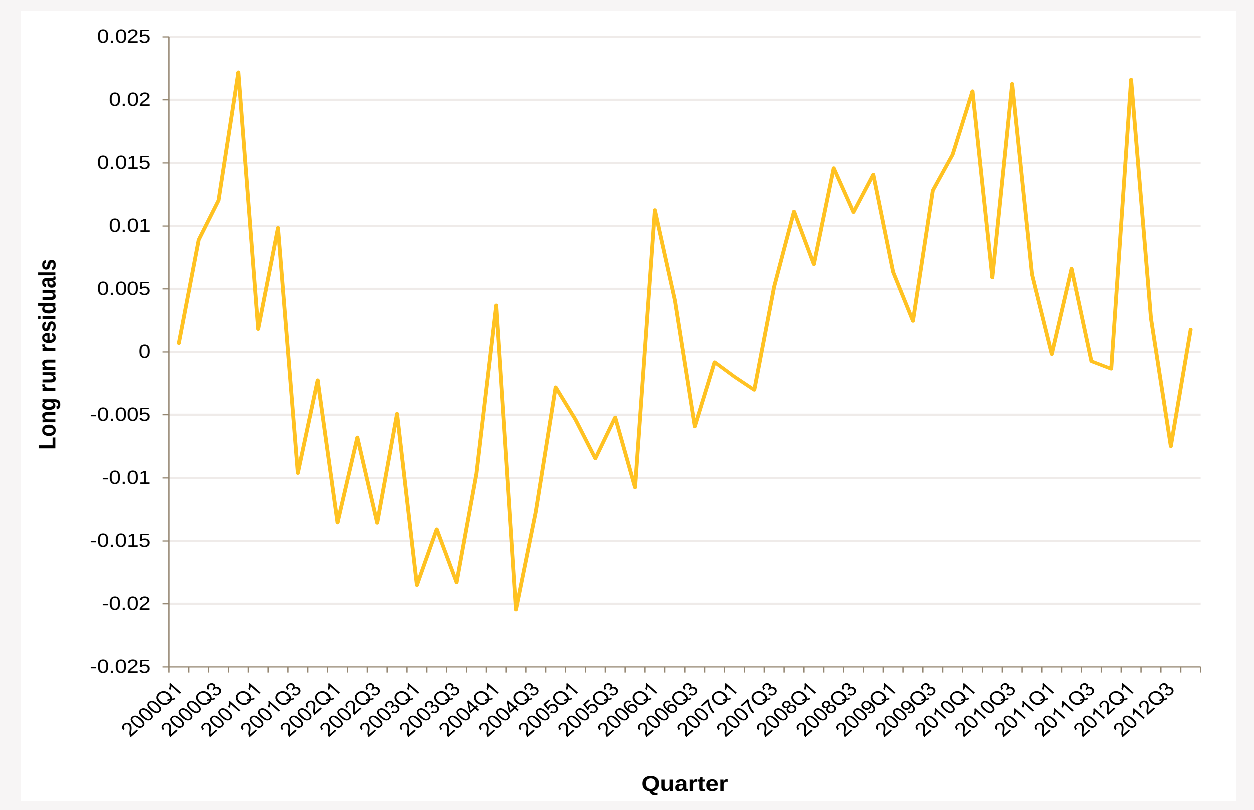


Figure 2-6 — Long-run residuals for Tasmania

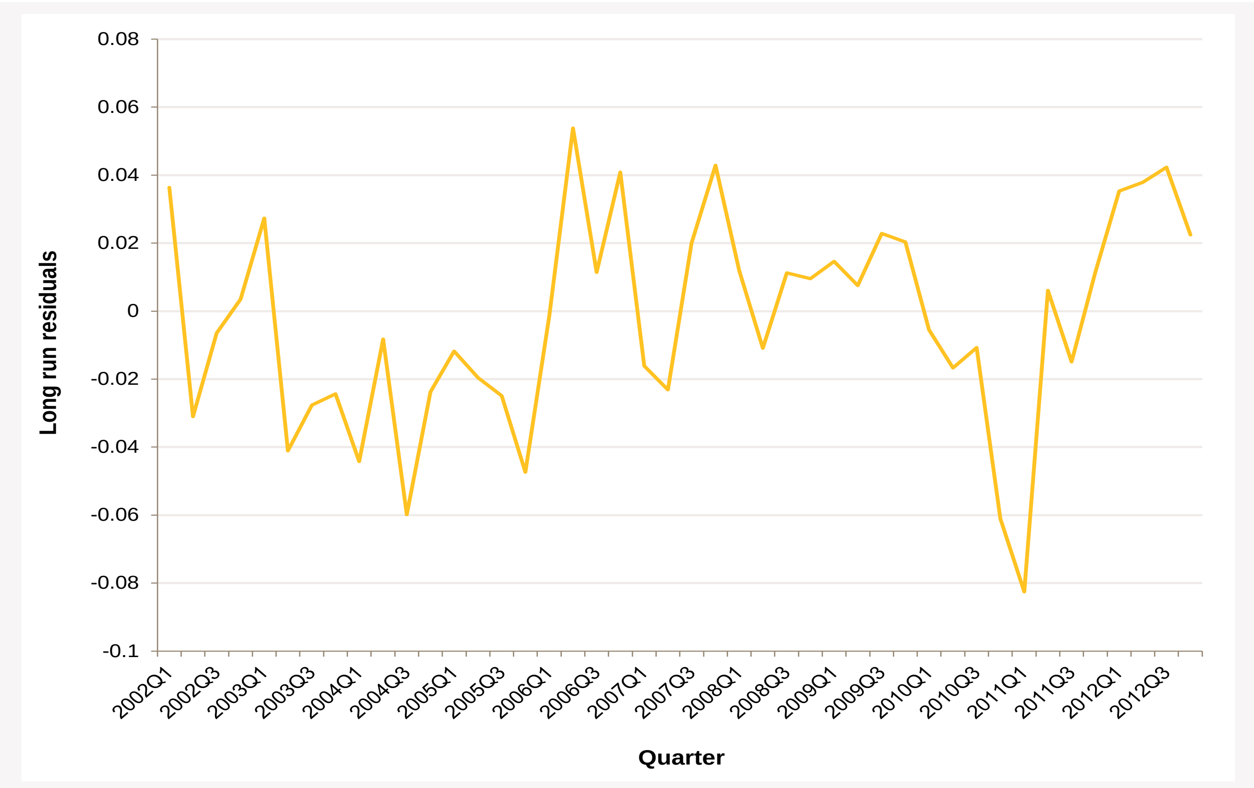


Figure 2-2 to Figure 2-6 present the residuals from the cointegrating equation for each region. The residuals appear to fluctuate and revert around a fixed point (zero). This strongly indicates that the residuals from the DOLS are stationary and that the variables are cointegrated so that a long run relationship between energy consumption and its drivers (income and electricity prices) exists.

The residuals from the DOLS estimator were then lagged and placed in a dynamic system similar to Equation 2-2 along with the lagged differences of all the main variables and temperature variables.

While an appropriate cointegrating long-run equation based on the DOLS was estimated for each region and an ECM was found that represented the data reasonably well, problems of interpretation followed because of the dominance of seasonality over trend in the data.

Seasonal data

The general approach when cointegrating is to place the lagged error correction (EC) term[15] within a dynamic system, such as an error correction model (ECM). 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.

However, energy consumption is highly seasonal due to varying temperatures throughout the year. AEMO found that the contemporaneous coefficients estimated in a standard ECM were unusually large. This led to large fluctuations in short-run consumption forecasts. This was possibly due to the ECM model being overwhelmed by the presence of seasonal effects in the data. For this reason, AEMO considered the ECM to be inadequate in forecasting energy consumption, and additional work was undertaken to develop more suitable annual energy models to handle the effects of seasonal data.

When developing the annual energy model, AEMO referred to the available literature on cointegration models specifically for seasonal data. Specifically, AEMO referred to the seasonal error correction model (SECM) discussed in Osborn (1993) and the periodic error correction model (PECM) discussed in Franses and Kloek (1995).

Integrated Dynamic Model

AEMO developed a forecast model similar to the seasonal models mentioned above. The aim was to integrate a long-run relationship between the variables (assuming cointegration) while allowing for short-run fluctuations consistent with the long-run equilibrium. AEMO refers to this model as the Integrated Dynamic Model (IDM).

The IDM provided AEMO with a model that assumes a long-run relationship between the variables that has satisfactory short-run and long-run solutions in the presence of seasonal data but also provides superior interpretational properties.

While AEMO could have developed two separate models (one for the short-run and one for the long-run), an integrated model that produces both short-run and long-run forecasts was preferred because the transition from short- to long-run does not need to be specified and can be gradual.

15 The residuals calculated from the DOLS equation.

The starting point for AEMO's IDM was to consider four separate models for each quarter; taking the first difference in this format is equivalent to fourth differencing in the standard quarterly times series. As such, the changes in the relevant variables have no seasonal component.[16]

If the elasticities are assumed to be common across quarters, then the separate four quarter equations can be seen as a 'stacked' system that can be estimated using Ordinary Least Squares (OLS) as a fixed effect panel data model. Essentially the model relates the fourth difference of demand to the fourth difference of each income, price, heating degree day, cooling degree day, and a constant. The model can be viewed as four separate models estimated in a single system.

However, such a model has no long-run solution. AEMO derived a long-run solution by integrating the EC term (the residuals estimated from the DOLS) lagged one period (one for each quarter) into the model. Such a model immediately suggests that, by adding an EC term lagged four periods, the enhanced model is the same as adding an EC term lagged one period (but four quarters) in a separately estimated quarterly model. This model can be viewed as four separate quarterly models estimated within a single system with the long-run solution embedded with the short-run dynamics.

Equation 2-3 — Integrated Dynamic Model

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

Where $\Delta 4$ 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, c2 through c5 are the estimates of the EC term and u is the error term.

The IDM is similar in form to an ECM and imposes constant elasticities for each variable across all seasons. By taking the fourth difference of the main variables, the IDM can account for seasonal differences so that short-run effects are seasonally adjusted.

The IDM allows for an equilibrium adjustment to vary across seasons so that the adjustment to the long run will also be seasonally corrected. To allow for an equilibrium adjustment in each quarter the first, second, third and fourth lagged residuals from the DOLS equation are placed in an IDM, similar to Equation 2-3, along with the fourth lagged differences of all the main variables and temperature variables to form the regional forecast models.

AEMO applied diagnostic tests on these models. The tests indicated a stable model for each NEM region. AEMO considered the IDM to be superior in modelling seasonal data than a standard ECM, based on impulse response functions for short-run demand response to innovations in the variables.

AEMO considers the regional models based on the IDM to be effective in providing stand-alone, short-run forecasting in the presence of seasonal data, while integrating a long-run component to remain consistent with the long-run relationship estimated by DOLS.

Lag length

Each of the estimated regional models would first incorporate four lags of the EC term to represent an equilibrium adjustment for each quarter. However, based on further analysis, AEMO found that not all of the lagged EC terms

[16] An ECM, in the traditional sense, will only take into account first differences. This would mean that changes will occur at a quarterly level. The IDM incorporates the fourth difference so that changes are from year to year rather than quarter by quarter.

were statistically significant. The following general strategy was used to select the lag length of the EC term in the IDM for each NEM region:

- Construct a model which includes four quarterly lagged EC terms.
- Check the significance of each of the lagged EC terms. Omit the EC term if it is not statistically significant at the 10% level of significance.
- For each lagged EC term, assess the coefficient. The coefficient for each lagged EC term must be negatively signed and is between zero and minus one to indicate a move back towards the long run.

For each IDM, only the fourth lagged EC term was found to be statistically significant with the correct sign and value. AEMO also investigated the impulse response of each model and found that all models exhibited sensible short- and long-run behaviours.

Impulse response function

An impulse response refers to the reaction of a dynamic system in response to some external shock or innovation to that system over time.

AEMO developed impulse response functions for each regional model to assess the dynamic response of energy consumption to one-off changes in the price and income variables. The regional impulse response functions provide assurance that the short-run effects are sensible and intuitive. The impulse response should show that electricity consumption responds positively to a one-off permanent increase in income and negatively to a one-off permanent increase in electricity prices. If there are no further disturbances to the system, the long-run response should be a smooth transition which demonstrates the estimated long-run elasticities.

Figure 2-7 — Regional response to permanent 1% increase in income

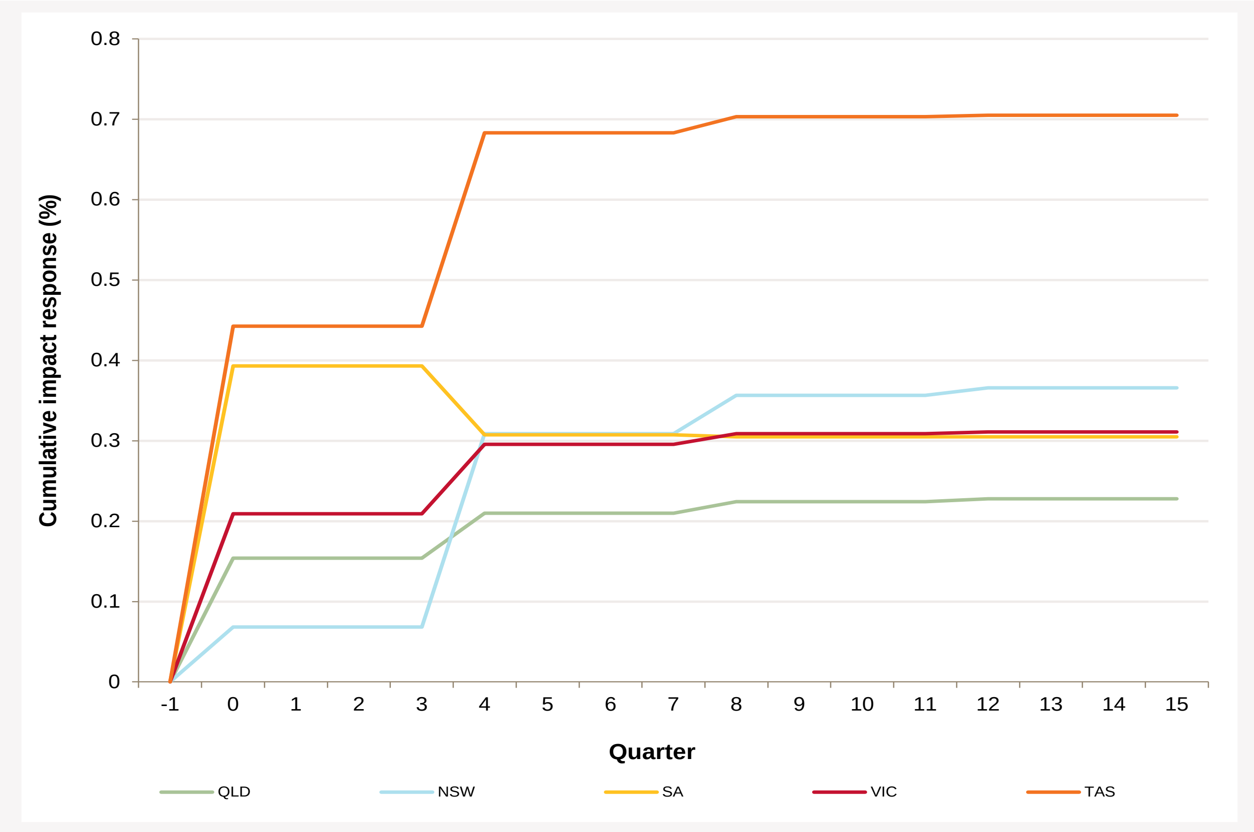


Figure 2-8 — Regional response to permanent 1% increase in electricity prices

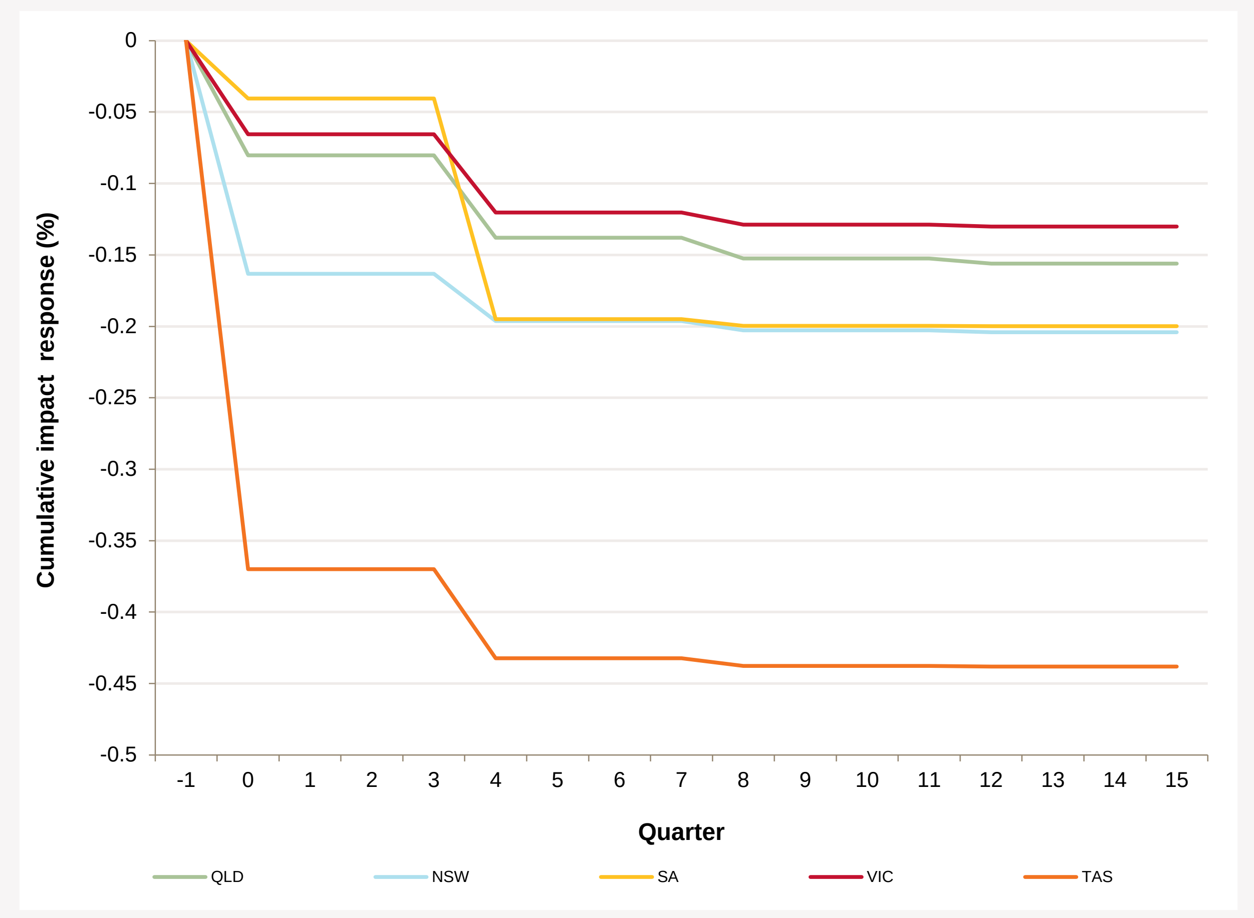


Figure 2-7 and Figure 2-8 show the impulse response of energy consumption for each regional model following a permanent 1% increase to income and retail electricity prices. The shocks do not appear transitory and appear to have long-run impacts on energy consumption, which is expected as AEMO found energy consumption to be cointegrated with income and electricity prices. After the initial shock, given that no further shocks enter the system, energy consumption in each region converges to a new long-run equilibrium that is consistent with the estimated long-run elasticities after approximately 10 quarters.

Intercept-corrected models

AEMO also produced additional alternative models which included dummy variables for the last four periods of 2012. This intercept-correction variable – which allows for a break in the last four periods – was included in the IDM after assessing the residuals produced from the final forecasting models. AEMO found that the forecast models trended higher than expected for the last four periods of 2012 in some regions. This could be a result of a permanent change in consumption patterns as a result of new policy implementation or could simply be a one-off event and consumption will revert back to historical trends.

While the intercept-correction variable was found to be marginally significant in some regions, the exact nature of this shift will remain unclear until AEMO has more data to assess. As a result there is not sufficient evidence to prefer the intercept-corrected model. Instead, AEMO has produced intercept-corrected models to provide a sanity check against its models, and will continue to monitor the forecast results as more data is made available.

2.1.3 New South Wales

The model adopted by AEMO to produce the 2013 New South Wales potential residential and commercial load forecast was based on a DOLS estimator to estimate the long-run income and price elasticities and an IDM to estimate the forecasting model.

The first step was to estimate a long-run equation using the DOLS estimator.

Equation 2-4 — New South Wales long-run DOLS

$$\mathrm{Log(y)} = 4.4178 + 0.3681\,\mathrm{Log(I)} - 0.2045\mathrm{Log(P)} + 0.0003\mathrm{HDD} + 0.0004\mathrm{CDD} + 0.0904\mathrm{s2} + 0.1122\mathrm{s3} + 0.0245\mathrm{s4}$$

Interpreting for the long-run model produces the following observations:

- Per capita consumption has a long-run income elasticity of +0.37, meaning that the long-run response to an increase of 1% in SFD per capita is a 0.37% increase in electricity consumption.
- Per capita consumption has a long-run price elasticity of -0.20, meaning that the long-run response to an increase of 1% in TPE per capita is a 0.20% decrease in electricity consumption.
- Heating degree days and cooling degree days are significant in explaining energy consumption in the long run but are only felt at the time of each heating or cooling event.
- Seasonal dummies are included to correct for seasonality in the data.

Once a long-run equation is estimated an EC term can be derived as the residuals from the long-run DOLS equation.

Equation 2-5 — New South Wales EC term

$$\mathrm{EC} = \mathrm{Log(y)} - [4.4178 + 0.3681\,\mathrm{Log(I)} - 0.2045\mathrm{Log(P)} + 0.0003\mathrm{HDD} + 0.0004\mathrm{CDD} + 0.0904\mathrm{s2} + 0.1122\mathrm{s3} + 0.0245\mathrm{s4}]$$

The EC term is lagged for each quarter and placed in an IDM along with the fourth differences of the price and income variables to derive the residential and commercial forecasting model. Only the fourth lagged EC term was found to be statistically significant with the correct sign and value so it was retained in the final model.

Equation 2-6 — New South Wales non-large industrial consumption forecasting model

$$\Delta_4\mathrm{y} = 0.0076 + 0.0684\Delta_4 I_s - 0.1631\Delta_4 P_s + 0.0003\Delta_4 CDD_s + 0.0003\Delta_4 HDD_s - 0.8019\mathrm{EC}(-4)$$

Interpreting the forecast model produces the following observations:

- The instantaneous response to a 1% increase in SFD per capita is a 0.07% increase in electricity consumption.
- The instantaneous response to a 1% increase in TPE per capita is a 0.16% decrease in electricity consumption.
- The adjustment to the new long-run following short-run disequilibria takes place at a rate of 80% after four quarters and gradually converges to the long-run equilibrium after approximately 10 quarters.

2.1.4 Queensland

The model adopted by AEMO to produce the 2013 Queensland potential residential and commercial load forecast was based on a DOLS estimator to estimate the long-run income and price elasticities and an IDM to estimate the forecasting model.

The first step was to estimate a long-run equation using the DOLS estimator and derive an EC term.

Equation 2-7 — Queensland long-run DOLS

$$\mathrm{Log(y)} = 5.8318 + 0.2289\,\mathrm{Log(I)} - 0.1573\mathrm{Log(P)} + 0.0004\mathrm{CDD} + 0.0321\mathrm{s2} + 0.0392\mathrm{s3} + 0.0096\mathrm{s4}$$

Interpreting for the long-run model produces the following observations:

- Per capita consumption has a long-run income elasticity of +0.23, meaning that the long-run response to an increase of 1% in GSP per capita is a 0.23% increase in electricity consumption.
- Per capita consumption has a long-run price elasticity of -0.16, meaning that the long-run response to an increase of 1% in TPE per capita is a 0.16% decrease in electricity consumption.
- Cooling degree days are significant in explaining energy consumption in the long-run but are only felt at the time of each cooling event.
- Seasonal dummies are included to correct for seasonality in the data.

Once a long-run equation is estimated an EC term can be derived as the residuals from the long-run DOLS equation.

Equation 2-8 — Queensland EC term

$$\mathrm{EC} = \mathrm{Log(y)} - [5.8318 + 0.2289\,\mathrm{Log(I)} - 0.1573\mathrm{Log(P)} + 0.0004\mathrm{CDD} + 0.0321\mathrm{s2} + 0.0392\mathrm{s3} + 0.0096\mathrm{s4}]$$

The EC term is lagged for each quarter and placed in an IDM along with the fourth differences of the price and income variables to derive the non-large industrial forecasting model. Only the fourth lagged EC term was found to be statistically significant and retained in the final model.

Equation 2-9 — Queensland non-large industrial consumption forecasting model

$$\Delta_4\mathrm{y} \;=\; 0.0016 \;+\; 0.1539\Delta_4 I_s - \;0.0803\Delta_4 P_s + 0.0003\Delta_4 CDD_s - 0.7486\mathrm{EC}(-4)$$

Interpreting the forecast model produces the following observations:

- The instantaneous response to an increase in GSP per capita of 1% is a 0.15% increase in electricity consumption.
- The instantaneous response to an increase in TPE per capita of 1% is a 0.08% decrease in electricity consumption.
- The adjustment to the long-run following short-run disequilibria takes place at a rate of 75% after four quarters and gradually converges to the long-run equilibrium after approximately 10 quarters.

2.1.5 Victoria

The model adopted by AEMO to produce the 2013 Victoria potential residential and commercial load forecast was based on a DOLS estimator to estimate the long-run income and price elasticities and an IDM to estimate the forecasting model.

The first step was to estimate a long-run equation using the DOLS estimator and derive an EC term.

Equation 2-10 — Victoria long-run DOLS

$$\mathrm{Log(y)} = 4.7165 + 0.3113\,\mathrm{Log(I)} - 0.1304\mathrm{Log(P)} + 0.0003\mathrm{HDD} + 0.0004\mathrm{CDD} + 0.0519\mathrm{s2} + 0.0682\mathrm{s3} + 0.0158\mathrm{s4}$$

Interpreting for the long-run model produces the following observations:

- Per capita consumption has a long-run income elasticity of +0.31, meaning that the long-run response to an increase of 1% in GSP per capita is a 0.31% increase in electricity consumption.
- Per capita consumption has a long-run price elasticity of -0.13, meaning that the long-run response to an increase of 1% in TPE per capita is a 0.13% decrease in electricity consumption.
- Heating degree days and cooling degree days are significant in explaining energy consumption in the long-run but are only felt at the time of each heating or cooling event.
- Seasonal dummies are included to correct for seasonality in the data.

Once a long-run equation is estimated an EC term can be derived as the residuals from the long-run DOLS equation.

Equation 2-11 — Victoria EC term

$$\mathrm{EC} = \mathrm{Log(y)} - [4.7165 + 0.3113\,\mathrm{Log(I)} - 0.1304\mathrm{Log(P)} + 0.0003\mathrm{HDD} + 0.0004\mathrm{CDD} + 0.0519\mathrm{s2} + 0.0682\mathrm{s3} + 0.0158\mathrm{s4}]$$

The EC term is lagged for each quarter and placed in an IDM along with the fourth differences of the price and income variables to derive the non-large industrial forecasting model. Only the fourth lagged EC term was found to be statistically significant and retained in the final model.

