FORECASTING METHODOLOGY INFORMATION PAPER

NATIONAL ELECTRICITY FORECASTING REPORT 2014

Published: **July 2014**

AEMO
AUSTRALIAN ENERGY MARKET OPERATOR

IMPORTANT NOTICE

Purpose

AEMO has prepared this document to provide information about the 2014 National Electricity Forecasting Report, as at the date of publication.

Disclaimer

This report contains data provided by or collected from third parties, and conclusions, opinions or assumptions that are based on that data.

AEMO has made every effort to ensure the quality of the information in this document but cannot guarantee that information and assumptions are accurate, complete or appropriate for your circumstances. This document does not include all of the information that an investor, participant or potential participant in the national electricity market might require, and does not amount to a recommendation of any investment.

Anyone proposing to use the information in this document should independently verify and check its accuracy, completeness and suitability for purpose, and obtain independent and specific advice from appropriate experts.

Accordingly, to the maximum extent permitted by law, AEMO and its officers, employees and consultants involved in the preparation of this publication:

- make no representation or warranty, express or implied, as to the currency, accuracy, reliability or completeness of the information in this publication; and
- are not liable (whether by reason of negligence or otherwise) for any statements, opinions, information or other matters contained in or derived from this publication, or any omissions from it, or in respect of a person's use of or reliance on the information in this publication.

Acknowledgement

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

ABOUT THIS INFORMATION PAPER

The 2014 Forecasting Methodology Information Paper is a companion document to the 2014 National Electricity Forecasting Report (NEFR). It is designed to assist in interpreting the electricity consumption forecasts contained in the NEFR.

This paper provides a detailed description of how the 2014 annual energy and maximum demand (MD) 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 since the 2013 NEFR.

In addition to explaining the methodology behind the forecasts, this paper provides further detail on the customer segments used in the 2014 NEFR and AEMO's approach to developing the forecasts for each forecasting component.

Key improvements since the 2013 NEFR include:

- A stronger focus on short term forecasts (2013-14 to 2016-17).
- Greater emphasis placed on recent declining residential and commercial consumption patterns in forecasting future trends.
- Increased sample size of large industrial loads, from 39 in 2013 to 93 in 2014.
- Impact of rooftop photovoltaic (PV) on MD was incorporated directly into the MD model.

The modelling and forecasting methodology processes for each component have been endorsed and approved by both AEMO's subject matter experts and external reviewer Woodhall Investment Research.

CONTENTS

TABLES

FIGURES

EQUATIONS

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 National Electricity Market (NEM) region. In 2014, AEMO made further improvements to this process.

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

AEMO collaborates with industry to ensure representative and reliable forecasts are consistently produced for each region. This report outlines the methodology used in the annual energy and MD forecasting process.
Table 1 summarises how the component forecasts relate to the 2014 NEFR scenarios

Table 1: 2014 NEFR component scenario mapping

2014 NEFR reference	Related economic scenario	Related large industrial scenario	Related rooftop PV scenario	Related energy efficiency scenario	Related small non-scheduled generation scenario
High	HCO5	High	Low uptake	Slow uptake	High uptake
Medium	MCO5	Medium	Medium uptake	Moderate uptake	Moderate uptake
Low	LCO5	Low	High uptake	Rapid uptake	Slow uptake

CHAPTER 2 – RESIDENTIAL & COMMERCIAL LOAD

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

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

2.1 Annual energy

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

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

The 2014 NEFR methodology is based on the 2013 NEFR, which was peer reviewed by Frontier Economics in 2013.[1] While the general model structure was not changed, several aspects were refined in response to external peer review feedback, changes in the market environment, and ongoing internal improvement initiatives.

The changes include:

- Incorporating an increased number of economic variables in the model.
- Emphasising more recent consumption data given the growth trend for electricity consumption has recently reversed and consumption has been declining.
- Incorporating the likelihood of a consumer response to the carbon price repeal.
- Changing the forecasting basis from native to operational consumption.
- Incorporating more weather stations in the weather variables.
- Reducing the size of the residential and commercial component due to a reallocation of customers as large industrial.[2]

As per the 2013 NEFR, AEMO engaged Woodhall Investment Research Ltd to assist in developing the annual energy models. The following sections detail the data used in modelling, the development of the model and the model specification.

2.1.1 Data sources and variable selection

The residential and commercial model uses historical data to estimate a relationship between energy consumption and four key drivers of consumption (income, price, weather, and population). It then uses these estimates and forecast values for the key drivers to calculate consumption forecasts. Historical and forecast economic variables were provided by Independent Economics and Frontier Economics.[3]

Historical weather data was provided by the Bureau of Meteorology. This section details the source of historical and forecast data and explains how specific variables were selected.

[1] Frontier Economics. *Review of AEMO's 2013 National Electricity Forecasts*. Available at http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report-2013.

[2] Residential and commercial load is a derived value; increasing the number of industrial customers decreases the estimated residential and commercial load. See below for more details on how residential and commercial load is calculated.

[3] Frontier Economics. *Economic Outlook*. Available at http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/NEFR-Supplementary-Information.

The data for economic variables from Independent Economics included:

- Real gross state product (GSP).
- Real state final demand (SFD).
- Population (POP).

The data for economic variables from Frontier Economics included:

- Real total price of electricity (TPE).
- Real residential price of electricity (RPE).
- Real business price of electricity (BPE).
- Real residential gas price (RGP).
- Real business gas price (BGP).
- Real total gas price (TGP).

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

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

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