Equation 2-12 — Victoria non-large industrial consumption forecasting model

$$\Delta_4 \mathrm{y} = -0.0011 + 0.2089\Delta_4 I_s - 0.0655\Delta_4 P_s + 0.0004\Delta_4 CDD_s + 0.0003\Delta_4 HDD_s - 0.8452\mathrm{EC}(-4)$$

Interpreting the forecast model produces the following observations:

- The instantaneous response to an increase in GSP per capita of 1% is a 0.20% increase in electricity consumption.
- The instantaneous response to an increase in TPE per capita of 1% is a 0.07% decrease in electricity consumption.
- The adjustment to the long-run following short-run disequilibria takes place at a rate of 85% after four quarters and gradually converges to the long-run equilibrium after approximately 10 quarters.

2.1.6 South Australia

The model adopted by AEMO to produce the 2013 South Australia potential residential and commercial load forecast was based on a DOLS estimator to estimate the long-run income and price elasticities and a IDM to estimate the forecasting model.

The first step was to estimate a long-run equation using the DOLS estimator and derive an EC term.

Equation 2-13 — South Australia long-run DOLS

$$\mathrm{Log(y)} = 5.0842 + 0.3048\,\mathrm{Log(I)} - 0.1999\mathrm{Log(P)} + 0.0004\mathrm{HDD} + 0.0005\mathrm{CDD} + 0.0033\mathrm{s2} + 0.0203\mathrm{s3} - 0.0121\mathrm{s4}$$

Interpreting for the long-run model produces the following observations:

- Per capita consumption has a long-run income elasticity of +0.30, meaning that the long-run response to an increase of 1% in SFD per capita is a 0.30% increase in electricity consumption.

- Per capita consumption has a long-run price elasticity of -0.20, meaning that the long-run response to an increase of 1% in RPE per capita is a 0.20% decrease in electricity consumption.
- Heating degree days and cooling degree days are significant in explaining energy consumption in the long run but are only felt at the time of each heating or cooling event.
- Seasonal dummies are included to correct for seasonality in the data.

Once a long-run equation is estimated an EC term can be derived as the residuals from the long-run DOLS equation.

Equation 2-14 — South Australia EC term

$$\mathrm{EC} = \mathrm{Log}(\mathrm{y}) - [5.0842 + 0.3048\,\mathrm{Log}(\mathrm{I}) - 0.1999\mathrm{Log}(\mathrm{P}) + 0.0004\mathrm{HDD} + 0.0005\mathrm{CDD} + 0.0033\mathrm{s2} + 0.0203\mathrm{s3} - 0.0121\mathrm{s4}]$$

The EC term is lagged for each quarter and placed in an IDM along with the fourth differences of the price and income variables to derive the non-large industrial forecasting model. Only the fourth lagged EC term was found to be statistically significant and retained in the final model.

Equation 2-15 — South Australia non-large industrial consumption forecasting model

$$\Delta_4\mathrm{y} \ = \ -0.0021 + \ 0.3929\Delta_4 I_s - \ 0.0406\Delta_4 P_s + 0.0005\Delta_4 CDD_s + 0.0004\Delta_4 HDD_s - 0.9689\mathrm{EC}(-4)$$

Interpreting the forecast model produces the following observations:

- The instantaneous response to an increase in SFD per capita of 1% is a 0.39% increase in electricity consumption.
- The instantaneous response to an increase in RPE per capita of 1% is a 0.04% decrease in electricity consumption.
- The adjustment to the long-run following short-run disequilibria takes place at a rate of 97% after four quarters and gradually converges to the long-run equilibrium after approximately 10 quarters.

2.1.7 Tasmania

The model adopted by AEMO to produce the 2013 Tasmania potential residential and commercial load forecast was based on a DOLS estimator to estimate the long-run income and price elasticities and a IDM to estimate the forecasting model.

The first step was to estimate a long-run equation using the DOLS estimator and derive an EC term.

Equation 2-16 — Tasmania long-run DOLS

$$\mathrm{Log}(\mathrm{y}) = 1.9616 + 0.7049\,\mathrm{Log}(\mathrm{I}) - 0.4381\mathrm{Log}(\mathrm{P}) + 0.0002\mathrm{HDD} + 0.1095\mathrm{s2} + 0.1687\mathrm{s3} + 0.0139\mathrm{s4}$$

Interpreting for the long-run model produces the following observations:

- Per capita consumption has a long-run income elasticity of +0.71, meaning that the long-run response to an increase of 1% in SFD per capita is a 0.71% increase in electricity consumption.
- Per capita consumption has a long-run price elasticity of -0.44, meaning that the long-run response to an increase of 1% in TPE per capita is a 0.44% decrease in electricity consumption.

- Heating degree days are significant in explaining energy consumption in the long run but are only felt at the time of each heating or cooling event.
- Seasonal dummies are included to correct for seasonality in the data.

Once a long-run equation is estimated an EC term can be derived as the residuals from the long-run DOLS equation.

Equation 2-17 — Tasmania EC term

$$\mathrm{EC} = \mathrm{Log(y)} - [1.9616 + 0.7049\,\mathrm{Log(I)} - 0.4381\mathrm{Log(P)} + 0.0002\mathrm{HDD} + 0.1095\mathrm{s2} + 0.1687\mathrm{s3} + 0.0139\mathrm{s4}]$$

The EC term is lagged for each quarter and placed in an IDM along with the fourth differences of the price and income variables to derive the non-large industrial forecasting model. Only the fourth lagged EC term was found to be statistically significant and retained in the final model.

Equation 2-18 — Tasmania non-large industrial consumption forecasting model

$$\Delta_4\mathrm{y} = -0.0008 + 0.4426\Delta_4 I_s - 0.3699\Delta_4 P_s + 0.0003\Delta_4 HDD_s - 0.9168\mathrm{EC}(-4)$$

Interpreting the forecast model produces the following observations:

- The instantaneous response to an increase in SFD per capita of 1% is a 0.44% increase in electricity consumption.
- The instantaneous response to an increase in TPE per capita of 1% is a 0.37% decrease in electricity consumption.
- The adjustment to the long-run following short-run disequilibria takes place at a rate of 92% after four quarters and gradually converges to the long-run equilibrium after approximately 10 quarters.

2.2 Maximum demand

This section outlines the methodology used to develop maximum demand forecasts for residential and commercial load. These forecasts were prepared by Monash University's Business and Economic Forecasting Unit.

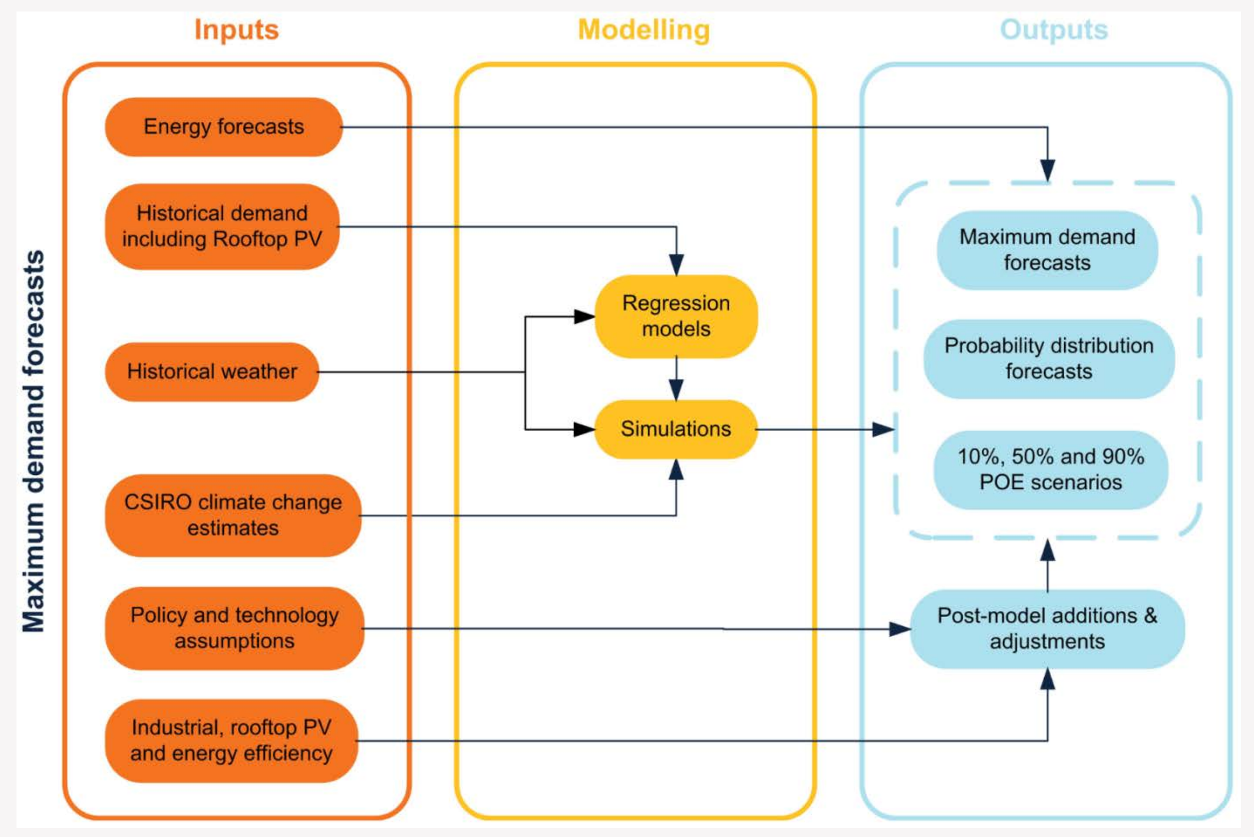
Maximum demand is the single highest demand that occurs in any half-hour period over an entire season. As this is the most extreme event that occurs in a season, and is highly dependent on weather, there is substantial uncertainty in its forecasts. For this reason a probabilistic distribution of maximum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

For each NEM region, forecasts are 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.[17] These models include calendar-dependent (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 energy forecasts. The models are used together with simulated half-hourly temperature data and residual re-sampling to develop POE forecasts of maximum demand.

[17] 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.

An overview of the maximum demand forecast methodology used in the 2013 NEFR is shown in Figure 2-9.

Figure 2-9 — Maximum demand forecasts diagram



2.2.1 Maximum demand model

For each summer and winter period, 48 separate models were built (one for each half-hourly period). The historical demand used to build the models is half-hourly non-large industrial demand, that is, native as generated demand with large industrial loads subtracted and estimates of rooftop PV added. This demand is equivalent to potential residential and commercial load plus transmission network losses and the generator auxiliary loads.

The model developed by Monash University to model the demand (after a log-transform) in each half-hour period, including short-run (half-hourly) and long-run (half-yearly) components, is presented in Equation 2-19.

Equation 2-19 — Short and long-run demand model

$$\log(y_{t,p}) = h_p(\mathrm{t}) + \mathrm{f}_p(\boldsymbol{w}_{1,t}, \boldsymbol{w}_{2,t}) + \mathrm{g}(\boldsymbol{z}_t) + \mathrm{u}_t$$

Where:

- $y_{t,p}$ denotes half-hourly demand (non-large industrial demand) on day t and half hour period p=1, 2, …, 48 (measured in megawatts).
- $h_p(\mathrm{t})$ models all calendar-dependent effects.
- $\mathrm{f}_p(\boldsymbol{w}_{1,t}, \boldsymbol{w}_{2,t})$ 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.

- $\boldsymbol{z}_t$ is a vector of current and past demographic and economic variables and degree days at time t (this term remains constant across each season). The term $\mathrm{g}(\boldsymbol{z}_{,t})$ is based on AEMO's annual energy model, in which forecasts are also developed on a quarterly basis. The component $\mathrm{g}(\boldsymbol{z}_{,t})$ for each season is based on the average of AEMO's forecasts for the two quarters in the season. (Note that the definition of summer and winter has been chosen to align with these quarterly forecasts.)
- u_t denotes the demand which is left unexplained by the model (the model residuals) at time t.

The model above separates out the seasonal average demand. The half-hourly demand across different years is normalised by dividing the half-hourly demand values by the seasonal average demand. Equation 2-20 represents the normalisation of half-hourly demand.

Equation 2-20 — Normalisation of half-hourly demand

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

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 h/1,000 where h is the number of hours in season i). The seasonal average demand $\bar{\mathrm{y}}_{\mathrm{i}}$ is equal to $\log(\mathrm{g}(\boldsymbol{z}_t))$ in Equation 2-19.
-
- The fixed relationship between half-hourly demand and average demand in Equation 2-20 means that forecasts generated using these models will reflect historical average load factors. Monash University included model enhancements to address this issue, discussed in Section2.2.3.
- The log-transform of half-hourly normalised demand is modelled across different years of data according to Equation 2-21.

Equation 2-21 — Half-hourly normalised demand models

$$\log(\mathrm{y}^*_{\mathrm{t,p}}) = h_p(\mathrm{t}) + \mathrm{f}_p(w_{1,t}, w_{2,t}) + \mathrm{u}_t$$

For half-hourly demand $y^*_{t,p}$, 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 are as follows:

- Variable selection followed a stage-wise process using groups of input variables to determine the model with the lowest mean square error.
- Calendar effects are modelled using dummy variables and include day-of-week, time-of-year and public holidays, including days immediately before and after public holidays.
- Temperature effects $\mathrm{f}_p(\boldsymbol{w}_{1,t}, \boldsymbol{w}_{2,t})$ are modelled using additive regression splines.
- Temperatures from the last three hours and the same period from the last six days are included, as are the maximum and minimum temperature in the last 24 hours and the average temperature in the last seven days.
- The daily temperature data, using the same locations, was used by both AEMO and Monash. The same warming trends based on the Commonwealth Scientific and Industrial Research Organisation (CSIRO), Department of Climate Change and Energy Efficiency, and the Bureau of Meteorology (2009) were applied to simulated future temperatures to allow for climate-change impacts.

The selected model was used to predict historical demand and the residuals were compared to predicted demand. From this procedure an evident bias for large demand predictions was subsequently used to adjust forecasts using this model.

2.2.2 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 simulates numerous temperature patterns based on historical data.[18]

Each of the 1,000 seasons of simulated temperature data allowed Monash 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 results 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 u_t in Equation 2-19 and Equation 2-21. To capture this random element, Monash 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 normalised maximum demands was re-constituted with the underlying seasonal average demand (as in Equation 2-20). The seasonal average demand, which is based on the annual energy models, also has a random element added in for each simulation to represent the uncertainty in the seasonal average demand forecast.

The 10%, 50% and 90% POE maximum demand forecasts were obtained by taking the appropriate percentile of the 1,000 simulated maximum demands for each season. A 10% POE maximum demand forecast has a 1-in-10 chance of being met or exceeded in any season. A 50% POE forecast has a 50-50 chance of being met or exceeded, and a 90% POE forecast has a chance of being met or exceeded in 9 times out of 10.

2.2.3 Changes from 2012

For the 2013 NEFR, Monash has implemented the following improvements to the modelling and forecasting work:

- Review of the previous price elasticity work for South Australia[19], which was extended to all NEM regions. This work found that customer sensitivities to price generally vary with time of day and time of year. Reflective peak price elasticities were incorporated into the seasonal average demand component of the maximum demand modelling.
- Use of the simulated temperature data to make an adjustment to the seasonal average demand in each simulation based on heating and cooling degree days. This allowed for temperature related variations in the seasonal average demand.
- Allowing for changes in the load factor over time. Based on research undertaken by Monash University on load factors[20], the maximum demand forecast model now adjusts over time to allow a superior model fit. This dynamic adjustment allows for changes over time in behaviour, such as air conditioning saturation effects.
- Incorporating half-hourly rooftop PV traces provided by AEMO to ensure consistency in rooftop PV measures used by AEMO and Monash.

[18] 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..

[19] See Fan, S. and R. J. Hyndman (2013). *The price elasticity of electricity demand in the National Electricity Market*. Report for Australian Energy Market Operator. Monash University Business and Economic Forecasting Unit.

[20] See Fan, S. and R. J. Hyndman (2013). *Load Factor Analysis in the National Electricity Market and the implications for the peak demand Forecast*. Report for Australian Energy Market Operator. Monash University Business and Economic Forecasting Unit.

CHAPTER 3 - LARGE INDUSTRIAL LOAD

3.1 Forecasting large industrial load

This chapter provides the methodology used to develop annual energy and maximum demand forecasts for large industrial-scale loads. These are typically transmission-connected customers. While this is a relatively small number of customers, this sector accounts for a large proportion of annual energy usage in each National Electricity Market (NEM) region.

The loads typically include aluminium and steel producers, liquefied natural gas (LNG) export and related facilities, paper and chemical producers, large grid-connected mines and water desalination. Significant changes in this sector are fairly rare; usually only when plants open, expand, close, or partially close. The half-hourly demand for this sector is not temperature sensitive, although desalination and water pumping is affected by rainfall.

The relatively small number of facilities means it is possible to discretely consider and individually to predict each customer's consumption trend.

Forecasting on a discrete basis is subject to the following limitations:

- The information AEMO receives from non-public sources is sensitive and cannot be made publicly available. This is managed by aggregating information to a regional level.
- Some new loads are from new customers with no historical data. AEMO will not necessarily be aware of all of these new loads for incorporation into the forecasts, particularly when these projects are speculative.
- Each facility is subject to different commercial pressures so changes to their operation are very difficult to predict. In particular, plant closures can be abrupt and information on them is not readily available.

3.2 Approach used for the 2013 NEFR

AEMO contacted operators of certain large industrial loads directly to discuss the public information about their future operations, and to give them an opportunity to provide their annual energy and maximum demand forecasts for confidential use by AEMO. Where sufficient information was not available from the operator, additional forecasts were sought from the relevant transmission network service provider (TNSP) or distribution network service provider (DNSP), and validated by industry. AEMO also reviewed historical metering data from the facilities.

This approach has provided forecasts that reflect the views of the operators, who are presumed to have the best information about potential future output.

AEMO used this technique for all transmission-connected customers in the NEM and a limited number of large distribution-connected customers of interest. All non-surveyed customers are in the residential and commercial sector, so that category contains many facilities that would generally be considered industrial.

One learning from the process used this year was that a consumption threshold, rather than connection voltage, could be a better classification for future forecasts. AEMO will investigate this approach for the 2014 NEFR.

The operators were asked to provide the following three forecasts:

- High, reflecting positive commercial circumstances for the facility in question.
- Medium, reflecting the current most likely level of operation for expected conditions.
- Low, reflecting unfavourable commercial conditions.

After appropriate consideration and assessment of the responses, AEMO in turn linked these responses to the high, medium and low economic growth scenarios used in the NEFR.

In some cases, prospective customers or expansions that are yet to be committed were included in the high case only. Where existing customers were known from public information to be assessing possible closure, a shutdown was included in the low scenario only. This was applied to Victoria's Point Henry aluminium smelter from 1 July 2014.[21]

In some cases, operators advised that the high scenario should include the installation of co-generation, which reduced the high scenario load forecast for those customers.

Prospective expansions, new projects or closures cause the majority of variation between economic scenarios.

To determine the large industrial load contributions to maximum demand forecasts, AEMO reviewed several years' historical consumption at times of regional summer and winter peak. From these a diversity factor was determined for each large industrial load and was applied to the corresponding growth forecasts.

Large industrial load representation issues to be noted

Desalination and water-supply pumping loads vary due to rainfall rather than economic conditions, so the economic scenarios were equalised. The initial years of the outlook period were estimated from information about likely short-term conditions, then trended to their expected long-term average consumption. For the maximum demand forecast, AEMO adjusted these loads down to account for their demand–response capability. This capability was excluded in the separate demand-side participation estimate to avoid double-counting (see Chapter 7).

The demand–response capability of a zinc refinery in Queensland was similarly presented as a reduction in large industrial load maximum demand. All other large industrial load demand–response capabilities are shown in Chapter 7. AEMO intends to consolidate demand–response capabilities in the 2014 NEFR.

The energy consumption of each New South Wales pumped storage schemes is included as large industrial load at their historical average consumptions, totalling approximately 470 GWh per year. These loads are highly variable depending on wholesale electricity market conditions, and the low scenario reduces their load by 50% over 20 years. They are all assumed to be shutdown at time of peak and therefore don't contribute to maximum demand. Queensland's Wivenhoe pumped hydro is not included. These approaches are consistent with the 2012 NEFR for each scheme. AEMO intends to investigate exclusion of all pumped hydro in the 2014 NEFR.

The LNG projects represent the most significant large industrial load growth, including an uncommitted project in the high scenario. The majority of LNG load occurs upstream, mainly in pipeline compression. Liquefaction energy is mostly supplied on-site.

Customer announcements occurring after survey completion and not taken into account

In Victoria, Ford has announced an intention to cease production in October 2016.[22] These plants were not part of the large industrial load assessment, so this change appears in the residential and commercial sector.

In Tasmania, Gunns (Longreach) has recommenced operations.[23] This is not taken into account in the forecasts.

In South Australia, Rex Minerals has announced an intention to proceed with the Hillside mine to begin operation in 2016.[24] This is not taken into account in the forecasts.

3.3 Changes from the 2012 methodology

The large industrial load methodology has been changed from the approach used in 2012.

In 2012 AEMO developed large industrial load forecasts using a combination of TNSP information and the best available public information in the short term, and assumptions based on long-term trends in the longer term. In

[21] Available at: http://www.alcoa.com/australia/en/news/releases/2012_06_29_Point_Henry_Review_Complete.asp#.
[22] Available at: http://www.ford.com.au/about/newsroom-result?article=1249024395989.
[23] Available at: http://www.bordermail.com.au/story/1563831/gunns-woodchip-mill-reopens/?cs=2452.
[24] Available at: http://www.rexminerals.com.au/wp-content/uploads/2013/02/20130604-Rex-signs-EPC-and-Financing-MOU-FINAL.pdf.

2012 customers were not directly contacted. Maximum demand forecasts were also drawn from this data using average megawatt values from the energy forecasts, as many of the large industrial loads were relatively constant throughout the year.

For New South Wales, a number of commercial consumers were moved from the residential and commercial category into the large industrial category. These were added to ensure adequate dilution of forecast profiles within the aggregated data to protect confidential customer lad information, after the closure of the Kurri Kurri aluminium smelter. As a result, the historical and forecast large industrial annual energy values have increased, and residential and commercial annual energy values have decreased, by this amount.

For Victoria, the 2013 large industrial annual energy forecasts and historical data include demand met by the generators, Anglesea Power Station and Portland Wind Farm. In 2012 forecasts the loads of Point Henry and Portland Aluminium were reduced by this generation. However, as this generation was included in the aggregate published, the 2012 residential and commercial, and non-large industrial energies were increased by this generation to ensure overall supply/demand remained in balance.

In the 2013 representation, the historical and forecast large industrial annual energy values have increased to include the component met by this generation, and residential, commercial, and non-large industrial annual energy has decreased by the same amount.

[This page is left blank intentionally]

CHAPTER 4 - ROOFTOP PHOTOVOLTAIC

4.1 Introduction

This chapter provides the methodology used to develop the 2013 National Electricity Forecasting Report (NEFR) rooftop photovoltaic (PV) forecasts. The 2013 methodology incorporates changes that address stakeholder responses to the 2012 forecasts and approach. The changes are summarised in Section 4.7.

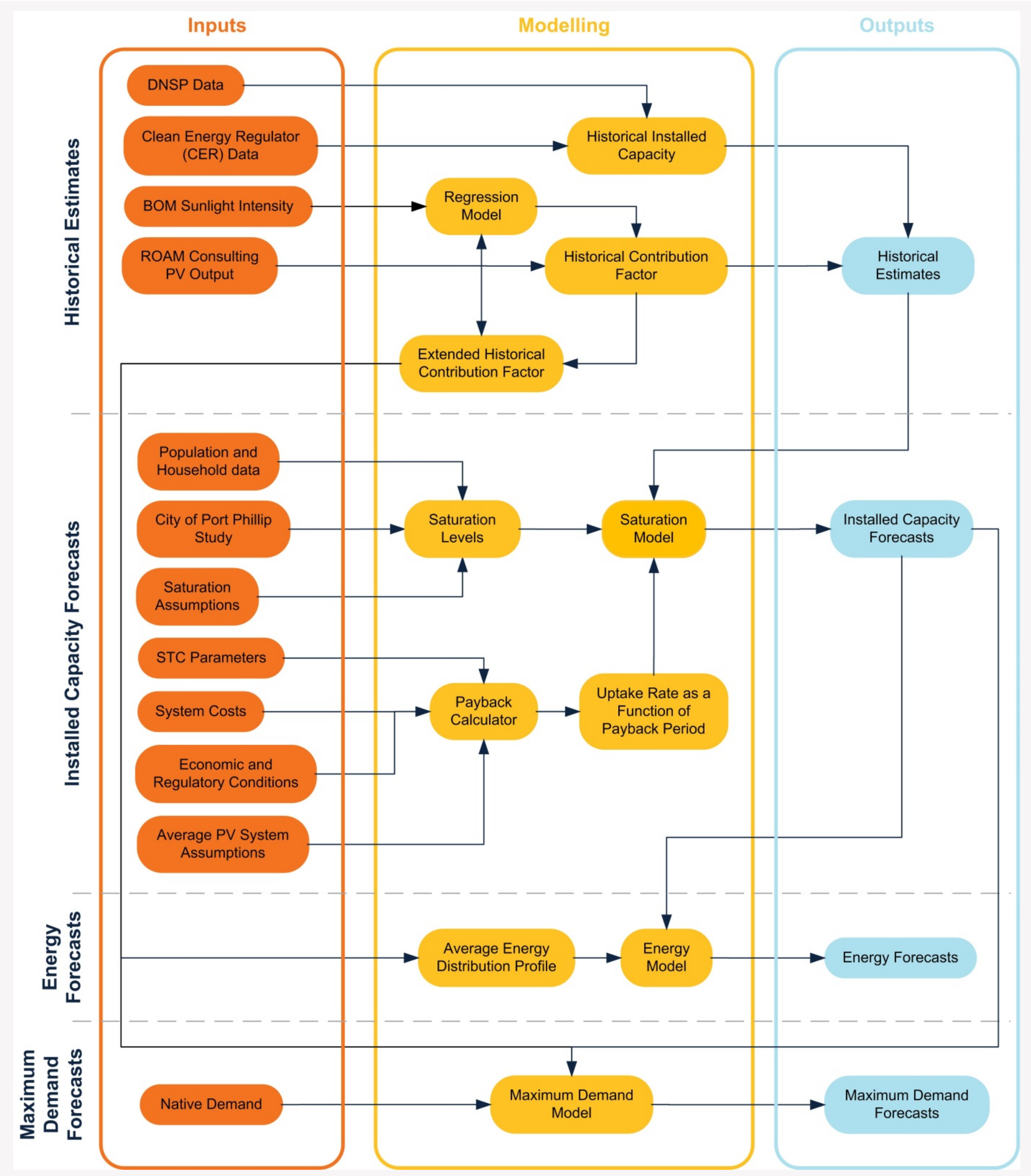
This is the second year that AEMO has considered the impact of rooftop PV generation in offsetting actual and forecast annual energy and maximum demand in the National Electricity Market (NEM). AEMO continues to improve and develop the rooftop PV modelling and forecast accuracy, as well as account for the main drivers to rooftop PV uptake.

Changes to the methodology used in the 2012 NEFR are as follows:

- Development of a comprehensive historical estimate of rooftop PV.
- Modelling of a typical rooftop PV system payback period using several key drivers.
- Estimating uptake rate as a function of the payback period.
- Application of saturation levels to installed capacity forecasts.
- Improvements in the methodology and data sources to estimate rooftop PV contribution at times of maximum demand.

An overview of the rooftop PV forecast methodology used in the 2013 NEFR is shown in Figure 4-1.

Figure 4-1 — Rooftop PV forecast diagram



4.2 Rooftop PV scenarios

This section describes the three rooftop PV scenarios used for the 2013 NEFR forecasts. The three scenarios reflect combinations of drivers that provide different levels of incentive for new rooftop PV installations. The three scenarios are:

- The Slow Uptake scenario, which is a combination of drivers that do not incentivise new installations.
- The Moderate Uptake scenario, which is a combination of drivers that provide moderate incentives for new installations. This is the most likely scenario.
- The Rapid Uptake scenario, which is a combination of drivers that strongly incentivise new installations.

All three scenarios assume the Australian Government's national Renewable Energy Target (RET) scheme remains in place until 2030.

Economic payback, through reduced electricity bills and government incentives, is the primary factor influencing whether a household or business installs a rooftop PV system. The scenarios reflect the following main drivers that determine economic payback periods:

- Economic conditions.
- Rooftop PV system costs.
- Government incentives.

The scenarios and drivers are shown in Table 4-1:

Table 4-1 — Drivers and mapping of rooftop PV scenarios

Driver	Slow Uptake scenario	Moderate Uptake scenario	Rapid Uptake scenario
Economic conditions	Conservative retail and wholesale electricity prices and CPI.	Medium retail and wholesale electricity prices and CPI.	High retail and wholesale electricity prices and CPI.
Rooftop PV system costs	Slow system cost reductions.	Moderate system cost reductions.	Rapid system cost reductions.
Government incentives[25]	Feed-in prices[a] largely below average historical values.	Export prices follow a similar trend to historical values.	Export prices largely above average recent values.

a. Refers to the feed-in tariff, which is the dollar amount per kWh that an electricity retailer pays for rooftop PV electricity fed into the power system.

Refer to Table 1-1 to see how the three rooftop PV scenarios map to the 2012 AEMO scenarios, the 2013 NEFR references, and other related scenarios.

4.3 Historical estimates

This section describes the development of a historical, 30-minute interval data trace of rooftop PV generation spanning from January 2009 to February 2013 and applicable in each NEM region. Scant rooftop PV data was available prior to January 2009, and generation was assumed to be negligible.

The data sources used to estimate historical rooftop PV data include a rooftop PV hourly average generation (MW) per installed capacity (MW) trace (termed "contribution factor traces") for each NEM jurisdiction developed by ROAM Consulting as part of the 100% Renewables Study[26]; estimates of rooftop PV installed capacity (MW)

[25] In all scenarios, the Renewable Energy Target (RET) is assumed to remain unchanged.

[26] Solar PV data from ROAM Consulting as part of the 100% Renewables Study is available at http://www.climatechange.gov.au/sites/climatechange/files/files/reducing-carbon/Solar_-_Rooftop_PV_-_1_MW_traces_-_version_2.xlsx.

provided to AEMO by distribution network service providers (DNSPs); and sunlight intensity data available from the Bureau of Meteorology (BOM).[27]

Reliable estimates of historical rooftop PV installed capacity and generation levels are important as these can be used in several ways when developing rooftop PV forecasts. This includes:

- Determining the starting point of rooftop PV forecasts.
- Assessing the accuracy of historical forecasts.
- In calibrating of model parameters used to develop rooftop PV forecasts.
- For statistical analysis and to identify rooftop PV data trends.
- Identifing correlations with other data such as sunlight intensity and as a means to project future data.

Two main historical half-hourly data traces were developed and used to estimate other historical data such as aggregate rooftop PV power and energy in each NEM jurisdiction. These traces are:

- Contribution factor trace (generation as a percentage of installed capacity).
- Installed capacity trace.

To determine historical power and energy, the following formulas were applied:

- Half-hourly average power (MW) = (half-hour average contribution factor) × (installed capacity (MW)
- Energy generation in any half hour (MWh) = half-hourly average power (MW) × (0.5 hour)

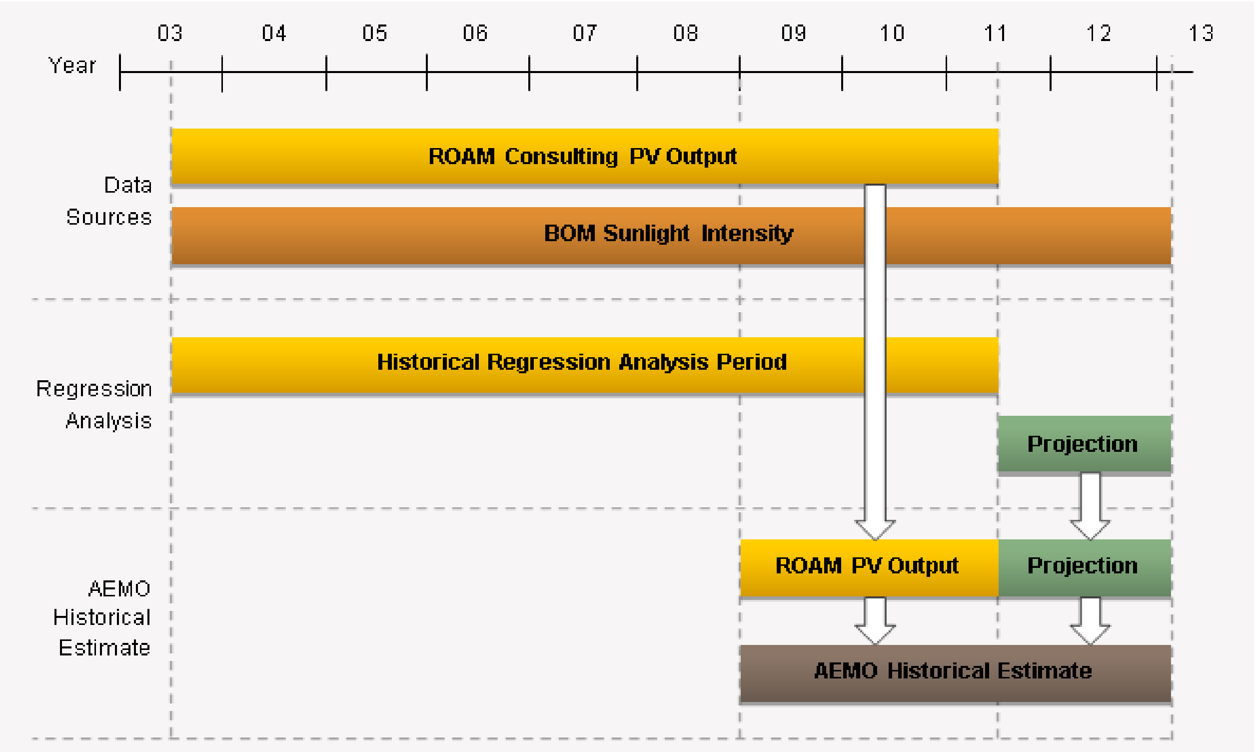
The methodology used to develop historical rooftop PV contribution factor data and historical rooftop PV installed capacity data is shown in the sections below.

4.3.1 Historical rooftop PV contribution factor

The historical contribution factor was estimated using a combination of ROAM Consulting data and projected rooftop PV data using sunlight intensity. A historical regression analysis between these datasets was carried out to project rooftop PV output data using sunlight intensity data. A summary of this process follows.

[27] Solar exposure data from the Bureau of Meteorology. Available at http://www.bom.gov.au/climate/data/?ref=ftr.

Figure 4-2 — Historical contribution factor process



The Roam Consulting and BOM datasets of daily sunlight and daily rooftop PV output are correlated based on matching load duration curves. The two datasets are sorted from largest to smallest and each BOM sunlight data point is used to retrieve the corresponding ROAM Consulting rooftop PV output data point. Daily rooftop PV output is projected from July 2011 to February 2013 using the correlations established between the two datasets and the BOM sunlight data from July 2003 to June 2011. This approach accounts for non-linear relationships between daily sunlight intensity and daily rooftop PV output.

AEMO's historical estimate was then formed by combining the ROAM Consulting rooftop PV output data with the projected data from the historical regression analysis.

The ROAM Consulting rooftop PV and BOM sunlight intensity datasets both relate to capital city location for each NEM region. Consequently, this approximation does not take into account the weather conditions and corresponding rooftop PV output from rooftop PV systems located remotely from the capital city. Given the concentration of population in the capital cities, AEMO does not expect that this would materially affect the results. The spread of rooftop PV panels across a NEM region may be the subject of future studies, as there may potentially be ways to estimate the output from these systems.

ROAM Consulting's rooftop PV data had an overall average contribution factor (generation as a percentage of installed capacity) of 18–19%. AEMO advised (based on PVoutput.org data), that the observed NEM contribution factor ranged from 14–16% (i.e., about one-tenth lower).

The ROAM solar output data was derived from calculating solar irradiation based on satellite imagery. As such, the output calculated by ROAM Consulting might be more reflective of ideal conditions and may not necessarily capture imperfections due to geographical shading, atmospheric interference, and in particular, low zenith angles particularly around sunrise and sunset.

One implication of this is the introduction of greater inaccuracy when considering output for a specific half-hour around this time. Estimated error ranged between -50% to +25% of peak output. However, this issue is irrelevant when considering annual energy, as the total energy output for each day is kept constant. Estimate error for annual energy was 4%.

4.3.2 Historical installed capacity

The historical installed capacity datasets for the period January 2009 to December 2012 are based on data provided by the DNSPs in each NEM region. AEMO considers this to be a reliable source of information that is both timely and accurate, given that installed capacity is a key component for estimating historical rooftop PV energy generation as well as developing installed capacity forecasts.

Data from the Clean Energy Regulator (CER)[28] is also used to validate the DNSP data. There are some discrepancies between the DNSP and CER installed capacity data sources, in particular an inherent lag in the CER data, which may take up to 12 months to be published. To account for this, AEMO performed a regression analysis using historical CER data to estimate CER data for the 12-month lag period.

In general the CER data closely matched the DNSP data and was consequently used to estimate historical installed capacity.

CER data was used to estimate historical installed capacity growth in January and February 2013 in the absence of DNSP data.

4.3.3 Adjustment of 2012 historical installed capacity

As part of the 2012 methodology, the DNSP data was scaled to match the approximate trend in the CER data; this accounted for historical discrepancies between these two data sources. Revisions of the data sources over the past 12 months have indicated there is a general agreement in recent months' data despite historical discrepancies.

As a result, in 2013 the DNSP data was not scaled, and has been used directly to estimate historical installed capacity for the period January 2009 to December 2012.

4.4 Installed capacity forecast

This section describes the methodology used to develop the rooftop PV installed capacity forecasts. These reflect the total rated output capacity of all systems in the NEM regions. These forecasts were used as inputs to develop the annual energy forecasts and the contribution to maximum demand forecasts.

The installed capacity forecasts were developed by following a number steps for each NEM region and for each uptake scenario. These steps are as follows:

1) Derive payback period forecasts for a typical rooftop PV system in each NEM jurisdiction.
2) Develop and calibrate a relationship between payback period and installed capacity uptake rate using historical and 2012 NEFR data.
3) Derive installed capacity forecasts as a function of the payback period.
4) Apply saturation levels to the installed capacity forecasts.

These steps and various components are described in more detail in the sections below.

4.4.1 Modelling the payback period

A payback calculator was developed to forecast the number of years required to repay initial rooftop PV system costs (i.e., the payback period). The payback period results were converted into installed capacity growth rates, which were then applied to existing installed capacity to generate the forecasts.

Table 4-2 below provides a summary of the parameters modelled in the payback period calculator and the values used in the simulations.

[28] CER. Available at: http://ret.cleanenergyregulator.gov.au/REC-Registry/Data-reports.

Table 4-2 — Payback period calculator parameters and assumptions

Parameter	Description	Value
Feed-in tariff rate	Rate paid to customer for surplus electricity sent back to the grid. This value is based on the actual rates as reported by local regulatory determinations or policies in each NEM region.	Varies by NEM region
System size	The average solar rooftop PV system size for new installations (moving average, non-cumulative).	3.5 kW
System cost per Watt	Represents the cost per Watt of a solar rooftop PV panel before a rebate is provided.	$3.00[29]
System cost reduction	The expected annual decrease in the cost per Watt of solar rooftop PV panels as a percentage of the previous year's cost.	5%
Percentage of energy exported	Represents the energy exported to the grid as a percentage of the energy generated by solar rooftop PV.	50%
Number of STCs	The number of small-scale technology certificates (STCs) eligible to be created for the system depending on region.	Varies by solar region[30]
STC price	The estimated market price for STCs.	$30.00
Abolishment year of STC rebate	The year when the STC rebate for new systems is expected to be abolished, after which no rebate would be provided for new rooftop PV systems.	2030
Retail electricity price[31]	The nominal electricity price for electricity that would be paid by consumers with no solar rooftop PV installed.	Varies by NEM state
Wholesale electricity price	The price at which retailers would be expected to purchase electricity.	Varies by NEM state
Consumer Price Index (CPI)	The forecast Consumer Price Index (CPI).	Varies by NEM state

Factors that the payback calculator does not account for are as follows:

- Impacts and costs of rooftop PV on transmission and distribution networks.
- Costs associated with enhancing the network to support rooftop PV uptake, including voltage control and protection settings.
- Impact of rooftop PV uptake on network tariffs.
- Market impact of rooftop PV increasing total generating capacity in the NEM.

4.4.2 Modelling the uptake rate as a function of the payback period

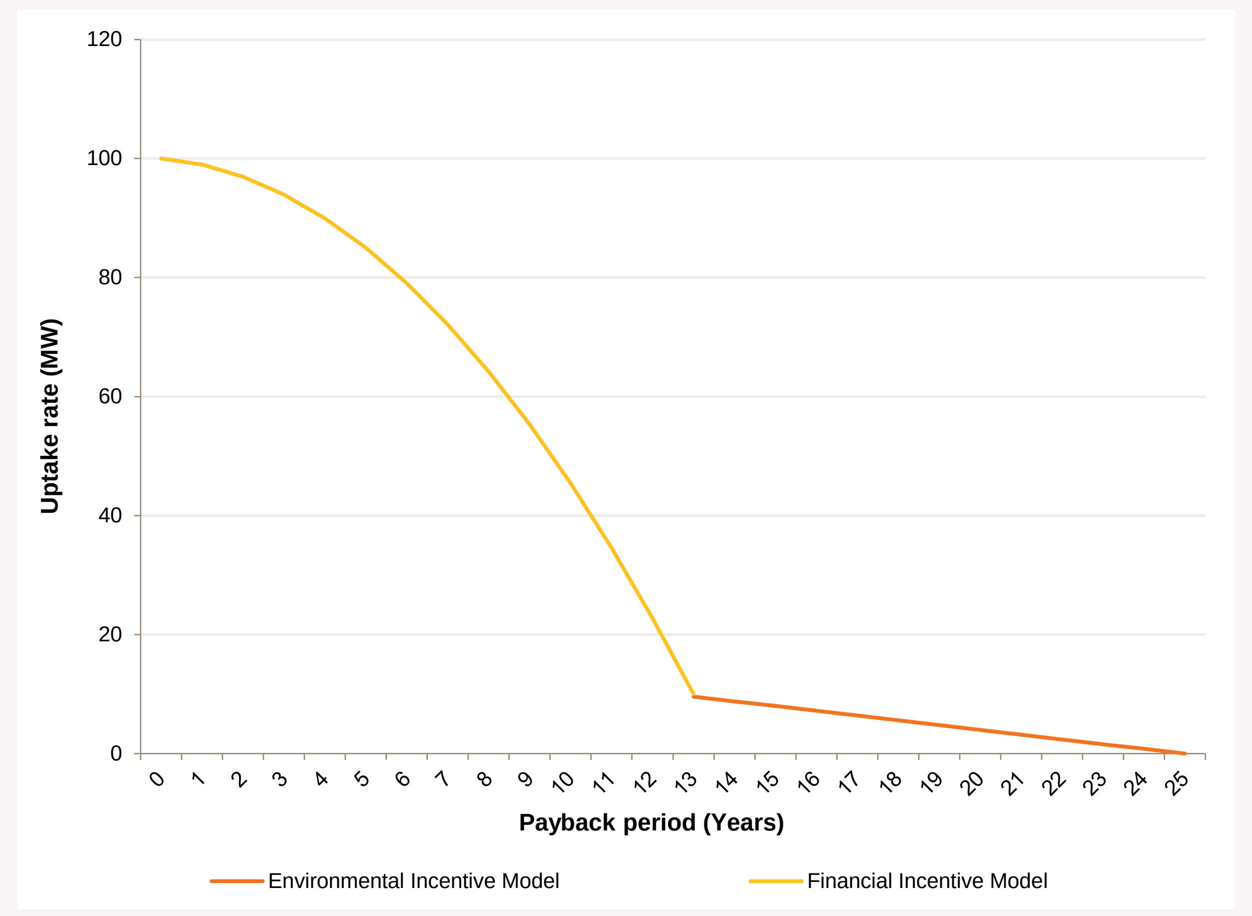
AEMO used a study conducted by Intelligent Energy Systems (IES) for the Clean Energy Council (CEC)[32] in June 2012, involving analysis of possible modifications to the Queensland solar feed-in tariff, as the basis for developing a relationship between the payback period and installed capacity growth rates.

In the report, this relationship is modelled using a mathematical function that models the primary driver (a financial incentive for relatively low payback periods) and an environmental/social conscience incentive (for relatively high payback periods.)

[29] $3.00 is accurate as at December 2012, in real 2011-12 dollars.
[30] The calculation of STC numbers is available at http://ret.cleanenergyregulator.gov.au/ArticleDocuments/205/solar-stc-calculations-1212.pdf.aspx.
[31] Retail and wholesale electricity price, and CPI forecasts, are sourced from NIEIR.
[32] IES. Available at: http://www.cleanenergycouncil.org.au/resourcecentre/reports.html.

AEMO used a similar structure to the relationship published in the IES report to model the relationship between the payback period and the growth rate. This is shown in Figure 4-3 below:

Figure 4-3 — Uptake rate as a function of payback period



As shown in Figure 4-3, most rooftop PV installed capacity growth is expected to be driven by a financial incentive in the form of a lower payback period. A relatively small proportion of growth is expected to be driven by an environmental/social conscience incentive.

The financial incentive was modelled using a second-order polynomial equation that applies for payback periods below a certain threshold year value. The equation has the form shown below, where y represents the rooftop PV uptake rate and x represents the payback period:

Equation 4-1 — Financial incentive modelling equation

$$y = ax^2 + bx + c$$

The environmental incentive was modelled using a linear equation that applies above the given threshold year value and is assumed to go to zero growth at a payback period of 25 years. The equation has the form shown below, where y represents the rooftop PV uptake rate and x represents the payback period:

Equation 4-2 — Environmental/conscious incentive modelling equation

$$y = ax + b$$

The coefficients of the equations as well as the threshold values were calibrated using best fit trend line equations in conjunction with historical and 2012 NEFR data. These parameters also varied between uptake scenarios and between NEM regions.

One difference in applying the transfer function between AEMO's and the IES methodology was the way the effects of saturation were modelled. Saturation is modelled implicitly in the IES methodology as an input into the transfer function, while saturation effects are modelled at a later stage in AEMO's methodology using a separate limit equation. (Refer to Section 4.4.3 for further details on the application of saturation levels to installed capacity forecasts).

As a result of the limited availability of historical rooftop PV installed capacity data in the NEM (approximately four years of data compared with the forecast outlook period of 20 years), there are inherent difficulties in the amount of data that is able to be used for a statistical regression analysis as the basis for forecasting future installed capacity.

The current forecasting methodology is based on this historical data and any small aberrations in the data may be overestimated by the regression analysis. This aspect is expected to improve in the future as more actual rooftop PV data becomes available.

4.4.3 Estimating saturation levels

Forecasting installed capacity requires information about the extent of suitable roof space for rooftop PV installations. Saturation capacity is the value at which all suitable roof space is used.

The Victorian Government Department of Sustainability and Environment commissioned Entura – Hydro Tasmania to undertake a study of rooftop PV saturation capacity in the City of Port Phillip in Melbourne.[33] Rooftops were mapped with aerial lasers, analysed by computer, and a sample verified manually. Allowing for roof orientation and tilt, solar exposure, shading, irregular geometry and minimum size, a conservative estimate of 220 MW of rooftop PV capacity was reached. This comprised 180 MW on dwellings and 40 MW on large flat roofs, assumed to be commercial.

According to census data, the City of Port Phillip is very densely populated by Australian standards. Only 14% of its 43,728 occupied private dwellings are separate houses, with the majority being units and apartments; the Australian average is 75%. Dividing the city's estimated residential potential of 180 MW by the number of occupied private dwellings results in an average installed capacity per dwelling of over 4 kW.

In the absence of a more comprehensive study, this result was used as the starting point for assessing the NEM's installed capacity at saturation. Due to the small study size, conservative assumptions were applied.

First, the average system size per household for saturation was reduced from 4 to 3.5 kW. This allows for aesthetic considerations and site-specific installation constraints that may not have been apparent in the study.

Across the outlook period, roof space per dwelling is forecast to increase, as the average size of newly-built houses is larger than the current average size of all dwellings. Also, as solar panel efficiency increases, capacity will increase for a given roof area. These factors were not considered when calculating an estimate for saturation.

Second, it was assumed that the uptake rate, even at saturation, would only be 75%. Some rooftops will remain unoccupied even if a rooftop PV installation makes economic sense for reasons including the following:

- Restrictions by authorities (e.g., heritage overlays).
- Aesthetic considerations.
- Lack of interest or awareness.
- Lack of incentive for rental properties.
- Lack of agreement by building management (e.g., body corporate).

[33] City of Port Philip report. Available at: http://www.enviroehub.com.au/index.php?nodeId=404.

The number of suitable dwellings in NEM regions at the last census (2006) was estimated as the number of occupied, detached houses, plus 30% of other dwelling types. An additional allowance for commercial installations was added, using the ratio of residential to commercial capacity in the Port Phillip study. The rooftop PV uptake modelling assumed residential uptake only, and the impact of commercial installations is not expected to have a material effect on the forecasts.

Saturation capacity was then calculated as the total number of suitable dwellings multiplied by the 75% uptake rate and by the 3.5 kW average.

4.4.4 Application of saturation levels to installed capacity forecasts

The impact of saturation on the installed capacity growth is applied at the last stage of installed capacity forecast development. To model the effects of saturation the following limit equation was used:

Equation 4-3 — Saturation growth rate equation

$$\begin{matrix} \mathit{Saturated} \\ \mathit{growth\ rate} \end{matrix} = \begin{matrix} \mathit{Unsaturated} \\ \mathit{growth\ rate} \end{matrix} \times \left[1 - \left(\frac{\begin{matrix} \mathit{Cumulative} \\ \mathit{saturated\ growth} \end{matrix}}{\begin{matrix} \mathit{Saturation} \\ \mathit{level} \end{matrix}} \right) \right]$$

It was assumed that the effects of saturation would only come into effect once the cumulative growth had reached a threshold percentage of the saturation level. As a result, the formula above was only applied to growth rates above this threshold. The value of the threshold was calibrated using 2012 historical data and installed capacity forecasts.

4.4.5 Barriers to uptake

Physical constraints within distribution networks can limit uptake volume. For example, to feed excess energy into the distribution network, rooftop PV systems must generate power at a higher voltage than in the street. If several systems do this simultaneously, this raises the street voltage. If the street voltage exceeds the threshold of a rooftop PV system, the latter will shut down and the system's owner will be deprived of expected revenue.

Anecdotal reports indicate that to prevent this, some distribution businesses are already imposing restrictions on the size of rooftop PV connections. Alleviating this constraint would involve distribution network augmentation. In the future, household electricity storage could also play a role in alleviating this constraint.

Analysis of physical limitations is beyond the scope of these forecasts, which assume they may delay installations in some localities, but will not affect overall uptake across the NEM.

Another potential barrier is the ability of the solar industry to service the rate of uptake. Given historical rooftop PV uptake this is not expected to have a material effect on the results.

4.5 Rooftop PV energy forecasts

This section describes the development of the rooftop PV forecasts used in the 2013 NEFR. The forecasts are derived using the installed capacity forecasts and the average monthly rooftop PV energy distribution profiles.

The methodology for developing the installed capacity forecasts is shown in Section 4.4.

The average monthly energy distribution profiles were calculated using the average monthly aggregated energy data from ROAM Consulting and AEMO's developed data ranging from July 2003 to December 2012. These profiles were then scaled to account for practical aspects of energy generation from a rooftop PV system. This was based on a comparison of the simulated data against actual rooftop PV sample data from PVOutput.org. The average energy profile was used for the remainder of the outlook period and was multiplied with the installed capacity forecasts to derive the energy forecasts.

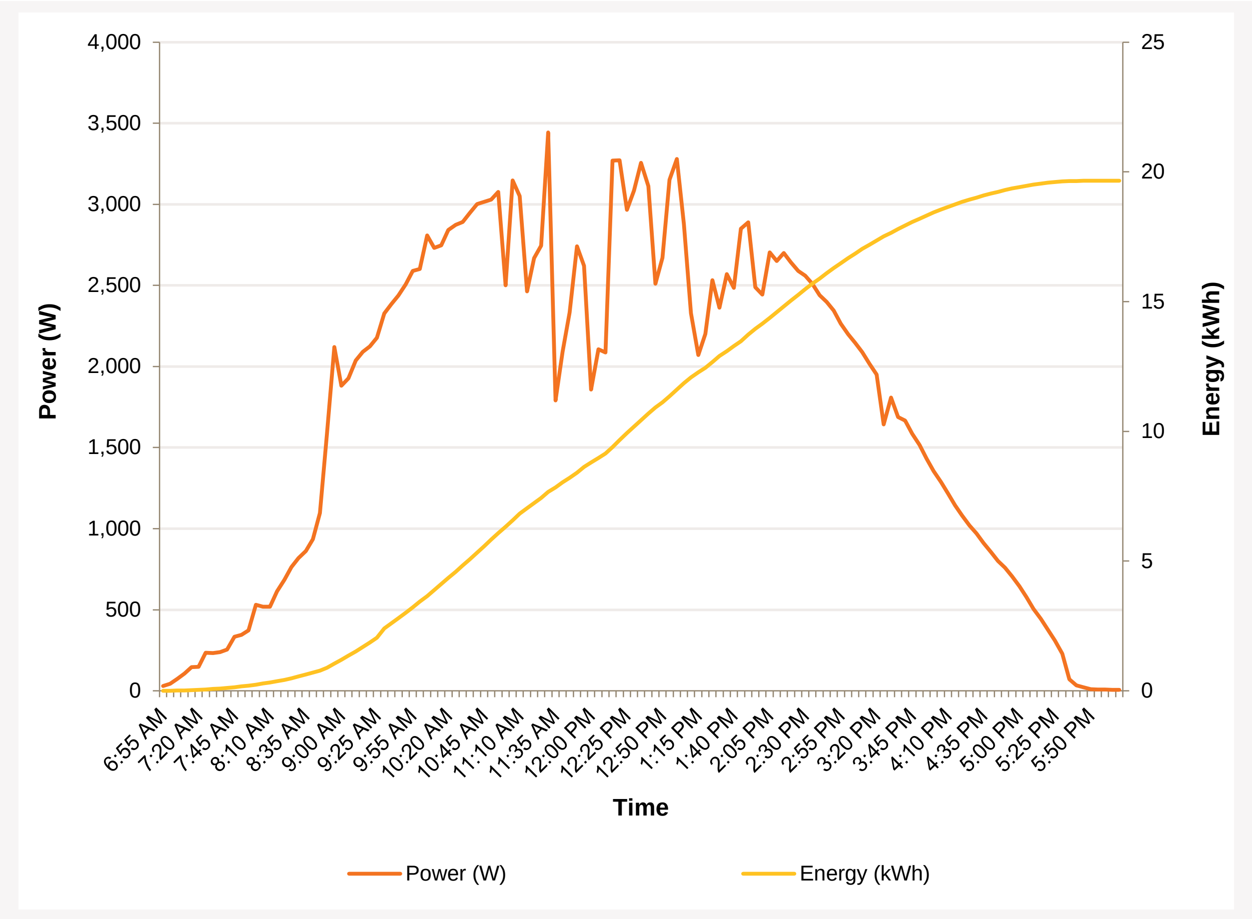
The current rooftop PV energy forecasts do not assume any improvements in energy efficiency or any technological improvements to solar panels in the future that may affect the amount of energy generated from a given amount of installed capacity. Also, the effect of panel degradation on energy output is not modelled as part of the rooftop PV energy forecasts.

Possible improvements in panel efficiency may occur in the future and would apply to new installations at the time. The majority of solar panels are expected to have a service life of over 10 years and as a result any potential improvements in efficiency may have only a small impact on energy generation forecasts. This is due to the cumulative generation from all systems, including those installed earlier and still in service.

4.5.1 Adjustment of results against actual data

The average monthly energy distribution profile results as calculated using ROAM Consulting's rooftop PV output data were compared to sample data obtained from PVOutput.org, which publishes actual rooftop PV generation data as reported by system owners.[34] This was done as a validation and cross check of simulated results against actual data. Figure 4-4 shows actual power and energy from a sample system obtained from PVoutput.org.

Figure 4-4 — Sample of actual power and energy



Source: PVOutput.org

For several reported rooftop PV systems, actual monthly energy generation was divided by the system's capacity to produce a normalised generation trace of a 1 kW system. This was then averaged across all sample systems in the NEM regions.

[34] PVOutput.org website is http://www.pvoutput.org/.

AEMO's estimates were compared to the reported generation of the sample systems. In comparison, generation from the sample systems were lower on average than AEMO's estimates. This result is expected due to a variety of practical aspects not modelled as part of AEMO's simulations, including:

- Different panel tilt and orientation.
- Shading.
- Overheating.
- Sub-optimal configuration and installation of components.

Based on this analysis, AEMO's estimated generation results were lowered to align with the sample generation data from PVOutput.org.

Adjusting energy profiles according to the comparison with actual sample data introduces the possibility of the sample systems not being representative of rooftop PV systems across the NEM. People who log their system generation and upload it to a website can reasonably be expected to also ensure that their system is configured, installed and maintained to above-average standards.

There is an opportunity for future work to analyse whether these energy generation results are over-estimated.

4.6 Rooftop PV contribution to maximum demand

Rooftop PV generation at the time of regional maximum demand was forecast for each region by multiplying the region's forecast installed capacity by a factor reflecting the ratio of rooftop PV output on high demand days to installed capacity.

The data sources used in calculating the contribution to maximum demand forecasts per NEM region included the half-hourly rooftop PV historical contribution factor and the half-hourly native demand. The following steps were taken to derive the rooftop PV contribution to maximum demand forecasts:

1) Calculate average time of maximum demand based on historical maximum native demand times.
2) Gather rooftop PV performance at the average maximum demand time +/-1 hour for each historical maximum demand day.
3) Calculate the average rooftop PV contribution from the sample data and multiply this with the installed capacity forecast to derive the contribution to maximum demand forecasts.

In Tasmania, data was gathered based on actual rather than averaged maximum demand times. This was due to the historical variability in the time of maximum demand in this region, which may occur either early morning or late afternoon. Separate analyses have also been performed for summer and winter.

One potential outcome of forecasting rooftop PV contribution to maximum demand in the long run is that as installed capacity and rooftop PV generation increases, more demand during the day would be offset. This could lead the maximum demand time shifting to later in the day and a decrease in the contribution of rooftop PV at future times of maximum demand. In the long term this may continue until the maximum demand time is close to sunset. The possible effects of this shift and reduction are not modelled and remain a subject for future analysis.

4.7 Changes from the 2012 methodology

Changes from the 2012 rooftop PV forecasting methodology are as follows:

- The impact of feed-in tariff changes legislated in 2012 (all regions except Tasmania introduced new legislation) was modelled more accurately and comprehensively.
- A new economic payback calculator replaced the regional economic payback models.
- Installed capacity and output data was updated to include 2012 data.

- Use of averaged data from ROAM Consulting and the historical traces to derive the monthly traces instead of traces from the PVWatts online calculator and daily generation data for typical systems from the Clean Energy Council.
- Development of a clearer link between the installed capacity forecasts and the payback and saturation estimates.

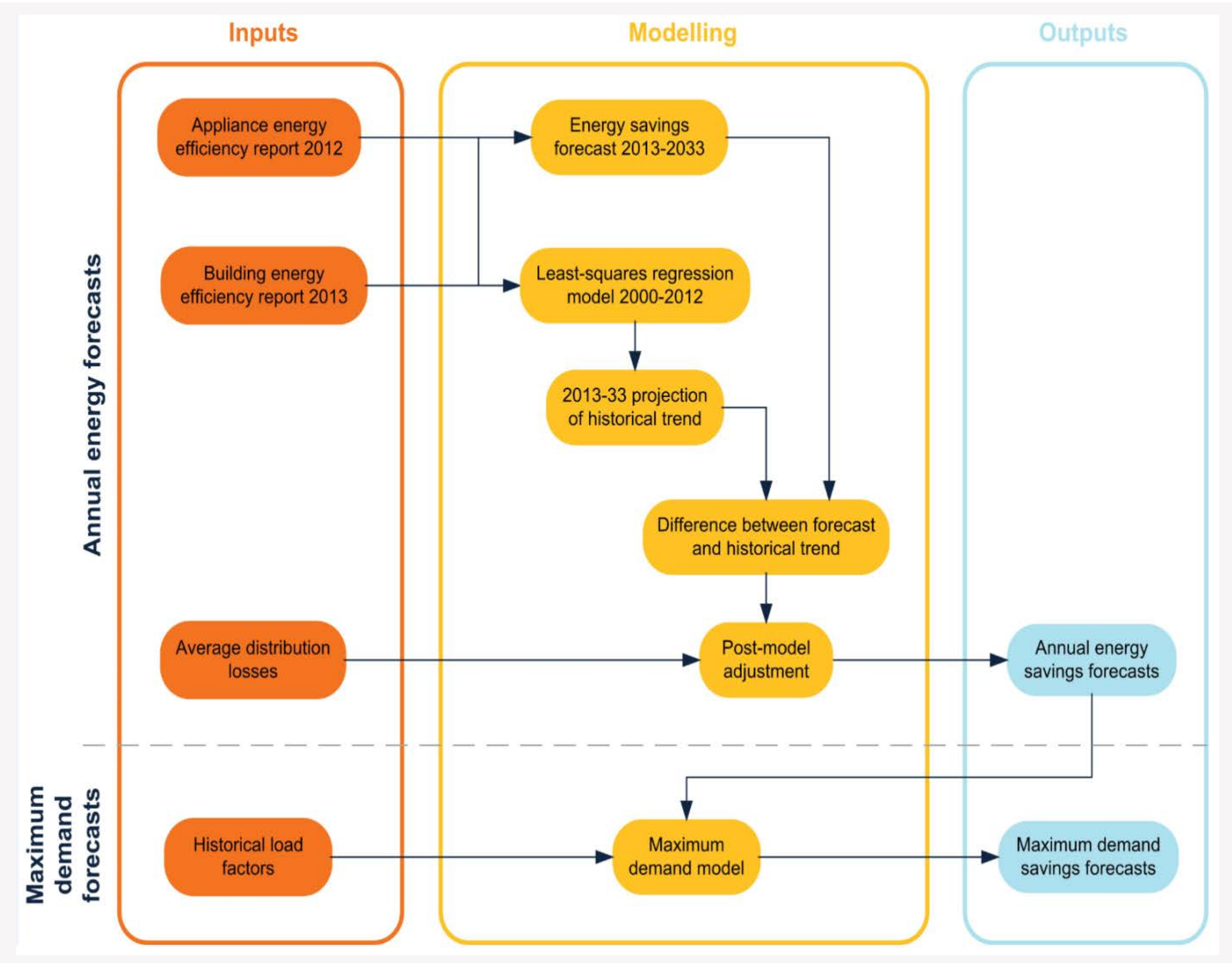
CHAPTER 5 - ENERGY EFFICIENCY

5.1 Introduction

This chapter provides the methodology used to develop the 2013 National Electricity Forecasting Report (NEFR) energy efficiency forecasts. The 2013 methodology incorporates changes from the 2012 methodology, which improve the transparency of the forecast approach and the quality of the results. The changes are summarised in Section 5.7. One key change was limiting potential energy savings to those derived from Commonwealth Government measures only, as state-based programs are much smaller and including them can introduce a risk of double-counting energy savings.

An overview of the energy efficiency forecast methodology used in the 2013 NEFR is shown in Figure 5-1.

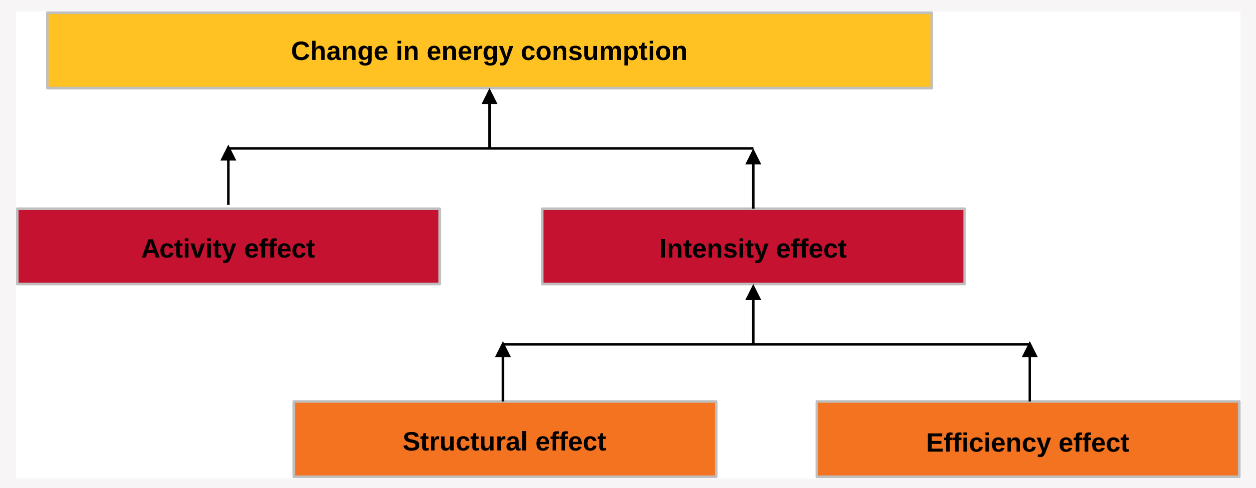
Figure 5-1 — Energy Efficiency forecasts diagram



Drivers of change in energy consumption

Energy efficiency is one of the three drivers of changes in energy consumption. The others are activity and structural effects. This is shown in Figure 5-2.

Figure 5-2 — Drivers of change in energy consumption[35]



The underlying econometric model used to forecast residential and commercial load uses state income (gross state product (GSP) or state final demand (SFD)) to model activity effects. The estimated income elasticity, representing the change in consumption for each change in state income, captures the long-term trends in structural and efficiency effects.

On the structural side, these include the reduction in manufacturing and growth in importance of service-based and resource extraction industries, and on the efficiency side these include the general trend that when appliances are replaced it is by more efficient ones.

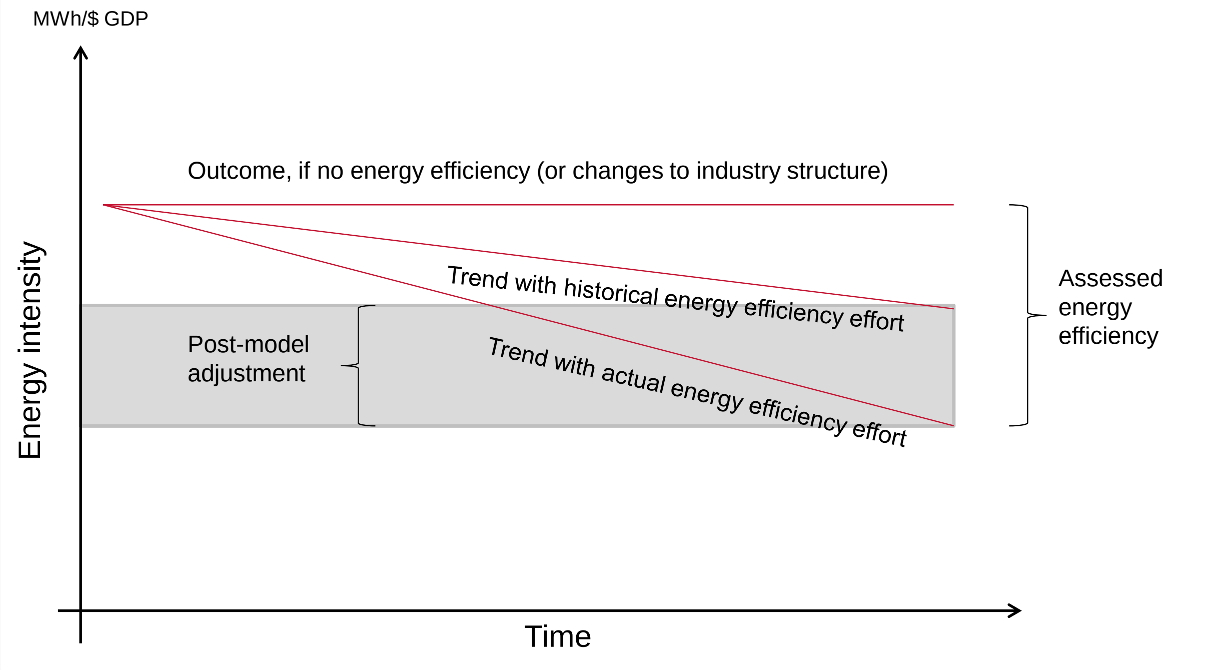
Any substantial deviations from the long-term efficiency trend will not be captured by the econometric model. These deviations are assessed separately and are the basis of the energy efficiency forecasts. The NEFR energy efficiency forecasts represent the reductions in annual energy and maximum demand due to the difference between historical and forecast energy efficiency improvements.

These are applied to the non-large industrial forecasts, along with the reduction in demand due to generation from rooftop PV, to determine residential and commercial load.

This is shown in Figure 5-3 with the “post-model adjustment”, which refers to the reduction applied to non-large industrial load.

[35] Bureau of Resources and Energy Economics. Economic Analysis of End-use Energy Intensity in Australia. 2012. Available: http://www.bree.gov.au/publications/energy-intensity.html. Viewed 19 March 2013.

Figure 5-3 — Scope of energy efficiency forecasts



Energy efficiency forecast approach

Forecasts were developed for three uptake scenarios; Rapid Uptake, Moderate Uptake, and Slow Uptake defined in Section 5.2.

The forecasts for each uptake scenario are developed using a three step approach:

a) Estimate the annual energy savings from energy efficiency policy measures from 2000 to 2033.

b) Calculate the difference between the annual energy savings trend for the aggregate of all NEM regions in the regression period (2000-12) and the energy efficiency savings expected in the forecast period (2013-33). This difference between the two is the NEFR energy efficiency forecast for annual energy. This is disaggregated into forecasts for each region based on region-specific savings determined in Step 1 or in previous studies, and is converted from savings measured at the end-user's premises to savings observed at transmission connection points (used for AEMO's forecasts) by adding distribution losses.

c) The NEFR regional energy efficiency forecasts for maximum demand (the impacts on summer and winter maximum demand) are calculated from the regional energy efficiency forecasts for annual energy developed in Step 2.

More information about the steps is provided in Section 5.3, Section 5.4, and Section 5.5. The forecasts themselves are provided in Appendix C.

Data sources

The energy efficiency forecast approach is based on the following two key data sources:

- George Wilkenfeld and Associates: "Review of Impact Modelling for E3 Work Program". Unpublished report to the Department of Climate Change and Energy Efficiency (DCCEE), August 2012.
- Pitt & Sherry: "Final Report: Qualitative Assessment of Energy Savings from Building Energy Efficiency Measures", unpublished report prepared for DCCEE, February 2013.

These recently-completed studies provide an up-to-date assessment of energy efficiency savings across programmes initiated at the Commonwealth Government level. The main source of information for these studies is regulation impact statements (RIS), which are impact assessments undertaken before programs are initiated.

Potential double counting and scheme interactions

Only savings from Commonwealth Government level measures are included, to reduce the risk of double counting as regional programs tend to target similar efficiency savings and bring their impact forward. Any risk of materially understating potential savings is low because state government level measures tend to be comparatively small.

Even when limiting the focus to Commonwealth Government programs, there is a risk of double counting savings from measures targeting appliances and measures targeting building stock as these schemes interact. For example, improvements in air conditioning (an appliance program) can lower the energy use in a particular building, as can insulation (a building program). Program savings can only be added together if, in each case, savings from programs that interact are assumed.

The risk is limited though as the studies used as the basis for the NEFR energy efficiency forecasts and the RIS account for potential double counts and scheme interactions. For example, a RIS generally considers savings against a baseline that assumes an improvement in energy efficiency without any measures being taken, including improvements driven by international standards.

5.2 Energy efficiency uptake scenarios

This section describes the three energy efficiency uptake scenarios used for the 2013 NEFR forecasts. The three scenarios reflect the uncertainty about the number of new energy efficiency programs that will be implemented in the forecast period. They are the following:

- The Slow Uptake scenario, which assumes no additional energy efficiency measures beyond those currently being implemented.
- The Moderate Uptake scenario, which assumes all current energy efficiency programs and those currently being implemented remain.
- The Rapid Uptake scenario, which assumes additional energy efficiency programs beyond those already approved are implemented.

Refer to Table 1-1 to see how the three energy efficiency scenarios are used in the 2013 NEFR scenarios along with the uptake scenarios e.g., for rooftop PV.

The three scenarios used in the 2013 NEFR use the Moderate Uptake energy efficiency scenario, as this is AEMO's best estimate of future energy efficiency uptake. The Slow Uptake and Rapid Uptake scenarios are provided to support sensitivity studies of different energy efficiency uptake assumptions.

5.3 Savings from energy efficiency policy measures

The first step in developing the forecasts is to estimate the annual energy savings from energy efficiency policy measures from 2000 to 2033.

Savings from two broad categories were estimated:

- Equipment/appliances (interchangeable terms in this report), based on the study by George Wilkenfeld and Associates.[36]
- Buildings, based on the study by Pitt & Sherry.[37]

The NEFR forecasts consider electricity only, and this forecast accordingly does not include the gas demand impacts considered in the George Wilkenfeld and Associates and Pitt & Sherry reports.

[36] See Data Sources in Section 5.1.
[37] See Data Sources in Section 5.1.

5.3.1 Equipment energy efficiency savings

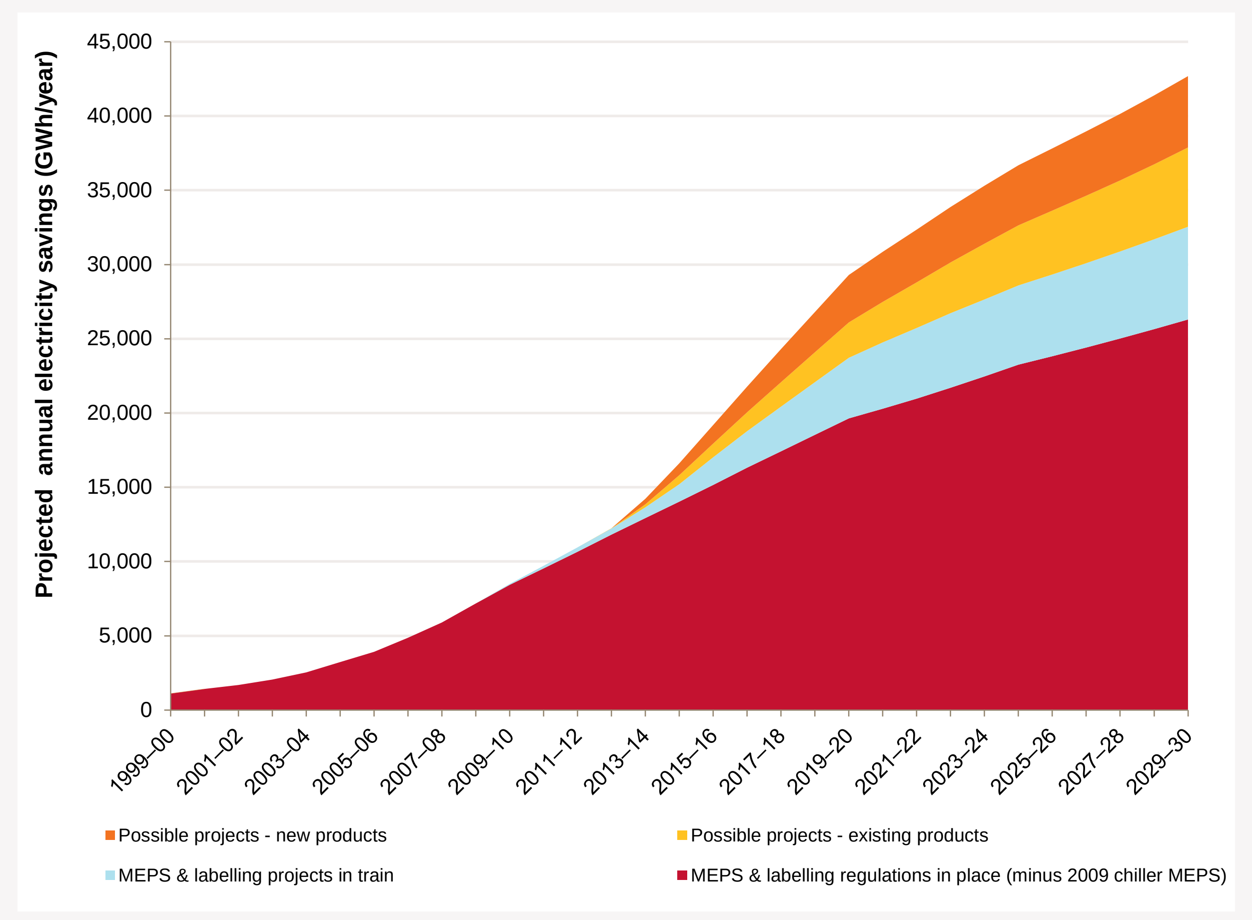
The projected electrical energy savings for the NEM from equipment labelling and Minimum Energy Performance Standards (MEPS) (collectively referred to in some studies as E3 – Equipment Energy Efficiency), based on the work by George Wilkenfeld and Associates, are up to 42 TWh by 2030. More than half of this comes from programs already in place.

The study does not provide a regional breakdown, and AEMO has determined regional values using the regional shares from an earlier, more comprehensive version of the report published in 2009. Potential savings from Western Australia and Northern Territory are excluded.

The George Wilkenfeld and Associates study includes forecast values to 2029-30, which were extended to 2032-33 for the NEFR using linear extrapolation from the last five years (2024-25 to 2029-30).

The projected savings for the NEM are shown in Figure 5-4. This shows stable growth over the last five years, which supports the extrapolation providing a reasonable approximation of savings beyond 2030.

Figure 5-4 — Appliance/equipment energy efficiency projected savings – E3 modelling categories

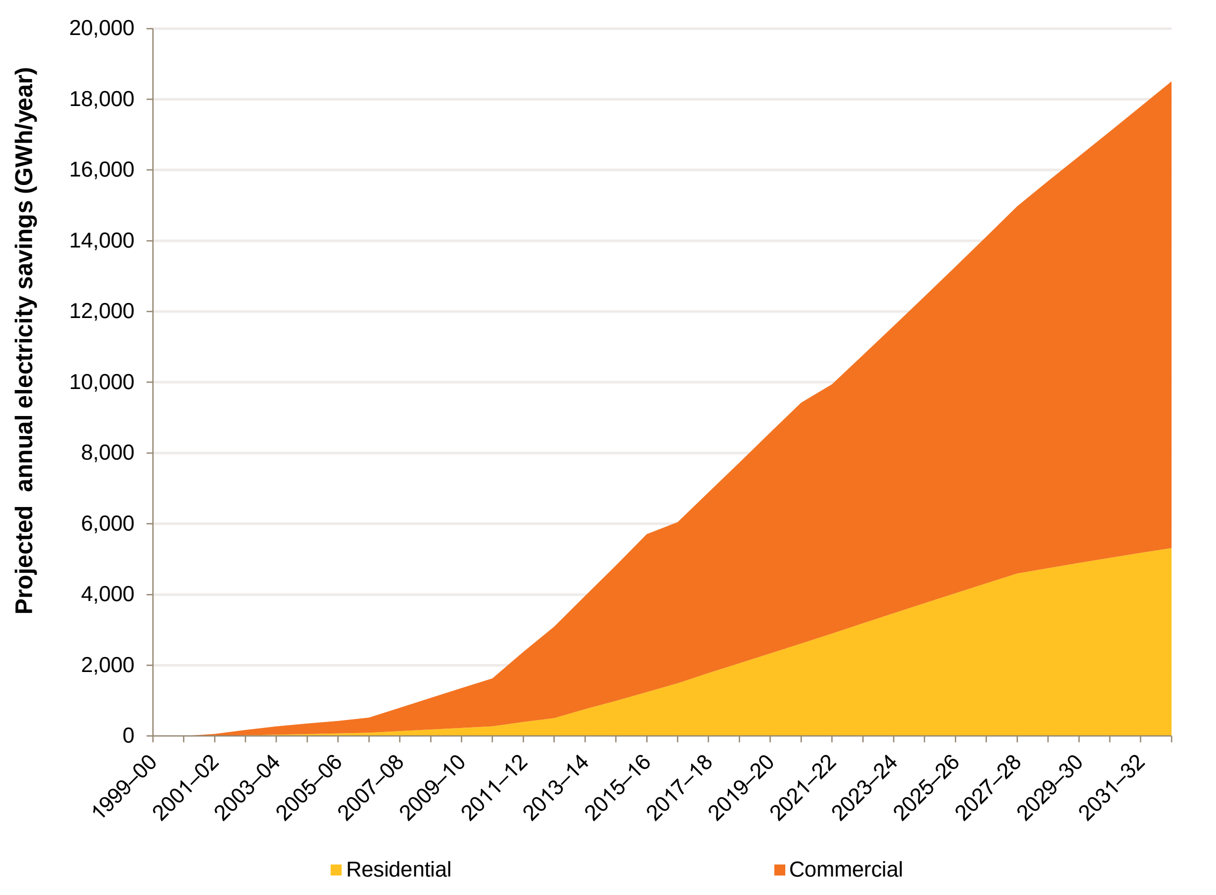


The 2009 chiller MEPS program was excluded from the “MEPS & labelling regulations in place” category because it is also treated as an existing project in the building energy efficiency assessment (as part of the baseline for the Pitt & Sherry assessment).

5.3.2 Building energy efficiency savings

Electrical energy savings from building-related energy efficiency measures were based on the Pitt & Sherry study. AEMO determined savings for the NEM based on the report's savings for each state. Figure 5-5 shows these projected savings.

Figure 5-5 — Building stock energy efficiency projected savings



5.4 Calculating the NEFR energy efficiency forecast for annual energy

As discussed in Section 5.1, the underlying econometric model (used to forecast the non-large industrial load) captures long-term trends, including efficiency effects. Substantial deviations from the long-term efficiency trend will not be captured by the model. Therefore, the NEFR energy efficiency forecast for annual energy is calculated from the difference between the actual energy efficiency savings expected in the forecast period (2013-33) as per Section 5.3, and the annual energy savings projected out to 2033 for the aggregate of all NEM regions based on the long-term efficiency trend observed in the regression period (2000-12).

The long-term efficiency trend is approximated using a least-square fit for calendar years within the regression period (2000-12). This calendar year-based trend is extended into the forecast period (2013-33), which uses financial years, as AEMO considers the financial year and calendar year trends to be sufficiently similar.

The calculated NEFR energy efficiency forecast for annual energy is disaggregated into forecasts for each region pro-rata based on the region-specific savings determined in the equipment and building stock studies.

Forecasts are developed for each of the three uptake scenarios described in Section 5.2. The Rapid Uptake scenario assumes all potential savings are made, both certain and probable. The Moderate Uptake scenario assumptions for equipment energy efficiency measures include only certain projects and are approximately 50% of the Rapid Uptake scenario forecast for both equipment and building stock.

This building stock figure represents delays in the implementation of some programs (such as the phase-out of carbon-intensive water heaters), uncertainty about whether some programs will be implemented (such as Residential Mandatory Disclosure), and allows for non-compliance.

No additional energy efficiency savings above the long-term trend are assumed for the Slow Uptake scenario.

Energy efficiency forecasts for the measures that target equipment and building stock are shown in Figure 5-6 and Figure 5-7 respectively.

Figure 5-6 — Energy efficiency forecasts for equipment energy efficiency measures

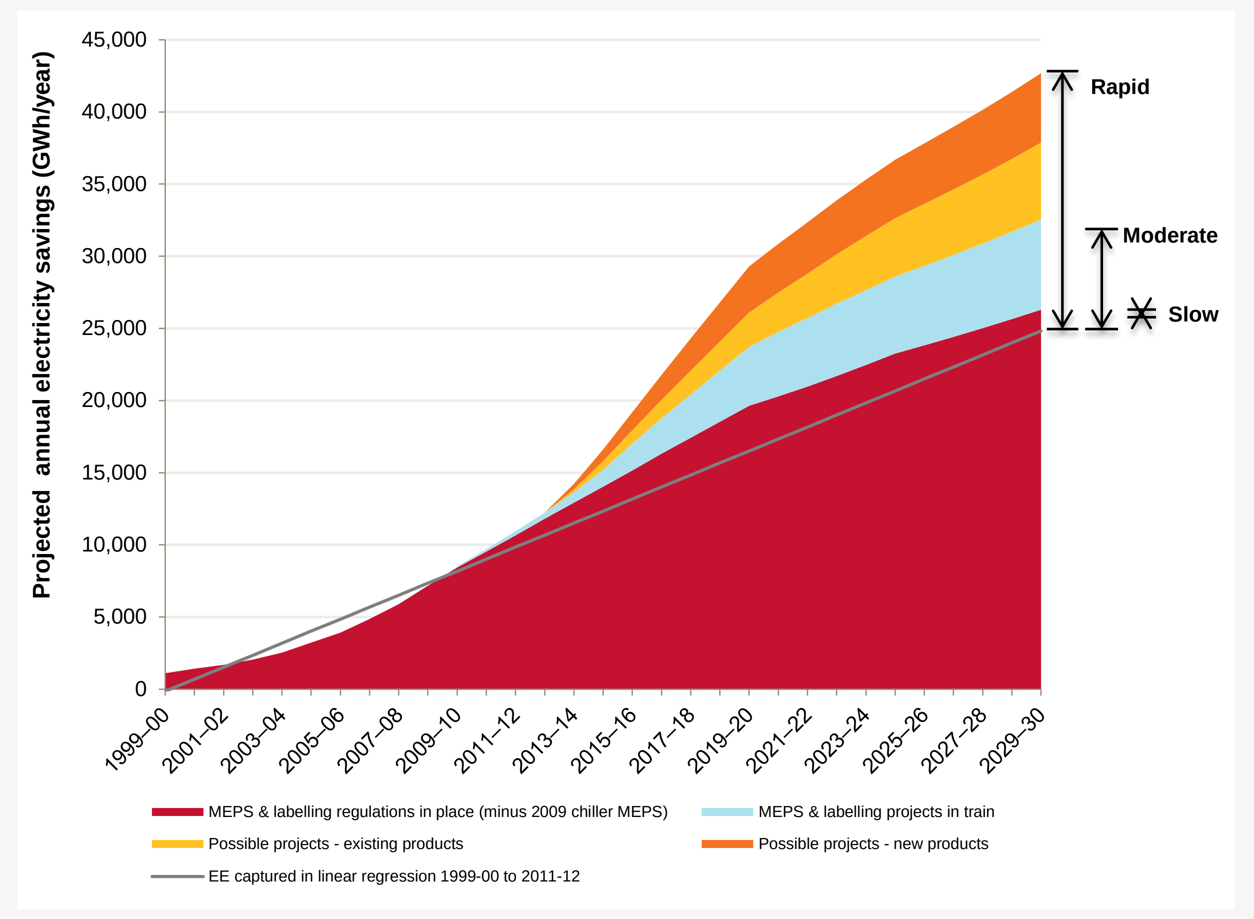
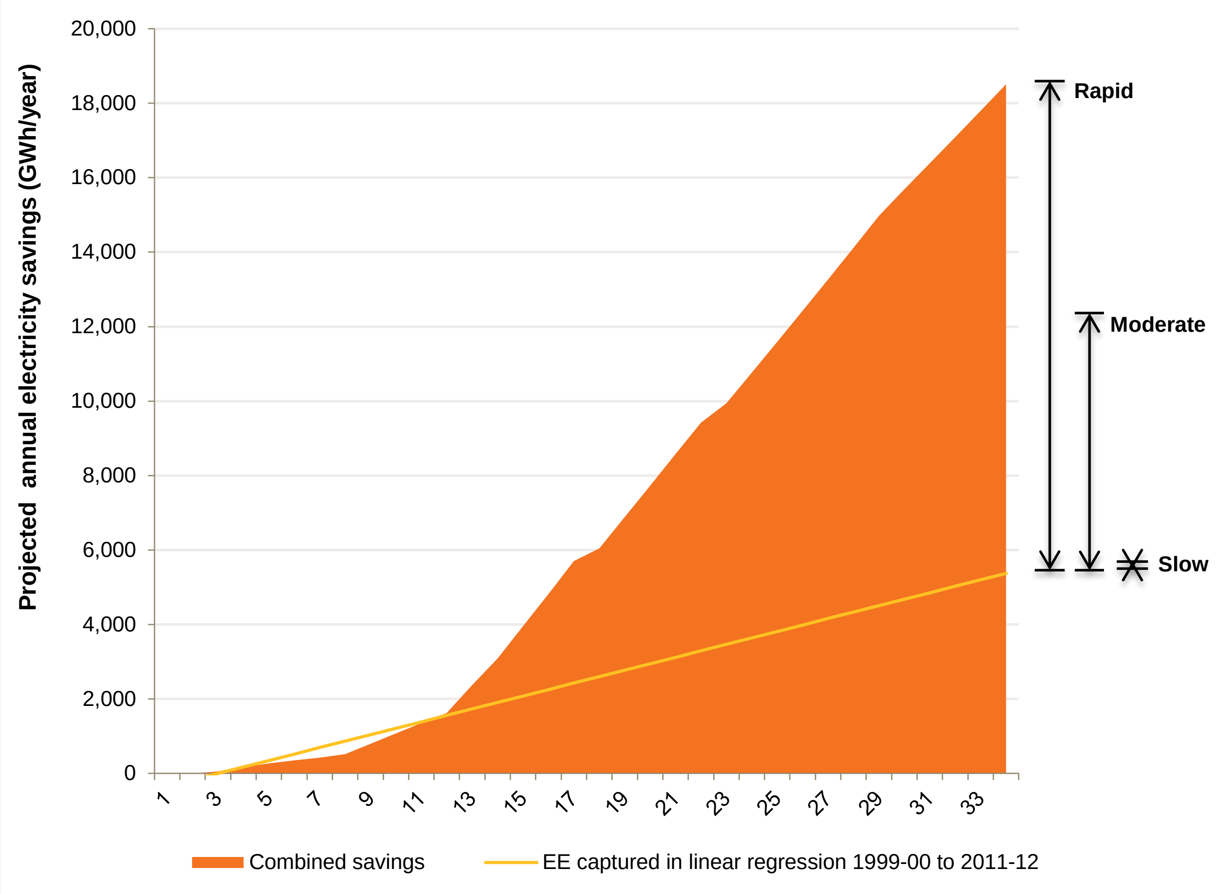


Figure 5-7 — Energy efficiency forecasts for building stock energy efficiency measures



The savings shown in the two previous figures are as measured at the end-user premises. To calculate the post-model adjustment to the energy forecast, which is transmission delivered demand, an allowance for distribution network losses needs to be added. This represents the additional savings in network losses if the energy saved would otherwise have been delivered from the transmission connection points to the end-users through the distribution networks.

The losses used in this analysis are shown in Table 5-1. 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 5-1 — Estimated distribution losses in Australia (% of transmitted energy)

NSW	QLD	SA	TAS	VIC
4.8%	5.4%	6.1%	5.4%	5.2%

Source: Reporting by network companies

Appendix C shows the forecast energy efficiency post-model adjustments for annual energy for all three uptake scenarios.

5.5 Calculating the NEFR energy efficiency forecasts for maximum demand

The NEFR regional energy efficiency forecasts for maximum demand (the impacts on summer and winter maximum demand) are calculated from the regional energy efficiency forecasts for annual energy described in Section 5.4, using the conservation load factor (CLF) approach.

The CLF is the ratio of the average demand savings for one year, to savings at the time of that years' system maximum demand. This is calculated as follows:

CLF = [Annual energy savings (MWh)/8,760 hours]/savings at system maximum demand (MW)

The CLF for appliances that operate constantly, such as refrigerators, is approximately one. Some appliances, such as air conditioners, are used heavily at the time of summer maximum demand, and generally have very low summer CLFs. Other appliances, such as off-peak electrical water heaters without an override function, never contribute to maximum demand. EES (2011)[38] provides appliance-based CLFs for each NEM region.

To take account of the wide diversity of appliances contributing to the forecast energy efficiency savings in Section 5.4, the NEFR energy efficiency forecasts for maximum demand use regional summer and winter system load factors instead of individual appliance CLFs. This reduces potential overstatement of savings at times of maximum demand, as the large annual energy savings can lead to unrealistically large maximum demand savings if using very low CLFs. The regional load factors used for the NEFR energy efficiency forecasts are provided in Table 5-2.

Table 5-2 — Regional load factors for maximum demand savings assessment

2011-12 data	Queensland	New South Wales (incl. ACT)	Victoria	South Australia	Tasmania	Aggregated NEM regions
Annual energy (MWh)	51,147,024	74,632,494	50,179,588	12,993,675	9,764,875	198,717,656
Summer maximum demand (MW)	8,757	11,942	9,110	2,956	1,349	30,218
Winter maximum demand (MW)	7,526	12,910	7,964	2,374	1,718	31,381
Summer load factor	66.5%	71.1%	62.7%	50.0%	82.4%	74.9%
Winter load factor	77.4%	65.8%	71.7%	62.3%	64.7%	72.1%

Appendix C shows the forecast energy efficiency post-model adjustments for both summer and winter maximum demand for all three uptake scenarios.

5.6 Modelling limitations and exclusions

The energy efficiency forecasts are based on existing and planned policies and measures, and exclude any consideration of future programs than those discussed today. This is a conservative approach for a 20-year

[38] Energy Efficient Strategies. "The Value of Ceiling Insulation", report to ICANZ, September 2011. Available http://icanz.org.au/wp-content/uploads/import/pdf/2011_ICANZ_Report_-_V04__final_260911.pdf. Viewed 20 March 2013.

forecast, given that Pitt & Sherry[39] considers the potential for additional savings to be large, some of which could be achieved by future policies.

The two data sources[40] used for the forecasts include all programs being run by the equipment energy efficiency branch and the building energy efficiency branch of the Department of Climate Change and Energy Efficiency DCCEE (now part of the Department of Resource, Energy and Tourism (DRET)). They do not include programs managed by other parts of DCCEE, such as the home insulation program, nor any programs run by other departments, such as the Energy Efficiency Opportunities program targeting industrial energy efficiency. Again, this is a conservative approach.

The impacts of state-based measures are excluded to reduce potential double counting. Their exclusion does not materially affect the results as they are minor compared with the Commonwealth Government level measures considered. Rebound effects, where some of the cost savings from energy efficiency measures are spent on additional energy services, have not been taken into account in the NEFR forecasts. Lighting, space conditioning (air conditioning and heating) and hot water use are likely to have an element of rebound. EES (2011)[41] estimated rebound to be approximately 15% (for each GWh of energy savings, 0.15 GWh of additional demand would occur leading to a net saving of 0.85 GWh).

The interaction of electricity price response, energy efficiency, and the uptake of distributed generation such as rooftop PV, as they affect annual energy and maximum demand is not considered in these forecasts, and the potential overlap is not measured.

5.7 Changes from the 2012 methodology

The 2013 methodology incorporates changes from the 2012 methodology, which improve the transparency of the forecast approach and the quality of the results.

A key change from the 2012 methodology is limiting potential energy savings to those from Commonwealth Government level measures. The impacts of state-based measures, which are minor compared with the Commonwealth Government level measures considered, are excluded to reduce potential double counting.

The 2012 NEFR energy efficiency forecasts separately analysed household, commercial, and industrial energy efficiency forecasts. A range of information sources were used including the following:

- Government reviews of the energy efficiency programs.
- Consultant reports.
- Australian Bureau of Statistics (ABS) demographic and electrical appliance statistics.
- Economic forecasts developed by the National Institute of Economic and Industry Research (NIEIR).

In contrast, the 2013 forecasts are based on two recent studies for DCCEE, providing consistent assumptions and information that specifically address the potential for energy efficiency savings for a large range of energy efficiency programs.

The annual energy and maximum demand savings were separate estimates in 2012. The 2013 approach is based on regional system load factors, based on the 2010-11 year.

In 2012, energy efficiency policy impacts were forecast for one base case scenario. This forecast was multiplied by assumed percentage factors to derive the forecasts for each of the NEFR scenarios. The percentage factor was mainly used to account for the historical trend in energy efficiency uptake. In 2013 the proportion of the potential savings forecast for each scenario is based on calculated outcomes rather than assumptions.

39 See Section 5.1.
40 See Section 5.1.
41 See Note 38.

CHAPTER 6 - SMALL NON-SCHEDULED GENERATION

6.1 Introduction

This chapter provides the methodology used to develop annual energy and contribution to maximum demand forecasts for small non-scheduled generation. The contribution from small non-scheduled generation is subtracted from both the annual energy and maximum demand forecasts to calculate operational generation forecasts used in the supply–demand outlook.

For a list of existing small non-scheduled generators used in these forecasts, see Appendix D.

Forecasts are developed using a database of existing and possible future small non-scheduled generators. Based on the characteristics of historical small non-scheduled generation, forecasts of annual energy, and summer and winter contribution to maximum demand are constructed for each generator. Forecasts for each relevant AEMO scenario are developed using estimates of the likelihood of future small non-scheduled generators advancing to commissioning and start-up.

6.2 Small non-scheduled generation scenarios

Forecasts for low, medium and high scenarios are determined using the project status. This project status is determined using various sources, including AEMO's generation information pages, company or ASX releases, or other official public sources. These project status categories are described as:

- Category A: Project has previously generated, and is currently generating, electricity.
- Category B: Project has advanced to a stage where a final investment decision has been made and the project is moving to, or currently in, construction phase.
- Category C: A final investment decision has not been made, but the project is in the later stages of the development approval process.
- Category D: A final investment decision has not been made, and the project is going through the intermediate stages of the approval process.

The project status relates to each 2013 NEFR scenario as follows:

2013 NEFR Scenario	Related SNSG scenario	Categories included
High	High Uptake	Categories A, B, C and D
Medium	Moderate Uptake	Categories A, B and C
Low	Sloow Uptake	Categories A and B

6.3 Calculating the NEFR small non-scheduled demand forecast for annual energy

Using the project list, an historical and future capacity profile is developed based on project-by-project estimated start-up dates and installed capacities. Estimates of installed capacity for each project over the outlook period are assumed to be unchanging over time.

Capacity factors are estimated for each existing project using actual generation data and installed capacities of these generators. With appropriate weights favouring recent years, a capacity profile over the forecast period is subsequently constructed for each existing generator.

Using the capacity factors implied from historical data, estimates of capacity factors to be applied to development projects are calculated. Estimates of capacity factors are found by averaging across generators from the same NEM region and generator class (fuel source). A capacity factor profile over the forecast period is subsequently constructed for potential new small non-scheduled generators.

Using this capacity factor profile, combined with the reported capacities of future projects and expected future start-up dates, a generation profile is constructed over the outlook period for each project. This profile is then filtered to accommodate each scenario described above.

6.4 Calculating the NEFR small non-scheduled demand forecast for contribution to maximum demand

Using the project list, an historical and future capacity profile is developed based on project-by-project estimated start-up dates and installed capacities. Estimates of installed capacity for each project over the outlook period are assumed to be unchanging over time.

Annual half-hourly points of native maximum demand are identified for each NEM region, both for winter and summer maximum demand points. The contribution of demand from each existing small non-scheduled generator at each annual maximum demand reading is extracted from the historical trace. This comprises an historical profile of the contribution of small non-scheduled generation to maximum demand.

Using this historical profile, annual factors of contribution to maximum demand can be determined for each project. These factors represent measured demand at regional system peak for each small non-scheduled generator, as a proportion of installed capacity for each of these projects. With appropriate weights favouring recent years, a profile of contribution to maximum demand factors over the forecast period is subsequently constructed for each existing generator.

Using the factors implied from historical data, estimates of contribution to maximum demand factors to be applied to development projects are calculated. Estimates of contribution to maximum demand factors are found by averaging across generators from the same NEM region and generator class (fuel source). Contribution to maximum demand factors for small non-scheduled wind generators are determined using separate a AEMO analysis.[42] A contribution to maximum demand factor profile over the forecast period is subsequently constructed for potential new small non-scheduled generators.

Using this contribution to maximum demand factor profile, combined with the reported capacities of future projects and expected future start-up dates, a summer and winter maximum demand profile is constructed over the outlook period for each project. This profile is then adapted to accommodate each scenario described above.

6.5 Modelling limitations and exclusions

Forecasts of small non-scheduled generation are constructed by developing profiles of both existing generators and future developments based on publicly available evidence.

While information on future projects planned for the early part of the forecast period is adequate, this information diminishes markedly in quality and quantity for projects scheduled for commissioning later into the forecast period.

[42] AEMO, Wind contribution to peak demand, July 2012. Available at http://aemo.com.au/Electricity/Planning/Related-Information/Wind-Contribution-to--Peak-Demand.

Towards the end of the forecast period there is no information regarding the development of small non-scheduled generation projects. As such, small non-scheduled generation profiles for annual energy and contribution to maximum demand display little variation over the forecast period.

6.6 Changes from the 2012 methodology

The 2013 methodology incorporates changes which improve the transparency of the forecast approach and the quality of the results. Major changes include:

- Construction of generator-by-generator forecasts based on a bottom-up appraisal of existing and future projects.
- Greater use of historical data to inform capacity factors and contribution to maximum demand factors.
- Increased disaggregation of generator characteristics to encompass specific NEM regions and technologies.

CHAPTER 7 - DEMAND-SIDE PARTICIPATION

7.1 Introduction

This chapter provides the methodology used to develop the demand-side participation (DSP) forecasts presented in Appendix D.

The term DSP generally covers a wide range of short-term demand responses by end-users to price and/or reliability signals. In this report it specifically means:

- Occasional DSP responding to different levels of high prices (market-driven response).
- Occasional DSP responding to critical system conditions (reliability-driven response).

It does not include daily or common changes in consumption such as electric hot water heaters being controlled by distribution companies or customer responses to time-of-use (TOU) tariff structures.

The forecast excludes DSP from scheduled loads in the market, as these would be accounted for in the market clearing itself. However, it should be noted that at present the only scheduled loads are those associated with pumped storage facilities, which would not be pumping at times when DSP is needed. (DSP is required when prices are high; pumped storage facilities would always be generating—not pumping—at such times.)

7.2 DSP methodology

Forecasts of the available DSP for winter 2013 and summer 2013-14 are done separately for two different segments:

- DSP from large industrial loads (based on the same loads as the large industrial load forecast discussed in Chapter 3).
- DSP from the remaining load.

The estimated DSP from large industrial loads is calculated based on historically observed responses at various price levels. This is explained in detail in Section 7.3. The estimated response from the remaining load is based on a survey of network businesses and market participants, and is explained in Section 7.4.

These estimates are added together for each NEM region to give the total expected DSP available for different price levels.

These totals are projected into the future for the three uptake scenarios: Slow uptake, moderate uptake and rapid uptake. The approach for these projections is explained in Section 7.6.

The three scenarios used for the 2013 NEFR use the moderate uptake DSP scenario, as this is AEMO's best estimate of DSP. The slow uptake and rapid uptake scenarios are provided to support sensitivity studies of different DSP assumptions.

7.3 Estimate of current DSP from large industrial loads

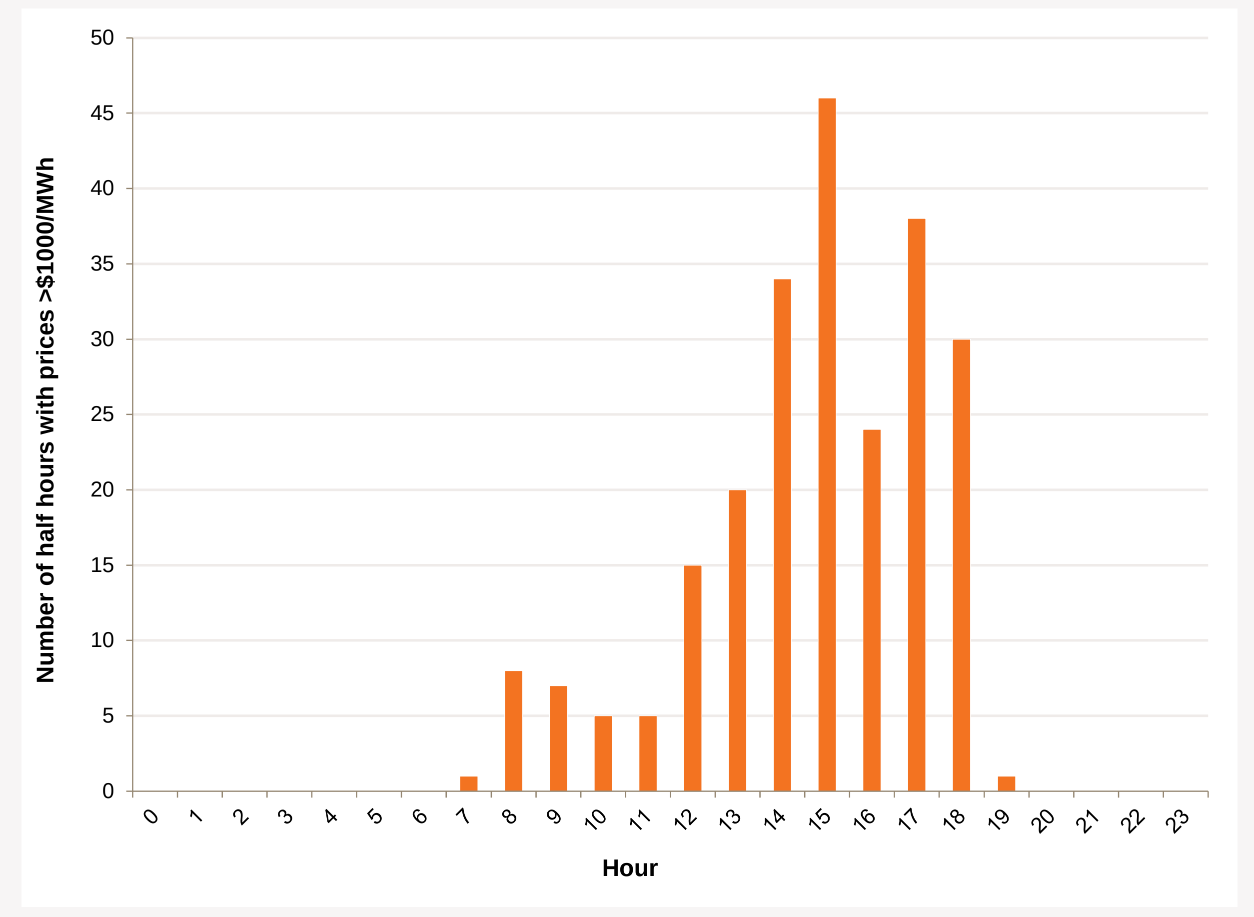
The expected DSP response (reduction in demand) for large industries was calculated based on half-hourly metered data from January 2002 to March 2013. The response was assessed for different regional wholesale price levels:

- Prices above $1,000/MWh.
- Prices above $2,500/MWh.
- Prices above $5,000/MWh.
- Prices above $7,500/MWh.

The response was calculated as the difference between the demand observed in the hours where prices were as listed above, compared to the average daytime demand for the same day. For average daytime demand, only hours from 7:00 AM to 7:00 PM with prices below $1000/MWh were considered.

From 7:00 AM to 7:00 PM is when high price events generally occur (as shown for Victoria in Figure 7-1); only these hours were used as night-time industrial demand tends to be slightly higher, driven by lower night-time electricity prices. Comparing against a daily average would have introduced a bias.

Figure 7-1 — Time of day with prices above $1000/MWh in Victoria (Jan 2002 – Mar 2013)

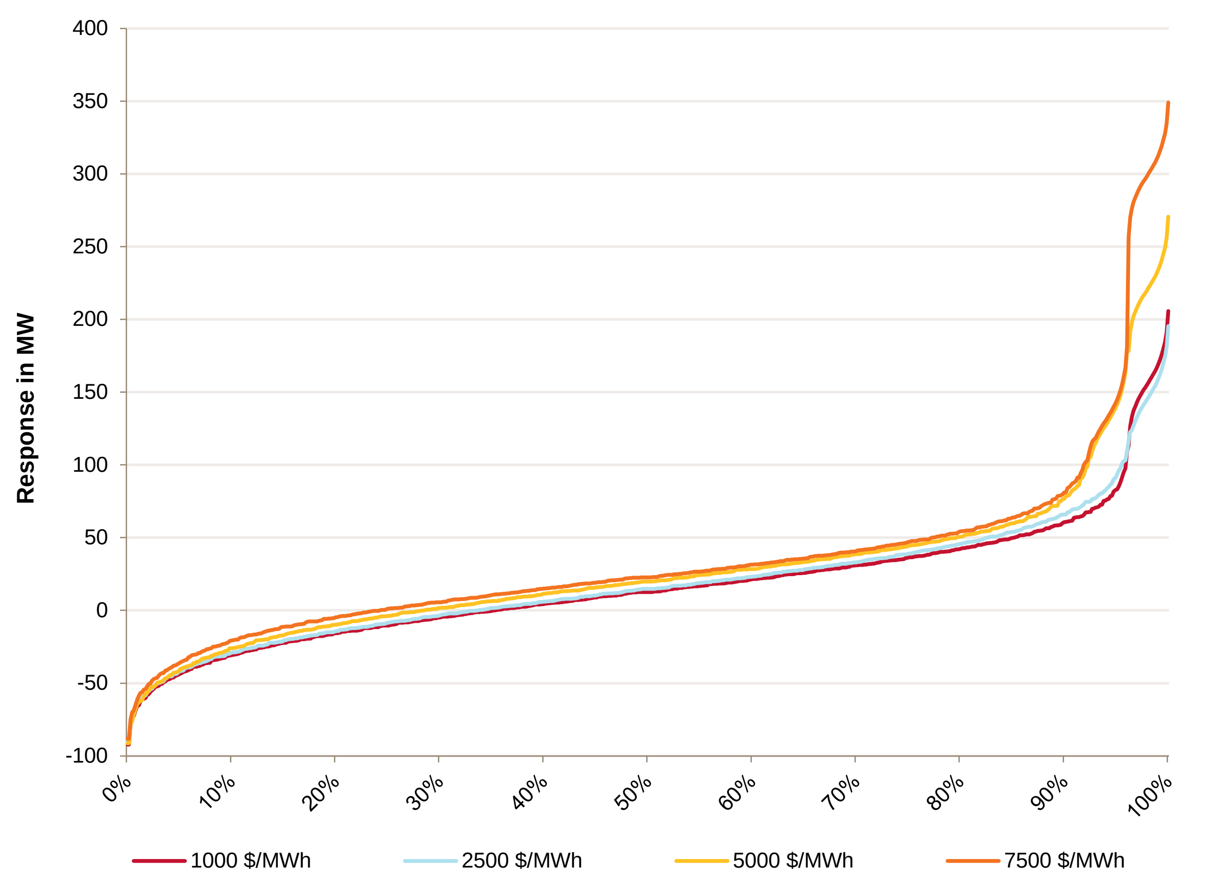


The DSP response for each high price occasion was calculated. The number of high-price events allowed for a reasonable estimate of the probability distribution of responses, as shown in Figure 7-2. This figure shows the historically observed probability of response in MW. For example, 90% of the time when prices have been or above 1000/MWh, the historically observed DSP response has been at least 65 MW.

This assessment is important given that DSP, at least from large industrial consumers, is a probable resource rather than a firm resource[43]; the response depends on a range of factors, such as their order book and flexibility of production. For these reasons, the same customer may respond differently at different times.

[43] It should be noted that DSP aggregators can and do provide "firm" DSP products by offering the aggregated response from a number of non-firm resources, levelling out the uncertainty of individual responses.

Figure 7-2 — Probability of DSP response in NSW based on historical responses[44] (Jan 2002 - Mar 2013)



In general, all NEM regions showed only small differences between the responses observed at different price levels. As a result, it was decided only to include the lowest ($1000/MWh) and highest ($7500/MWh) response curves in the forecast.

Due to the limited data available, it is not possible to reliably estimate the response for prices above $7500 using the same approach. For use in reliability assessments, discussed later in Section 7.5, DSP response during system crises—just before involuntary load shedding is required—had to be estimated. Prices would at that point equal the market price cap (MPC). AEMO assumed that DSP response during system crises would be equal to the response seen in the 90–98% interval of the $7500/MWh curve on Figure 7-2 (the 98–100% interval is excluded as it include outliers, including mandated load shedding).

So the lowest expected response equals the plotted value for 90% (corresponding to 10% probability of exceedence) and the highest expected response equals the value for 98%, with the midpoint (50% probability of exceedence) equal to the 96% value.

These regional estimates are higher than the forecast DSP responses reported by AEMO in previous years but consistent with actual responses seen in extreme events.[45]

44 This excludes any historical response from the Kurri Kurri smelter.

45 See Attachment 1 (pages 13 & 14) of AER's submission to AEMC's Power of Choice review - Direction paper, available on: http://www.aemc.gov.au/Media/docs/AER---120508-af5529b8-d12f-40d9-98f1-6546921c645c-0.PDF. Viewed 10 June 2013.

Following this assessment, the impact of large industrial load on the maximum demand forecast was evaluated to see if any historical price response might have interfered with the maximum demand forecast assessment. This was done to avoid any double counting of price impacts already accounted for in the maximum demand forecast.

AEMO found that some degree of price response was present in the summer maximum demand forecast for Queensland and South Australia and that the DSP applied for these regions should therefore be lowered. The DSP forecast includes this minor adjustment (15 MW for Queensland and 10 MW for South Australia) to ensure the numbers applied are correct, but noting that the actual DSP available is the higher amount.

7.4 Estimate of current DSP from smaller loads

The DSP response from smaller loads is based on a survey undertaken by AEMO in early 2013 asking network companies (transmission and distribution), retailers and DSP aggregators about the DSP available to them for 2013-14.

For companies that did not respond, AEMO made estimates to the extent possible from data provided in the previous (2011) survey.

AEMO also used the 2011 survey results to investigate and validate major differences between the 2013 and 2011 survey responses.

Some respondents provided seasonal data, indicating that DSP responses would be different depending on the season. Also, critical peak pricing type programs run in Victoria and New South Wales target summer peaks only and cannot be used in winter. The data allowed AEMO to estimate different DSP responses for summer and winter.

Some retailers and aggregators provided information about the price at which DSP would be called. While this price varied, in general the numbers provided allowed AEMO to assume that all DSP responses by retailers and DSP aggregators had occurred at $1000/MWh or above.

DSP from network companies is more often used to manage local peaks than system peaks. At very high prices, these are assumed to coincide, so AEMO assumed all network-driven DSP to be active at $7500/MWh or above.

7.5 The combined DSP forecast for 2013-14

AEMO added together the results from the large industrial analysis and survey responses to create the combined DSP forecast, which is presented in Appendix D.

The DSP forecast is used differently by AEMO's stakeholder, so multiple numbers are provided. The following explains how the different numbers should be used.

7.5.1 Seasonal data

Both summer and winter DSP forecasts are provided. Summer values should be used for the three summer months (December to February) plus March. Outside of these months, winter values should be used.

7.5.2 Different price levels

DSP responses at different price levels[46] are provided for use in market simulations. The responses are based on 50% probability of exceedance responses from large industrial loads, plus smaller load responses estimated at the given price level (as per Section 7.4).

Reliability assessments (adequacy of supply), such as AEMO's Electricity Statement of Opportunities and MT-PASA, should use the market price cap (MPC) response level should be used. This represents the expected response by industry just before involuntary load shedding is required.

[46] Price levels are given in real $2012.

7.5.3 Probability of exceedence maximum demand forecasts

For reliability assessments, it should be noted that numbers do not differ regardless of whether DSP is used to meet demand corresponding to the 10% POE or 50% POE maximum demand forecast. As DSP is mainly provided by temperature-insensitive sources, the same amount of DSP is assumed.

7.6 Assumed growth of DSP in the future

The combined forecast from Section 7.5 was projected into the future based on the following methodology.

The base assumption is that the maximum demand forecast represents the full potential for DSP, with the actual DSP being the realised potential at any point in time.

Each year a certain percentage of the DSP potential (as defined by the maximum demand) is converted into available DSP, representing more customers actively reducing demand at times of high prices either directly or through aggregators.

AEMO developed three different DSP uptake scenarios (rapid, moderate and slow) using different assumed conversion rates. Within each uptake scenario, the same conversion rate was used across all NEM regions, with the exception of Tasmania, where half the conversion rate was applied given the lower incentives for developing DSP in Tasmania.

AEMO assumed the following conversion rates:

- Slow uptake: 0.05% (0.025% for Tasmania)
- Moderate uptake: 0.10% (0.050% for Tasmania)
- Rapid uptake: 0.25% (0.125% for Tasmania)

For example, a region with a stable maximum demand of 1000 MW over time and an initial DSP resource of 10 MW (1% penetration), a conversion factor of 0.05% will add 0.5 MW of available DSP to the portfolio per year.

Noted that for all three uptake scenarios, the assumed conversion rates result in DSP growing faster than maximum demand growth; this is supported by survey respondents' comments around future expectations as well as the aspirations listed in Power of Choice review.

In general, DSP remains less than 5% of the maximum demand across the NEM for the moderate uptake scenario. For comparison, the PJM[47] market in the USA has DSP matching approximately 10% of maximum demand. This is considered very high by world standards.

The estimated DSP by NEM region out to 2032-33 based on the assumptions above are presented in Appendix D.

7.7 Modelling limitations and exclusions

The DSP forecast is subject to the following limitations and exclusions:

- The large industrial analysis is based on historical responses, which may change over time. With electricity prices rising, AEMO expects that DSP responses would be higher today than in previous years, so the DSP resource is potentially underestimated.
- Survey responses were not received from all market participants. This could lead to an underestimation of the DSP resource.

[47] PJM is a market serving 60 million customers on the US East coast. In its 2012 capacity auction it procured 14,833 MW of demand response (and an additional 923 MW of energy efficiency). For comparison, PJM's all-time peak at that time was 158,448 MW. Nearly 20,000 MW of demand response was offered in the auction, making the demand participation rate above 10%. See: www.pjm.com.

- To ensure confidentiality of the capabilities and bidding behaviour of individual DSP resources, results have been presented in aggregate, without the level of detail available to AEMO. AEMO has sought to ensure that the aggregation has not introduced any bias into the forecast.
- Estimating the growth (or decline) of the DSP resource into the future is difficult due to lack of data. The future DSP levels presented in Section 7.6 rather than being “forecast”, are made by assumptions guided by policy objectives and verified against achieved levels of DSP in other electricity markets.
- The DSP forecast excludes any daily or common customer response (whether voluntary or though load control enabled by tariff type). There are significant developments in this area, both in terms of mandating “peak smart” capabilities of various appliance types, but also through mandating tariffs that incentivise customer response, such as TOU pricing or controlled tariff types.

7.8 Changes from the 2012 methodology

The 2013 methodology incorporates changes from the 2012 methodology, which improve the quality of the results. The key changes are:

- DSP from large industrial loads are based on statistical analysis of metered data to give:
  - Better coverage (all large industrial loads have been considered this year).
  - Improved consistency (all loads are treated the same way).
  - Price-dependent responses.
- The survey of small DSP loads included seasonal data.
- Assumed growth of DSP into the future is based on a different methodology:
  - Start point is current maximum demand (potential for DSP) rather than current realised DSP.
  - Growth is based on an assumed conversion rate of loads contributing to maximum demand into DSP resources each year.

APPENDIX A - INPUT DATA, CHANGES AND ESTIMATED COMPONENTS

Calculations for annual energy (native) and maximum demand 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 (native) and maximum demand calculations • Transmission losses • Auxiliary load
Metering Settlements and Transfer Solution (MSATS): the retail market system (containing the database MDM) used for financial settlement of the NEM.	• Individual small non-scheduled generators (SNSG) for annual energy (native) and maximum demand calculations • Industrial load

Data for rooftop photovoltaic (PV) is estimated based on data provided by various government departments and distribution businesses.

A.1 Changes to historical data

Except for Metering Settlements and Transfer Solution (MSATS) data, which is subject to revisions as part of the settlement process, historical data should never change. While the individual component data used to create AEMO's datasets does not change, certain components of this data have been included or excluded in response to inconsistencies revealed by detailed analysis.

Changes to historical data compared to the 2012 NEFR are outlined below.

A.1.1 All NEM regions

Rooftop PV was revised up in the 2013 NEFR calculations due to a change in methodology and access to better data. This revision did not impact any other numbers, as rooftop PV is added to AEMO's dataset to forecast total usage, and is then removed as a post-model adjustment.

A.1.2 New South Wales

AEMO identified that Tumut and Shoalhaven pumping loads were inadvertently treated as generation thereby increasing the level of generation in the 2012 dataset. This was removed, resulting in a 200–1000 GWh/year reduction in annual energy in New South Wales.

Small non-scheduled generation (SNSG) was revised down due to a change in methodology, (see section 7.6) resulting in a 300–400 GWh/year reduction. This resulted in an increase in New Sales Wales operational demand.

With the closure of Kurri Kurri last year, energy in the large industrial sector was significantly reduced. Given AEMO's commitment to ensuring the confidentiality of individual customers' energy use, AEMO increased the number of large industrial loads included in that sector by reclassifying light industrial customers from the residential and commercial sector (defined as the energy remaining once large industrial has been removed). This resulted in a decrease in demand for the residential and commercial sector over the historical period.

A.1.3 Queensland

The energy produced by Wivenhoe Small Hydro (2–7 GWh/year) was inadvertently excluded last year, despite it being listed as included. This resulted in an increase to annual energy of 2-7 GWh/year in each of the historical years in Queensland.

SNSG was revised up in some years and down in others due to changes in methodology (see section 7.6). This increased and decreased operational demand by the same amount (10–600 GWh/year).

Large industrial demand was revised down 50–200 GWh/year. This was due to the removal of Wivenhoe pumping load from the large industrial demand sector. It was moved to the residential and commercial sector, increasing demand in that sector by the same amount.

A.1.4 Victoria

SNSG was revised down due to changes in methodology. This increased operational demand by 20–100 GWh/year.

Large industrial demand was revised up by 1,400–1,600 GWh due to a change in methodology around two large embedded generators in Victoria (Portland Wind Farm and Anglesea Power Station).

Previously AEMO used the energy flowing through the transmission connection point as the industrial load amounts for Alcoa and Point Henry; this year, the demand for these loads was altered to include all energy generated by both Alcoa and Point Henry. These new values were confirmed with Alcoa and Point Henry. As a consequence, residential and commercial demand was revised down; residential and commercial demand is the residual energy after removing industrial demand, auxiliary load and transmission losses, so increases in the large industrial sector will see a corresponding drop in this sector.

A.1.5 South Australia

SNSG was revised down by 3-6 GWh/year due to changes in methodology. This resulted in operational demand being revised up by the same amount.

Large industrial load was revised up by 9 GWh due to more accurate data being provided by industrial load customers.

Residential and commercial load was revised down given it is the residual energy after removing industrial demand, auxiliary load, and transmission losses.

A.1.6 Tasmania

SNSG was revised down by 60–200 GWh/year due to changes in methodology. This resulted in operational demand being revised up by the same amount.

A.2 Estimated components for the forecasts

A.2.1 Transmission loss forecasts

Transmission losses are determined as a percentage of large industrial and residential and commercial energy. AEMO assessed historical transmission losses against historical energy data in each region and found that the percentage of transmission losses as a percentage of energy consumption remained fairly constant.

Table A-1 shows the historical transmission losses as a percentage of energy consumption in each NEM region.

Table A-1 — Historical transmission losses as a percentage of industrial and non-large industrial consumption

	NSW	QLD	VIC	SA	TAS
2000-01	2.15%	3.74%	3.16%	2.30%	2.22%
2001-02	2.27%	4.32%	2.99%	2.01%	2.35%
2002-03	2.22%	3.91%	3.67%	2.30%	2.38%
2003-04	2.51%	3.76%	3.49%	2.44%	2.73%
2004-05	2.59%	3.55%	3.18%	2.32%	2.26%
2005-06	2.77%	3.35%	2.97%	2.34%	2.35%
2006-07	2.75%	3.40%	2.68%	2.10%	2.50%
2007-08	2.91%	3.33%	2.42%	1.88%	2.88%
2008-09	2.67%	3.12%	2.66%	2.21%	2.85%
2009-10	2.76%	3.14%	2.85%	2.35%	2.60%
2010-11	2.46%	3.00%	2.87%	2.32%	2.51%
2011-12	2.40%	3.02%	2.97%	2.37%	2.22%
Average	**2.54%**	**3.47%**	**2.99%**	**2.25%**	**2.35%**

As Table A-1 shows, the percentage of transmission losses remains fairly consistent over the years, as a result AEMO decided to apply an average percentage of transmission losses calculated from available historical data to forecast transmission losses going forward. The forecast for transmission losses is derived by using the historical average of transmission losses multiplied by the forecast for non-industrial and industrial energy consumption. This method of calculation is found to be more accurate compared to using a regression model, as was used in the 2012 NEFR.

A.2.2 Auxiliary loads forecast

Auxiliary losses are forecast based on the expected auxiliary loads as a percentage of total generation. The expected percentage is determined by historical percentages and anticipated changes in the generation mix. This methodology is applied to annual energy forecasts as well as summer and winter maximum demand forecasts, allowing for the fact that auxiliary loads can be different in each case.

Tables A-2 to A-4 show the expected estimated percentages for the annual energy and maximum demand forecasts following the historical percentages and anticipated changes in the generation mix.

Table A-2 — Auxiliary loads expected percentages for the annual energy demand forecasts

Annual Energy	NSW	QLD	SA	TAS	VIC
2013-14	5.23%	6.97%	4.46%	1.13%	8.60%
2014-15	5.23%	6.97%	4.46%	1.13%	8.60%
2015-16	5.23%	6.97%	4.46%	1.13%	7.00%
2016-17	4.93%	6.84%	4.46%	1.13%	7.00%
2017-18	4.93%	6.84%	2.23%	1.13%	7.00%
2018-19	4.93%	6.84%	2.23%	0.87%	7.00%
2019-20	4.93%	6.84%	2.23%	0.87%	5.95%

Annual Energy	NSW	QLD	SA	TAS	VIC
2020-21	4.93%	6.84%	2.23%	0.87%	5.95%
2021-22	4.93%	6.84%	2.23%	0.87%	5.95%
2022-23	4.93%	6.84%	2.23%	0.87%	5.95%
2023-24	4.93%	6.84%	2.23%	0.87%	5.95%
2024-25	4.93%	6.84%	2.23%	0.87%	5.95%
2025-26	5.07%	6.70%	2.81%	0.87%	5.95%
2026-27	5.07%	6.70%	2.81%	0.87%	5.95%
2027-28	5.07%	6.70%	2.81%	0.87%	5.95%
2028-29	5.07%	6.70%	2.81%	0.87%	5.95%
2029-30	5.07%	6.70%	2.81%	0.87%	5.95%
2030-31	5.07%	6.70%	1.44%	1.22%	5.95%
2031-32	5.07%	6.70%	1.44%	1.22%	5.95%

Table A-3 — Auxiliary loads expected percentages for the summer maximum demand forecasts

Summer MD	NSW	QLD	SA	TAS	VIC
2013-14	4.44%	5.39%	5.06%	1.34%	5.82%
2014-15	4.44%	5.39%	5.06%	1.34%	5.82%
2015-16	4.11%	5.39%	5.06%	1.34%	4.83%
2016-17	4.11%	5.31%	5.06%	1.34%	4.83%
2017-18	4.11%	5.31%	2.37%	1.34%	4.83%
2018-19	4.11%	5.31%	2.37%	0.99%	4.83%
2019-20	4.22%	5.31%	2.37%	0.99%	4.10%
2020-21	4.22%	5.31%	2.37%	0.99%	4.10%
2021-22	4.22%	5.31%	2.37%	0.99%	4.10%
2022-23	4.22%	5.31%	2.37%	0.99%	4.10%
2023-24	4.22%	5.31%	2.37%	0.99%	4.10%
2024-25	4.22%	5.31%	2.37%	0.99%	4.10%
2025-26	4.22%	5.20%	2.98%	0.99%	4.10%
2026-27	4.22%	5.20%	2.98%	0.99%	4.10%
2027-28	4.22%	5.20%	2.98%	0.99%	4.10%
2028-29	4.22%	5.20%	2.98%	0.99%	4.10%
2029-30	4.22%	5.20%	2.98%	0.99%	4.10%
2030-31	4.22%	5.20%	1.52%	1.39%	4.10%
2031-32	4.22%	5.20%	1.52%	1.39%	4.10%

Table A-4 — Auxiliary loads expected percentages for the summer maximum demand forecasts

Winter MD	NSW	QLD	SA	TAS	VIC
2013	4.27%	5.69%	3.74%	0.76%	6.32%
2014	4.27%	5.69%	3.74%	0.76%	6.32%
2015	3.93%	5.69%	3.74%	0.76%	5.08%
2016	3.93%	5.62%	3.74%	0.76%	5.08%
2017	3.93%	5.62%	1.95%	0.76%	5.08%
2018	3.93%	5.62%	1.95%	0.54%	5.08%
2019	4.04%	5.62%	1.95%	0.54%	4.31%
2020	4.04%	5.62%	1.95%	0.54%	4.31%
2021	4.04%	5.62%	1.95%	0.54%	4.31%
2022	4.04%	5.62%	1.95%	0.54%	4.31%
2023	4.04%	5.62%	1.95%	0.54%	4.31%
2024	4.04%	5.62%	1.95%	0.54%	4.31%
2025	4.04%	5.51%	2.45%	0.54%	4.31%
2026	4.04%	5.51%	2.45%	0.54%	4.31%
2027	4.04%	5.51%	2.45%	0.54%	4.31%
2028	4.04%	5.51%	2.45%	0.54%	4.31%
2029	4.04%	5.51%	2.45%	0.54%	4.31%
2030	4.04%	5.51%	1.25%	0.76%	4.31%
2031	4.04%	5.51%	1.25%	0.76%	4.31%

APPENDIX B - ROOFTOP PHOTOVOLTAIC FORECAST

This appendix specifies the forecast rooftop photovoltaic (PV) uptake scenarios based on the methodology described in Chapter 4. All 2013 NEFR scenarios used the moderate uptake scenario, but given the uncertainty around rooftop PV impacts in future years, rapid and slow uptake scenarios are also provided here to enable sensitivity studies.

B.1 Annual energy

The forecast NEM-wide rooftop PV post-model adjustments for annual energy are shown in Figure B-1. A regional breakdown is shown in Table B-1.

Figure B-1 — Post-model adjustments by scenario measured at transmission level

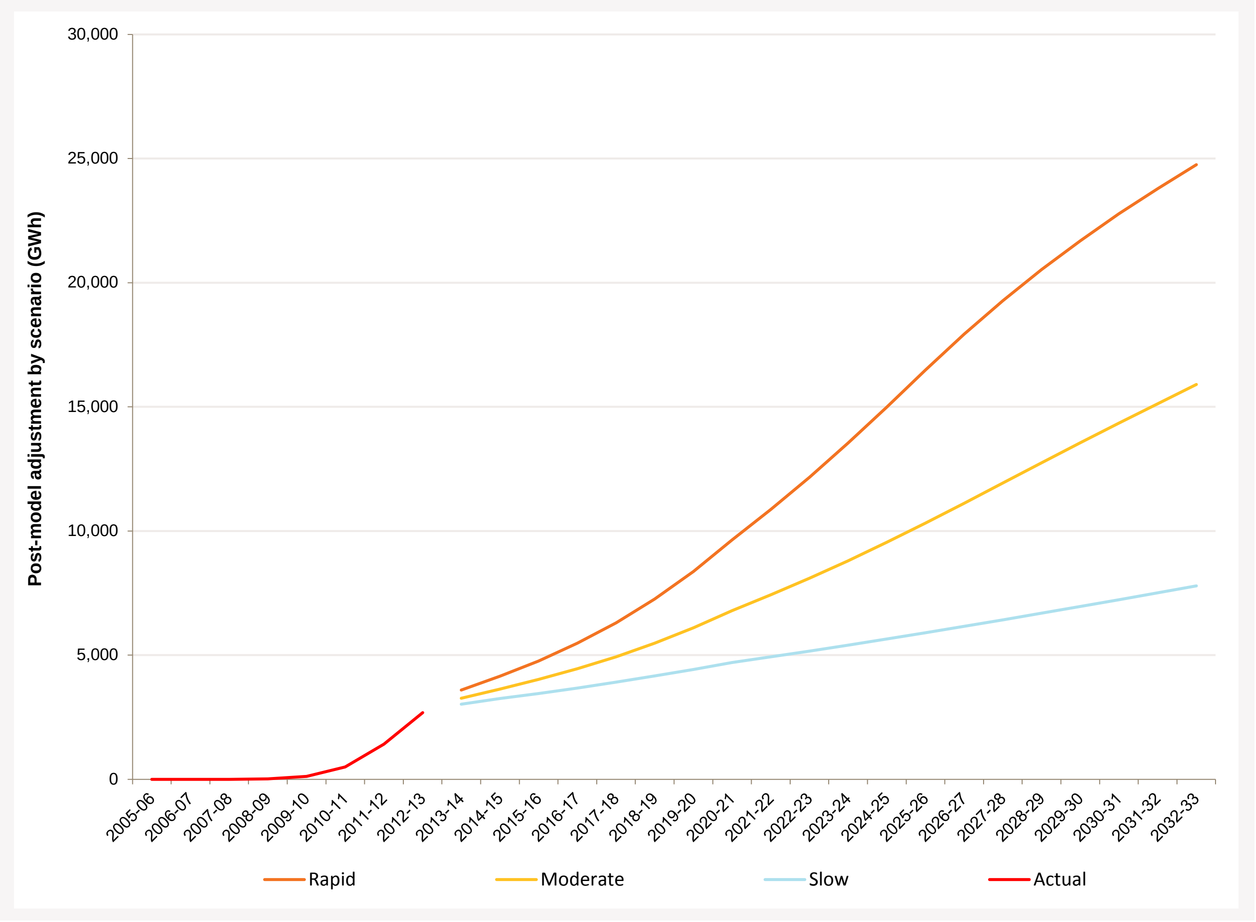


Table B-1 — Post-model adjustments by state for each scenario (GWh/year)

Region	Uptake scenario	2012–13	2022–23	2032–33
QLD	Rapid	1,031	3,748	7,819
QLD	Moderate	1,023	2,440	4,916
QLD	Slow	1,018	1,772	2,535
NSW	Rapid	666	4,658	9,098
NSW	Moderate	659	3,059	5,935
NSW	Slow	653	1,659	2,746
VIC	Rapid	470	1,929	4,605
VIC	Moderate	465	1,294	2,672
VIC	Slow	462	851	1,298
SA	Rapid	501	1,558	2,650
SA	Moderate	497	1,119	2,010
SA	Slow	496	782	1,048
TAS	Rapid	39	274	582
TAS	Moderate	38	185	366
TAS	Slow	38	104	167.5
NEM	Rapid	2,707	12,166	24,754
NEM	Moderate	2,684	8,097	15,898
NEM	Slow	2,667	5,168	7,795

B.2 Maximum demand

The forecast regional rooftop PV post-model adjustments for summer and winter maximum demand are shown in Table B-2 and Table B-3 respectively.

Table B-2 — Post-model adjustment to summer maximum demand forecast (MW)

Region	Scenario	2012–13	2022–23	2032–33
QLD	Rapid	215	999	1,995
QLD	Moderate	215	639	1,267
QLD	Slow	215	452	645
NSW	Rapid	166	1,302	2,408
NSW	Moderate	166	843	1,586
NSW	Slow	166	448	734
VIC	Rapid	103	662	1,538
VIC	Moderate	103	438	888
VIC	Slow	103	281	426
SA	Rapid	141	484	782

Region	Scenario	2012–13	2022–23	2032–33
SA	Moderate	141	342	601
SA	Slow	141	232	313
TAS	Rapid	6	37	75
TAS	Moderate	6	25	47
TAS	Slow	6	14	22

Table B-3 — Post-model adjustment to winter maximum demand forecast (MW)

Region	Scenario	2013	2023	2033
QLD	Rapid	-	-	-
QLD	Moderate	-	-	-
QLD	Slow	-	-	-
NSW	Rapid	-	-	-
NSW	Moderate	-	-	-
NSW	Slow	-	-	-
VIC	Rapid	4	13	30
VIC	Moderate	4	9	17
VIC	Slow	3	5	8
SA	Rapid	-	-	-
SA	Moderate	-	-	-
SA	Slow	-	-	-
TAS	Rapid	-	-	-
TAS	Moderate	-	-	-
TAS	Slow	-	-	-

APPENDIX C - ENERGY EFFICIENCY FORECAST

This appendix specifies the forecast energy efficiency uptake scenarios based on the methodology described in Chapter 5. All the 2013 NEFR scenarios used the moderate energy efficiency uptake scenario, but given the uncertainty around energy efficiency impacts in future years, a rapid and slow uptake scenario are also provided in this appendix to enable sensitivity studies.

C.1 Annual energy

The forecast NEM-wide energy efficiency post-model adjustments for annual energy are shown in Figure C-1 . A regional breakdown is shown in Table C-1.

The NEFR forecast for 2012–13 annual energy is based on historical observed demand for half the period and estimated demand for the remaining half. The post-model adjustment should only be applied to the latter. Therefore, the 2012–13 estimate has been reduced by 50% compared to the estimate for the full financial year.

Figure C-1— Post-model adjustments by scenario measured at transmission level

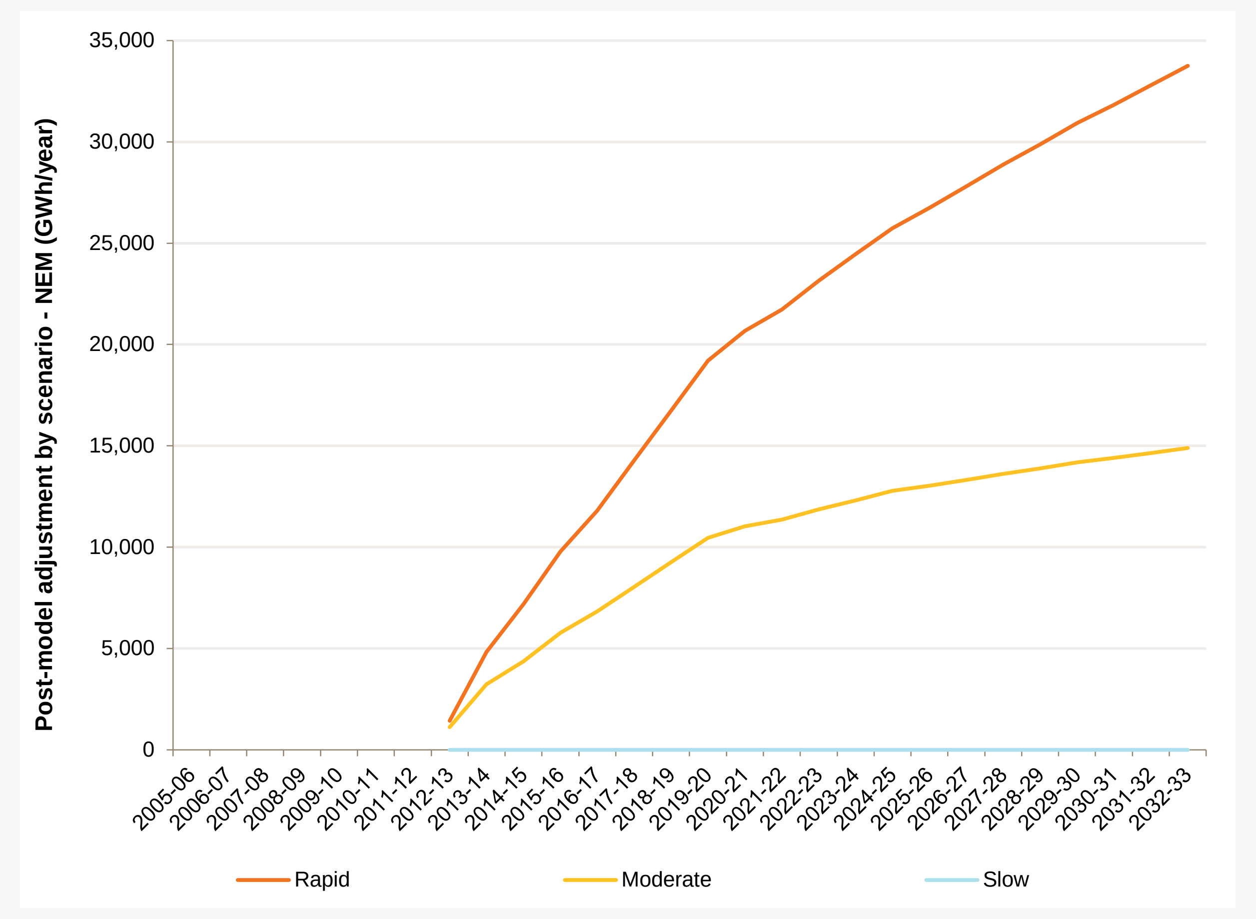


Table C-1 — Post-model adjustments by state for each scenario (GWh/year)

Region	Uptake scenario	2012–13	2022–23	2032–33
QLD	Rapid	387	6,170	9,036
QLD	Moderate	304	3,168	3,977
QLD	Slow	-	-	-
NSW	Rapid	533	8,819	12,681
NSW	Moderate	425	4,528	5,568
NSW	Slow	-	-	-
VIC	Rapid	369	5,608	8,337
VIC	Moderate	276	2,872	3,722
VIC	Slow	-	-	-
SA	Rapid	110	1,770	2,606
SA	Moderate	84	907	1,161
SA	Slow	-	-	-
TAS	Rapid	46	776	1,091
TAS	Moderate	37	399	475
TAS	Slow	-	-	-
NEM	Rapid	1,445	23,143	33,751
NEM	Moderate	1,127	11,874	14,903
NEM	Slow	-	-	-

C.2 Maximum demand

The forecast regional energy efficiency post-model adjustments for summer and winter maximum demand are shown in Table C-2 and Table C-3 respectively.

Both NEFR summer and winter maximum demand forecast for 2012–13 is assumed to capture all energy efficiency impacts and the values have been set to zero.

Table C-2 — Post-model adjustment to summer maximum demand forecast (MW)

Region	Scenario	2012–13	2022–23	2032–33
QLD	Rapid	-	1,059	1,551
QLD	Moderate	-	544	683
QLD	Slow	-	-	-
NSW	Rapid	-	1,415	2,035
NSW	Moderate	-	726	893
NSW	Slow	-	-	-
VIC	Rapid	-	1,021	1,518
VIC	Moderate	-	523	678

Region	Scenario	2012–13	2022–23	2032–33
VIC	Slow	-	-	-
SA	Rapid	-	404	594
SA	Moderate	-	207	265
SA	Slow	-	-	-
TAS	Rapid	-	108	151
TAS	Moderate	-	55	66
TAS	Slow	-	-	-

Table C-3 — Post-model adjustment to winter maximum demand forecast (MW)

Region	Scenario	2013	2022–23	2032–33
QLD	Rapid	-	910	1,333
QLD	Moderate	-	467	587
QLD	Slow	-	-	-
NSW	Rapid	-	1,530	2,200
NSW	Moderate	-	785	966
NSW	Slow	-	-	-
VIC	Rapid	-	893	1,327
VIC	Moderate	-	457	592
VIC	Slow	-	-	-
SA	Rapid	-	324	477
SA	Moderate	-	166	213
SA	Slow	-	-	-
TAS	Rapid	-	137	193
TAS	Moderate	-	70	84
TAS	Slow	-	-	-

APPENDIX D - DEMAND-SIDE PARTICIPATION FORECAST

This appendix presents the forecast values for demand-side participation (DSP) based on the methodology presented in Chapter 7. These should be read in conjunction with the guidance provide in Section 7.5.

D.1 Estimate of current DSP capacity

The following tables show a summary of estimated DSP capacity for the 2013 winter and 2013–14 summer respectively by price band. MPC refers to electricity wholesale prices reaching the market price cap (MPC), which is the maximum spot price allowed in the NEM, as stipulated in the National Electricity Rules.[1]

Commentary about the regional numbers is provided in the following sections.

Table D-1 — Expected DSP (MW), winter 2013

	QLD	NSW	VIC	SA	TAS
Prices > $1000/MWh	60.8	16.8	93.1	36.8	3.0
Prices > $7500/MWh	70.8	38.8	167.1	39.8	36.0
Prices = MPC	132.5	147.9	347.8	53.1	65.0

Table D-2 — Expected DSP (MW), summer 2013–14

	QLD[1]	NSW	VIC	SA[2]	TAS
Prices > $1000/MWh	45.8	16.8	113.1	29.8	3.0
Prices > $7500/MWh	55.8	43.8	241.2	35.8	36.0
Prices = MPC	117.5	152.9	421.9	62.4	65.0

1 The actual DSP has been estimated to be 15 MW higher, but this amount has already been accounted for in AEMO's summer maximum demand forecast.

2 The actual DSP has been estimated to be 10 MW higher, but this amount has already been accounted for in AEMO's summer maximum demand forecast.

[1] As of July 2013, this level is $13,100/MWh. See: http://www.aemc.gov.au/electricity/guidelines-and-standards.html

D.2 Queensland DSP to 2032–33

The following figures show the assumed growth in DSP for the moderate uptake scenario.

The estimated DSP for 2013–14 is significantly higher than estimated in the 2012 NEFR. Up to 133 MW of DSP is forecast to be available in 2013–14 at times when the electricity wholesale price reaches market price cap (MPC).

This increase in forecast DSP is mainly due to a more comprehensive study of the response of large industrial loads at time of high prices.

DSP available at lower prices are more in line with last year's forecast.

Figure D-1 — Assumed DSP growth in Queensland, winter

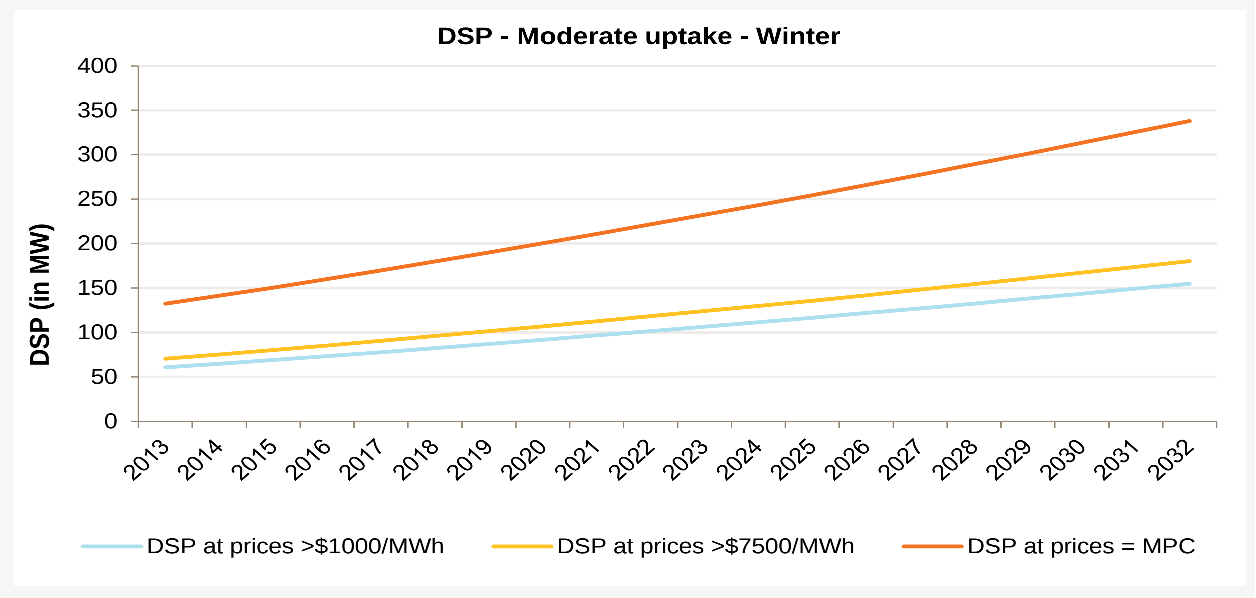
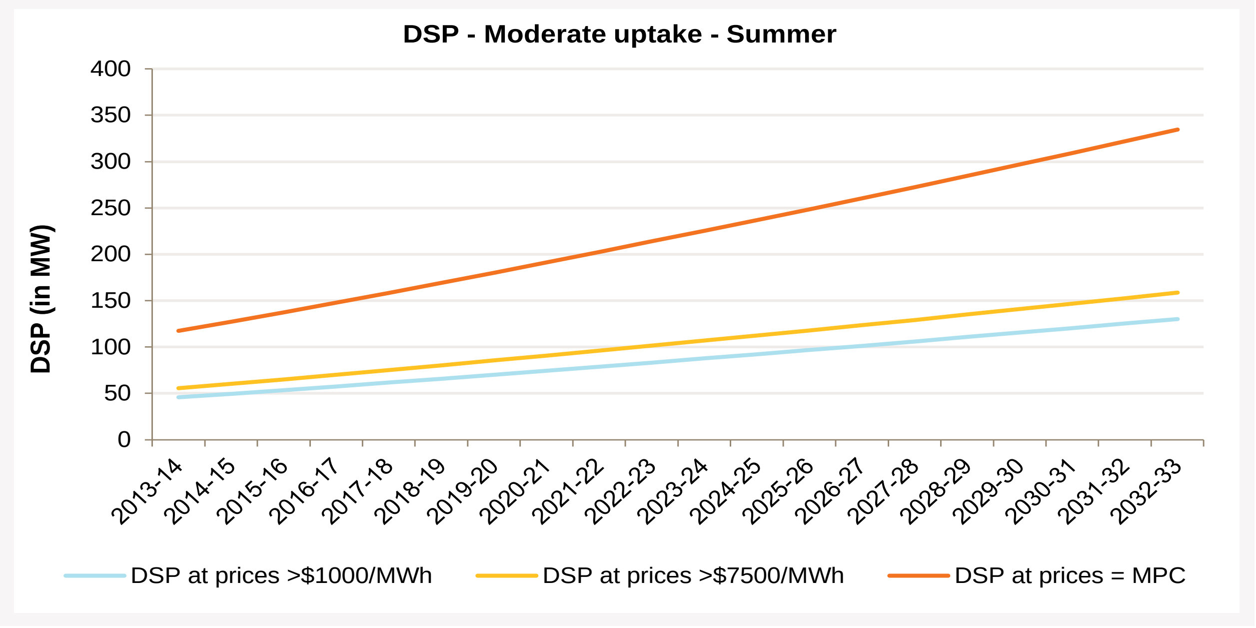


Figure D-2 — Assumed DSP growth in Queensland, summer



D.3 New South Wales (incl. ACT) DSP to 2032–33

The following figures show the assumed growth in DSP in New South Wales (including the Australian Capital Territory) for the moderate uptake scenario.

The estimated DSP for 2013–14 is significantly higher than estimated in the 2012 NEFR. Up to 153 MW of DSP is forecast to be available in 2013–14 at times when the electricity wholesale price reaches market price cap (MPC).

This increase in forecast DSP is mainly due to a more comprehensive study of the response of large industrial loads at time of high prices.

DSP available at lower prices are more in line with last year's forecast.

Figure D-3 — Assumed DSP growth in New South Wales (incl. ACT), winter

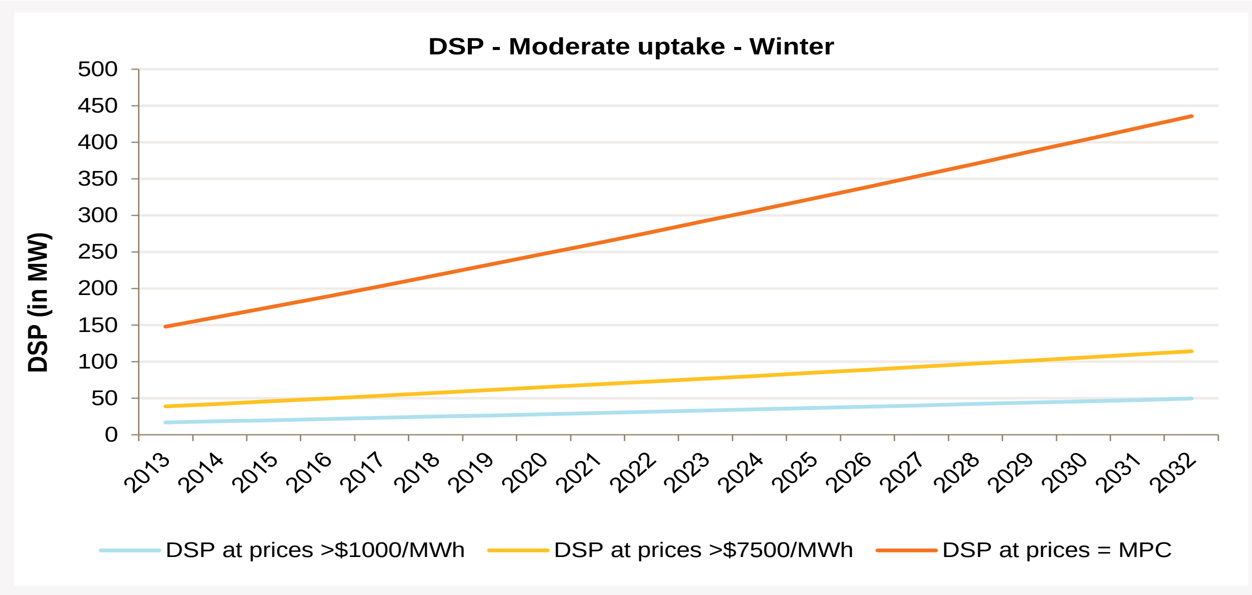
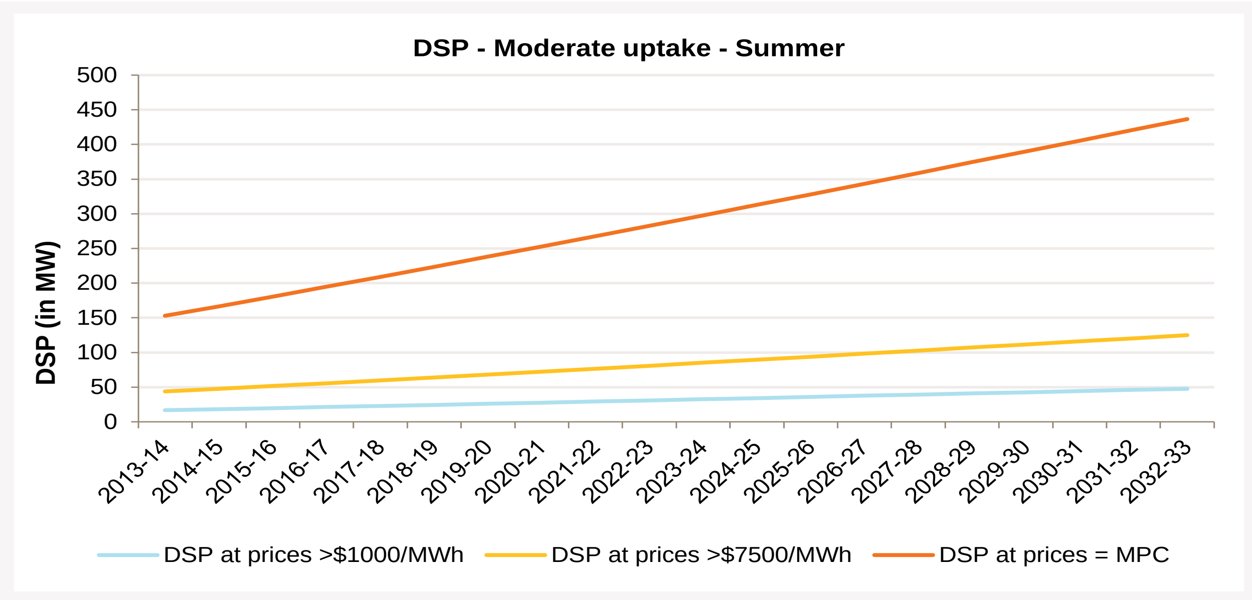


Figure D-4 — Assumed DSP growth in New South Wales (incl. ACT), summer



D.4 Victorian DSP to 2032–33

The following figures show the assumed growth in DSP in Victoria for the moderate uptake scenario.

The estimated DSP for 2013–14 is significantly higher than estimated in the 2012 NEFR. Up to 422 MW of DSP is forecast to be available in 2013–14 at times when the electricity wholesale price reaches market price cap (MPC)

This increase in forecast DSP is mainly due to a more comprehensive study of the response of large industrial loads at time of high prices.

DSP available at lower prices are more in line with last year's forecast.

Figure D-5 — Assumed DSP growth in Victoria, winter

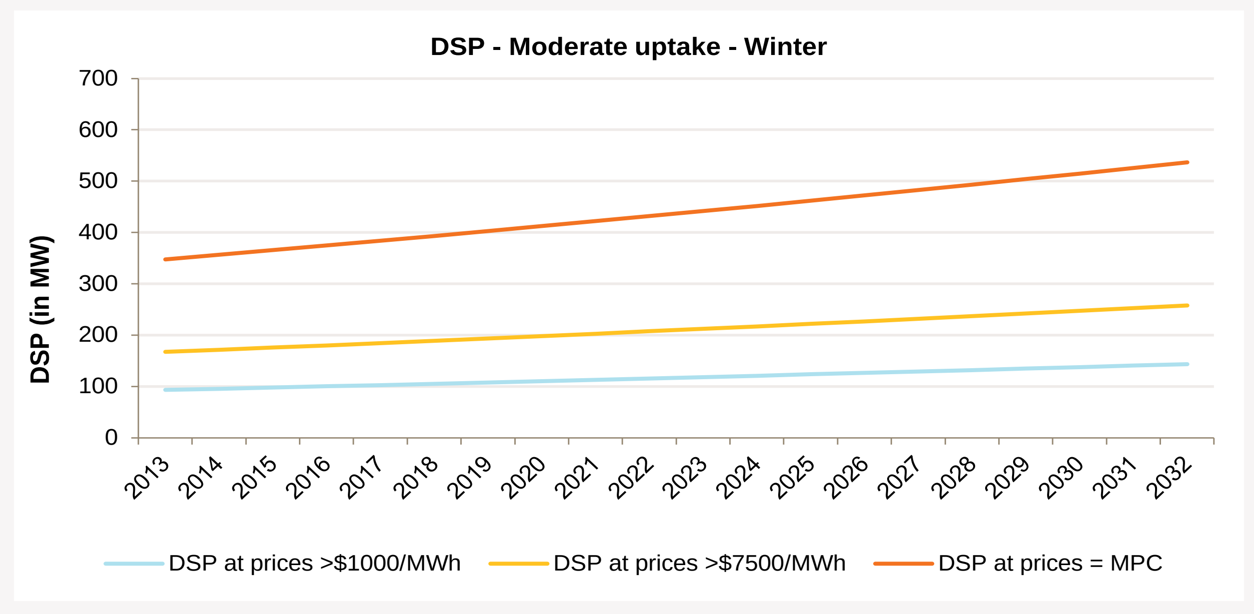
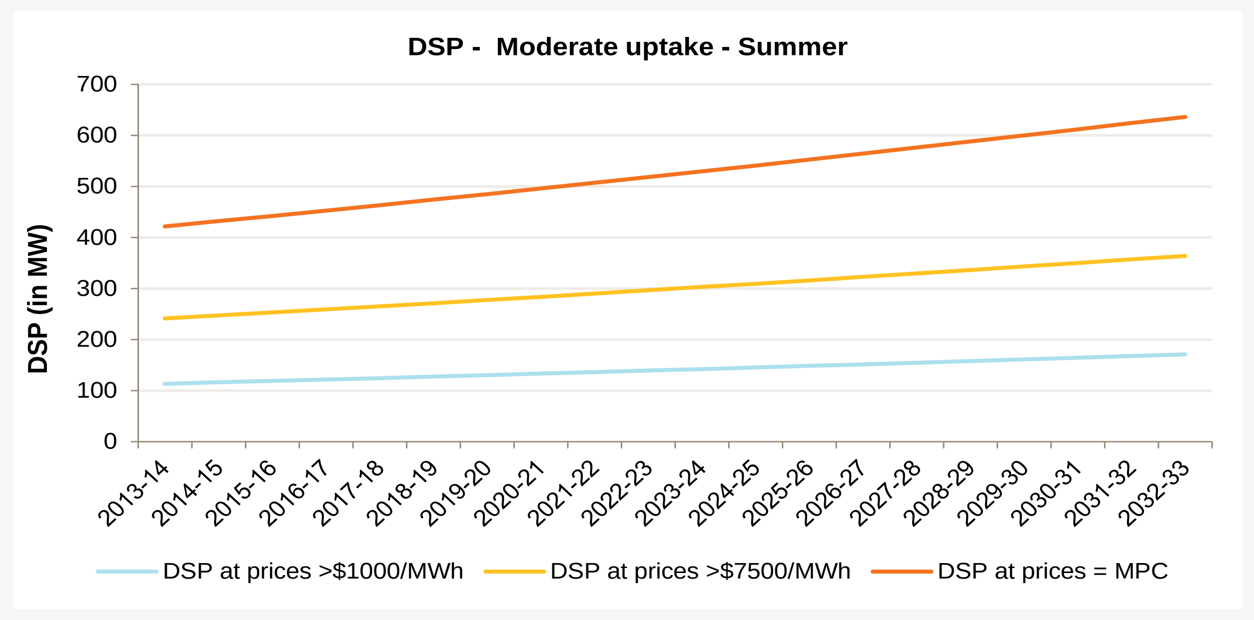


Figure D-6 — Assumed DSP growth in Victoria, summer



D.5 South Australian DSP to 2032–33

The following figures show the assumed growth in DSP in South Australia for the moderate uptake scenario.

The estimated DSP for 2013–14 cannot be compared with previous estimates as it has not previously been reported independently.

There is a clear difference in the available capacity in summer and winter, with a substantial amount of capacity available during summer only.

Figure D-7 — Assumed DSP growth in South Australia, winter

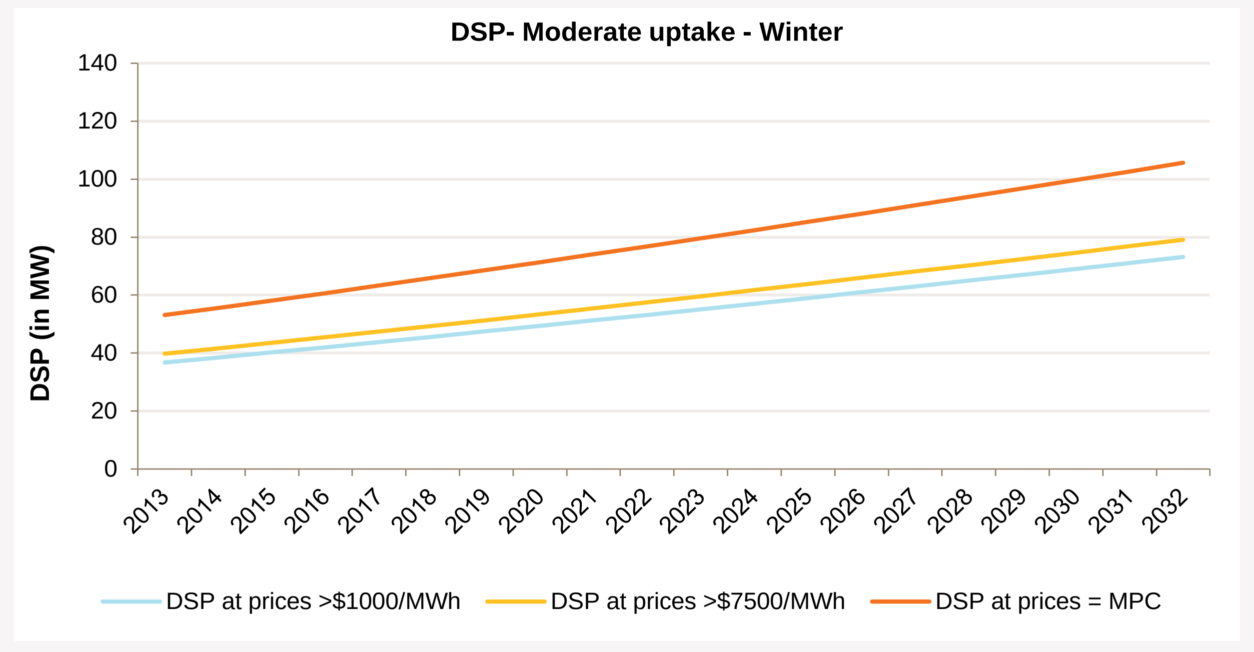
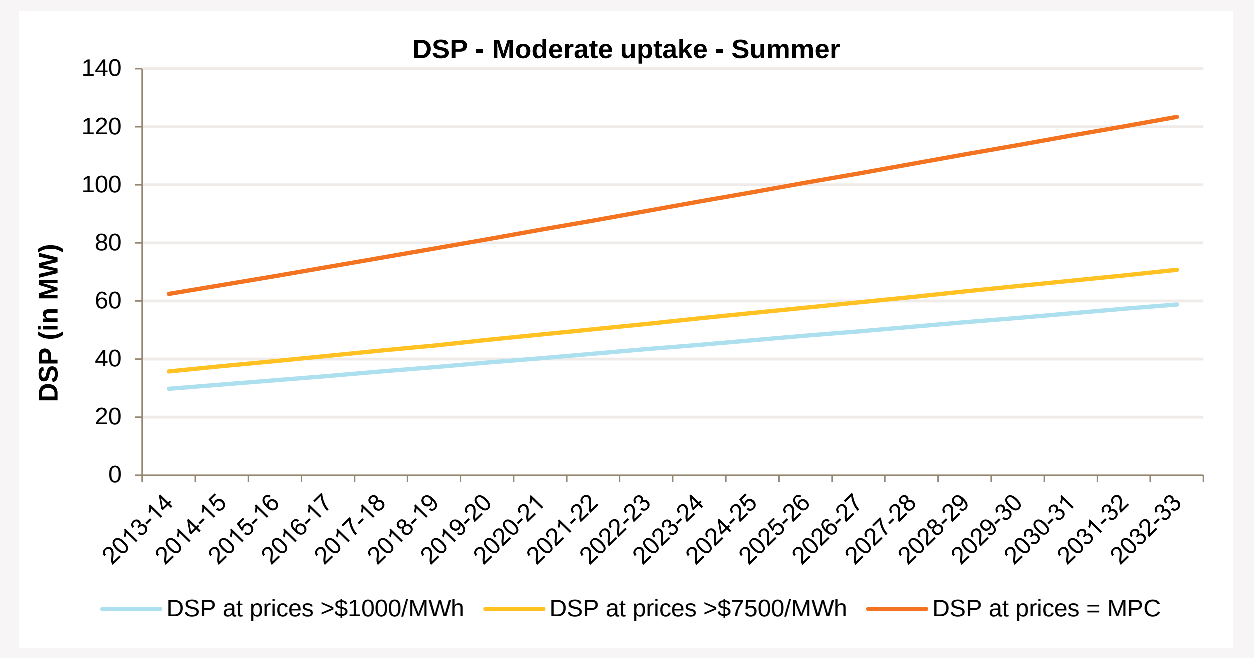


Figure D-8 — Assumed DSP growth in South Australia, summer



D.6 Tasmanian DSP to 2032–33

The following figures show the assumed growth in DSP in Tasmania for the moderate uptake scenario.

The results differ from earlier years as DSP has not previously been reported in Tasmania; however, it should be noted that the amount of DSP available is negligible when electricity wholesale prices are below $7,500/MWh.

Figure D-9 — Assumed DSP growth in Tasmania, winter

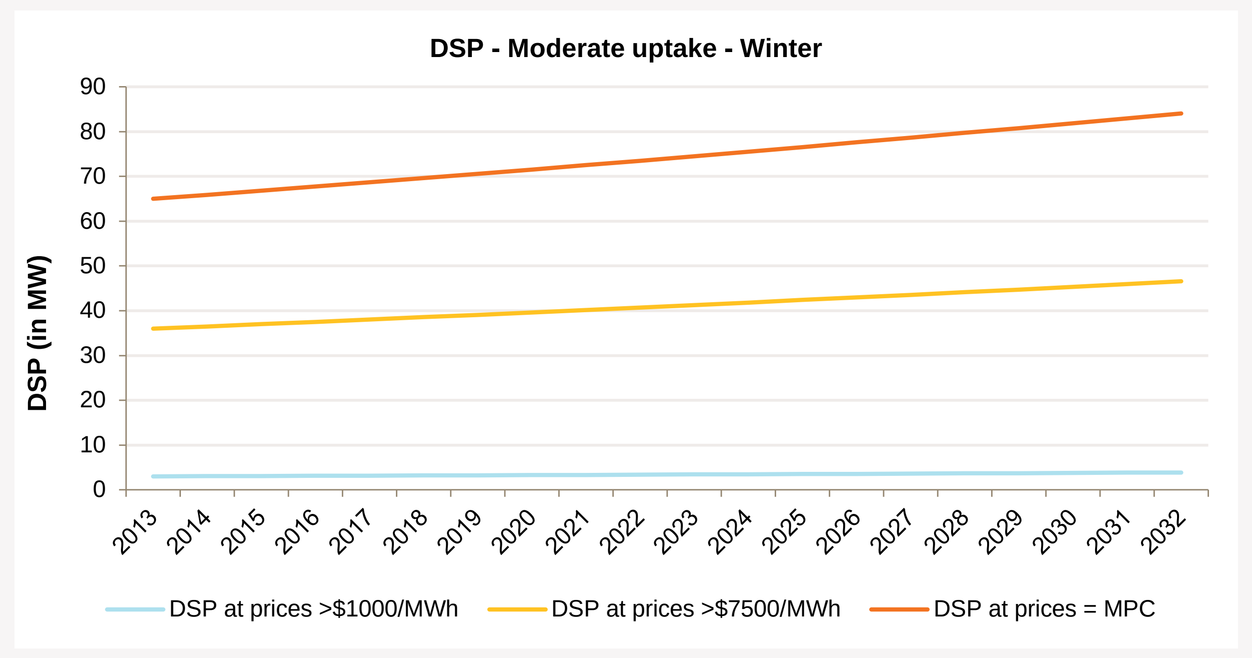
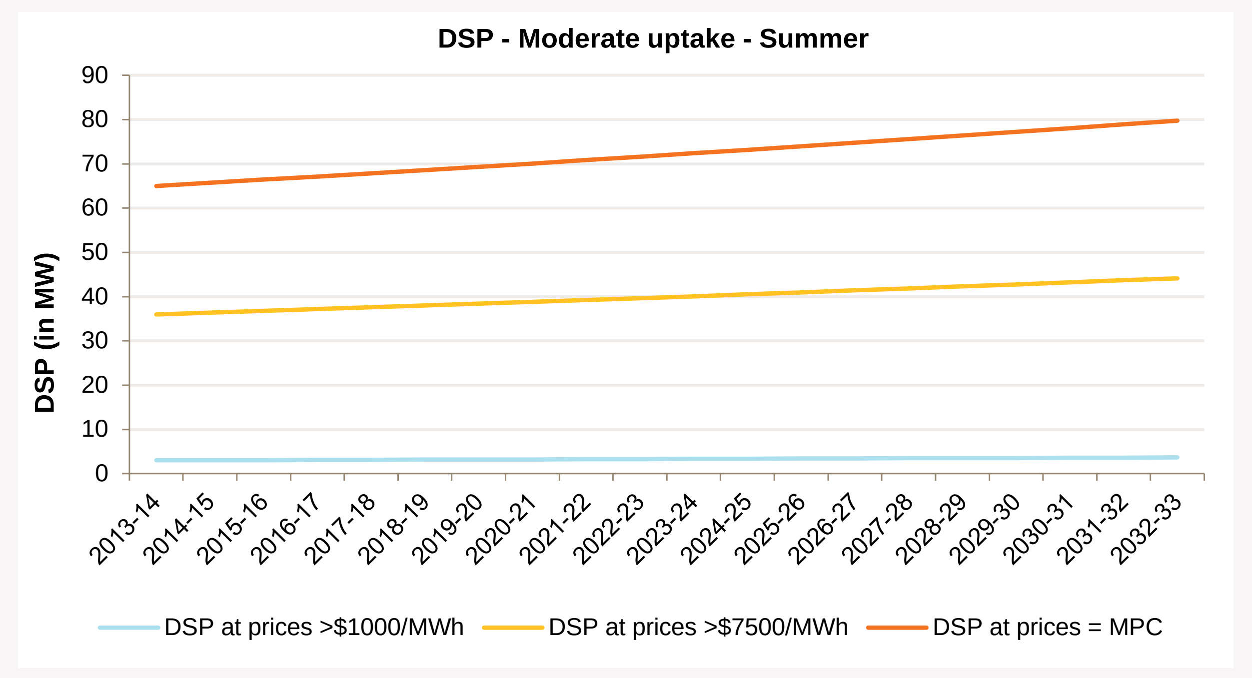


Figure D-10 — Assumed DSP growth in Tasmania, summer



APPENDIX E - GENERATORS INCLUDED

This appendix provides two lists of power stations for each region:

- The first lists the power stations used to develop operational demand forecasts.
- The second lists the power stations used to develop annual energy demand forecasts.

These lists separately identify the scheduled, semi-scheduled and small non-scheduled generators that contribute to these forecasts.

E.1 Queensland

E.1.1 Power stations used for operational demand 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 Power Plant	950	Steam Super Critical	Black Coal	Scheduled
Collinsville	190	Steam Sub Critical	Black Coal	Scheduled
Condamine A	144	CCGT	Coal Seam Methane	Scheduled
Darling Downs	644	CCGT	Coal Seam Methane	Scheduled
Gladstone	1,680	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	Kerosine Aviation fuel used for stationary energy - avtur	Scheduled
Oakey	282	OCGT	Diesel	Scheduled
Roma Gas Turbine	80	OCGT	Natural Gas Pipeline	Scheduled
Stanwell	1,460	Steam Sub Critical	Black Coal	Scheduled
Swanbank B	250	Steam Sub Critical	Black Coal	Scheduled
Swanbank E GT	385	CCGT	Coal Seam Methane	Scheduled
Tarong	1,400	Steam Sub Critical	Black Coal	Scheduled
Tarong North	450	Steam Super Critical	Black Coal	Scheduled
Townsville Gas Turbine (Yabulu)	242	CCGT	Coal Seam Methane	Scheduled
Wivenhoe	500	Pump Storage	Water	Scheduled
Yarwun	154	CCGT	Natural Gas Pipeline	Non scheduled

E.1.2 Power stations used for annual energy forecasts for Queensland

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Barcaldine	55	CCGT	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 A4	30	Steam Sub Critical	Black Coal	Non scheduled
Callide B	700	Steam Sub Critical	Black Coal	Scheduled
Callide Power Plant	840	Steam Super Critical	Black Coal	Scheduled
Collinsville	190	Steam Sub Critical	Black Coal	Scheduled
Condamine A	144	CCGT	Coal Seam Methane	Scheduled
Daandine	30	Compression Reciprocating Engine	Coal Seam Methane	Non scheduled
Darling Downs	644	CCGT	Coal Seam Methane	Scheduled
German Creek	31.8	Spark Ignition Reciprocating Engine	Waste Coal Mine Gas	Non scheduled
Gladstone	1,680	Steam Sub Critical	Black Coal	Scheduled
Invicta	50.3	Steam Sub Critical	Bagasse	Non scheduled
ISIS Central Sugar Mill Cogen	25	Steam Sub Critical	Bagasse	Non scheduled
Kareeya	88	Run of River	Water	Scheduled
Kogan Creek	744	Steam Super Critical	Black Coal	Scheduled
KRC Cogen	5	Steam Sub Critical	Natural Gas Pipeline	Non scheduled
Mackay Gas Turbine	34	OCGT	Diesel	Scheduled
Millmerran Power Plant	856	Steam Super Critical	Black Coal	Scheduled
Moranbah North PS	45.6	Spark Ignition Reciprocating Engine	Waste Coal Mine Gas	Non scheduled
Moranbah PS	12	Compression Reciprocating Engine	Waste Coal Mine Gas	Non scheduled
Mt Stuart	424	OCGT	Kerosine Aviation fuel used for stationary energy - avtur	Scheduled
Oakey	282	OCGT	Diesel	Scheduled
Oaky Creek	20	Compression Reciprocating Engine	Coal Seam Methane	Non scheduled
Pioneer	67.8	Steam Sub Critical	Bagasse	Non scheduled
Rochedale Renewable Energy	4.2	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non scheduled
Rocky Point	30	Steam Sub Critical	Green and air dried wood	Non scheduled
Roghan Road LFG Plant	1	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non scheduled
Roma Gas Turbine	80	OCGT	Natural Gas Pipeline	Scheduled
Somerset Dam	4	Run of river	Water	Non scheduled
Southbank Institute of Tech	1	OCGT	Diesel	Non scheduled
Stanwell	1,460	Steam Sub Critical	Black Coal	Scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Suncoast Gold Macadamias	1.5	Steam Sub Critical	Macadamia Nut Shells	Non scheduled
Swanbank B	250	Steam Sub Critical	Black Coal	Scheduled
Swanbank E GT	385	CCGT	Coal Seam Methane	Scheduled
Tarong	1,400	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
Veolia Ti Tree Bioreactor	3.3	Compression Reciprocating Engine	Landfill Methane / Landfill Gas	Non scheduled
Victoria Mill	24	Steam Sub Critical	Bagasse	Non scheduled
Whitwood Road Renewable	1.1	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non scheduled
Windy Hill	12	Wind - Onshore	Wind	Non scheduled
Wivenhoe	500	Pump Storage	Water	Scheduled
Wivenhoe Small Hydro	4.5	Run of river	Water	Non scheduled
Yarwun	154	CCGT	Natural Gas Pipeline	Non scheduled

E.2 New South Wales

E.2.1 Power stations used for operational demand forecasts for New South Wales (including ACT)

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Bayswater	2,640	Steam Sub Critical	Black Coal	Scheduled
Blowering	70	Hydro - Gravity	Water	Scheduled
Capital Wind Farm	140.7	Wind - Onshore	Wind	Non scheduled
Collongra	724	OCGT	Natural Gas Pipeline	Scheduled
Cullerin Range Wind Farm	30	Wind - Onshore	Wind	Non scheduled
Eraring	2,880	Steam Sub Critical	Black Coal	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	2,000	Steam Sub Critical	Black Coal	Scheduled
Mt Piper	1,400	Steam Sub Critical	Black Coal	Scheduled
Munmorah	600	Steam Sub Critical	Black Coal	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

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Tumut 3	1,500	Hydro - Gravity	Water	Scheduled
Upper Tumut	616	Hydro - Gravity	Water	Scheduled
Uranquinty	664	OCGT	Natural Gas Pipeline	Scheduled
Vales Point B	1,320	Steam Sub Critical	Black Coal	Scheduled
Wallerawang C	1,000	Steam Sub Critical	Black Coal	Scheduled
Woodlawn Wind Farm	48.3	Wind - Onshore	Wind	semi scheduled

E.2.2 Power stations used for annual energy forecasts for New South Wales (including ACT)

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Awaba PS	1.1	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non scheduled
Bankstown Sports Club	2.1	Compression Reciprocating Engine	Diesel	Non scheduled
Bayswater	2,640	Steam Sub Critical	Black Coal	Scheduled
Blowering	70	Hydro - Gravity	Water	Scheduled
Broadwater Power Station	30	Steam Sub Critical	Bagasse	Non scheduled
Broken Hill GT	50	Diesel	OCGT	Non scheduled
Brown Mountain	5.4	Hydro - Gravity	Water	Non scheduled
Burrendong Hydro	18	Hydro - Gravity	Water	Non scheduled
Burrinjuck PS	27.2	Hydro - Gravity	Water	Non scheduled
Capital Wind Farm	140.7	Wind - Onshore	Wind	Non scheduled
Colongra	724	OCGT	Natural Gas Pipeline	Scheduled
Condong PS	30	Steam Sub Critical	Bagasse	Non scheduled
Copeton Hydro	20	Hydro - Gravity	Water	Non scheduled
Cullerin Range Wind Farm	30	Wind - Onshore	Wind	Non scheduled
EarthPower Biomass	3.9	Spark Ignition Reciprocating Engine	Biomass recycled municipal and industrial materials	Non scheduled
Eastern Creek PS	5	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non scheduled
Eraring	2,880	Steam Sub Critical	Black Coal	Scheduled
Glenbawn Hydro	5	Hydro - Gravity	Water	Non scheduled
Glennies Creek PS	13	Compression Reciprocating Engine	Coal Seam Methane	Non scheduled
Grange Avenue	2	Compression Reciprocating Engine	Landfill Methane/Landfill Gas	Non scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
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
Jacks Gully	2.3	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non scheduled
Jindabyne	1.1	Hydro - Gravity	Water	Non scheduled
Jounama	14.4	Hydro - Gravity	Water	Non scheduled
Keepit	6.5	Hydro - Gravity	Water	Non scheduled
Liddell	2,000	Steam Sub Critical	Black Coal	Scheduled
Mt Piper	1,400	Steam Sub Critical	Black Coal	Scheduled
Munmorah	600	Steam Sub Critical	Black Coal	Scheduled
Nine Network Willoughby	3.2	Compression Reciprocating Engine	Diesel	Non scheduled
Pindari Hydro	5.7	Hydro - Gravity	Water	Non 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
St Georges League Club	1.5	Compression Reciprocating Engine	Diesel	Non scheduled
Tallawarra	420	CCGT	Natural Gas Pipeline	Scheduled
Teralba	3	Compression Reciprocating Engine	Waste Coal Mine Gas	Non scheduled
Tumut 3	1,500	Hydro - Gravity	Water	Scheduled
Upper Tumut	720	Hydro - Gravity	Water	Scheduled
Uranquinty	664	OCGT	Natural Gas Pipeline	Scheduled
Vales Point B	1,320	Steam Sub Critical	Black Coal	Scheduled
Wallerawang C	1,000	Steam Sub Critical	Black Coal	Scheduled
West Illawarra Leagues Club	1	Compression Reciprocating Engine	Diesel	Non scheduled
West Nowra Landfill	1	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non scheduled
Western Suburbs League Club	1.3	Compression Reciprocating Engine	Diesel	Non scheduled
Whytes Gully	2.5	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non scheduled
Wilga Park	10	Spark Ignition Reciprocating Engine	Natural Gas - Unprocessed	Non scheduled
Woodlawn Bioreactor	4.3	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non scheduled
Woodlawn Wind Farm	48.3	Wind - Onshore	Wind	semi scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Wyangala A	20	Hydro - Gravity	Water	Non scheduled
Wyangala B	4	Hydro - Gravity	Water	Non scheduled

E.3 South Australia

E.3.1 Power stations used for operational demand forecasts for South Australia

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
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
Quarantine Power Station	224	OCGT	Natural Gas Pipeline	Scheduled
Snowtown Wind Farm Units 1 and 47	98.7	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

E.3.2 Power stations used for annual energy forecasts for South Australia

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Amcor Glass	4.02	Compression Reciprocating Engine	Diesel	Non scheduled
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
Lonsdale	20.7	Compression Reciprocating Engine	Diesel	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
Pt Stanvac	58	Compression Reciprocating Engine	Diesel	Non scheduled
Quarantine Power Station	224	OCGT	Natural Gas Pipeline	Scheduled
Snowtown Wind Farm Units 1 And 47	98.7	Wind - Onshore	Wind	Semi scheduled
Snuggery Power Station	63	OCGT	Diesel	Scheduled
Starfish Hill Wind Farm	34.5	Wind - Onshore	Wind	Non scheduled
Tatiara	0.5	Compression Reciprocating Engine	Diesel	Non scheduled
Terminal Storage Mini Hydro	2.5	Hydro - Gravity	Water	Non scheduled
Torrens Island A	480	Steam Sub Critical	Natural Gas Pipeline	Scheduled

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

E.4 Victoria

E.4.1 Power stations used for operational demand 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
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	1,600	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	2,180	Steam Sub Critical	Brown Coal	Scheduled
Loy Yang B	1,000	Steam Sub Critical	Brown Coal	Scheduled
Macarthur Wind Farm	420	Wind - Onshore	Wind	Semi scheduled
Mortlake Units	566	OCGT	Natural Gas Pipeline	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	1,480	Steam Sub Critical	Brown Coal	Scheduled
Yambuk Wind Farm	30	Wind - Onshore	Wind	Non scheduled

E.4.2 Power stations used for annual energy 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
Ballarat Base hospital	2.04	Spark Ignition Reciprocating Engine	Natural Gas Pipeline	Non scheduled
Banimboola PS	12.5	Hydro - Gravity	Water	Non scheduled
Berwick	4.6	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non scheduled
Bogong/McKay	300	Hydro - Gravity	Water	Scheduled
Brooklyn Landfill	2.83	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non scheduled
Challicum Hills Wind Farm	52.5	Wind - Onshore	Wind	Non scheduled
Codrington Wind Farm	18.2	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
Hallam Hydro - SEW	0.25	Hydro - Gravity	Water	Non scheduled
Hallam Road	6.7	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non scheduled
Hazelwood	1,600	Steam Sub Critical	Brown Coal	Scheduled
Hepburn Wind Farm	4.1	Wind - Onshore	Wind	Non scheduled
HRL Tramway Road	5	OCGT	Diesel	Non 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
Longford	31.8	OCGT	Natural Gas Pipeline	Non scheduled
Loy Yang A	2,180	Steam Sub Critical	Brown Coal	Scheduled
Loy Yang B	1,000	Steam Sub Critical	Brown Coal	Scheduled
Macarthur Wind Farm	420	Wind - Onshore	Wind	Semi scheduled
Mornington Waste Disposal	0.77	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non scheduled
Mortlake Units	566	OCGT	Natural Gas Pipeline	Scheduled
Mortons Lane	19.5	Wind - Onshore	Wind	Non 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
Rubicon	13.5	Hydro - Gravity	Water	Non scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Shepparton Wastewater	1.1	Spark Ignition Reciprocating Engine	Sewerage/Waste Water	Non scheduled
Somerton	160	OCGT	Natural Gas Pipeline	Scheduled
Sunshine Energy	8.7	Spark Ignition Reciprocating Engine	Landfill Methane / Landfill Gas	Non scheduled
Symex	5.9	OCGT	Natural Gas Pipeline	Non scheduled
Tatura Biomass	1.1	Spark Ignition Reciprocating Engine	Sewerage/Waste Water	Non scheduled
Toora Wind Farm	21	Wind - Onshore	Wind	Non 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
Wonthaggi Wind Farm	12	Wind - Onshore	Wind	Non scheduled
Wyndham Waste Disposal	1	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non scheduled
Yallourn W	1480	Steam Sub Critical	Brown Coal	Scheduled
Yambuk Wind Farm	30	Wind - Onshore	Wind	Non scheduled
Yarrawonga Hydro	9.5	Hydro - Gravity	Water	Non scheduled

E.5 Tasmania

E.5.1 Power stations used for operational demand forecasts for Tasmania

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Bastyan	79.9	Hydro - Gravity	Water	Scheduled
Bell Bay Three	120	Hydro - Gravity	Water	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
Trevallyn	93	Hydro - Gravity	Water	Scheduled

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

E.5.2 Power stations used for annual energy forecasts for Tasmania

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Bastyan	79.9	Hydro - Gravity	Water	Scheduled
Bell Bay Three	120	Hydro - Gravity	Water	Scheduled
Butlers Gorge Rev	14.4	Hydro - Gravity	Water	Non scheduled
Catagunya/Liapootah/Wayatinah	170.1	Hydro - Gravity	Water	Scheduled
Cethana	85	Hydro - Gravity	Water	Scheduled
Cluny (includes Repulse)	17	Hydro - Gravity	Water	Non 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
Paloona	28	Hydro - Gravity	Water	Non scheduled
Poatina	300	Hydro - Gravity	Water	Scheduled
Reece	231.2	Hydro - Gravity	Water	Scheduled
Remount	2.2	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non scheduled
Repulse	28	Hydro - Gravity	Water	Non scheduled
Rowallan	10.5	Hydro - Gravity	Water	Non scheduled
Tamar Valley Combined Cycle	208	CCGT	Natural Gas Pipeline	Scheduled
Tamar Valley Peaking	58	OCGT	Natural Gas Pipeline	Scheduled
Tarraleah	90	Hydro - Gravity	Water	Scheduled
Trevallyn	93	Hydro - Gravity	Water	Scheduled
Tribute	82.8	Hydro - Gravity	Water	Scheduled
Tungatinah	125	Hydro - Gravity	Water	Scheduled
Woolnorth Studland Bay/Bluff Point Wind Farm	140	Wind - Onshore	Wind	Non scheduled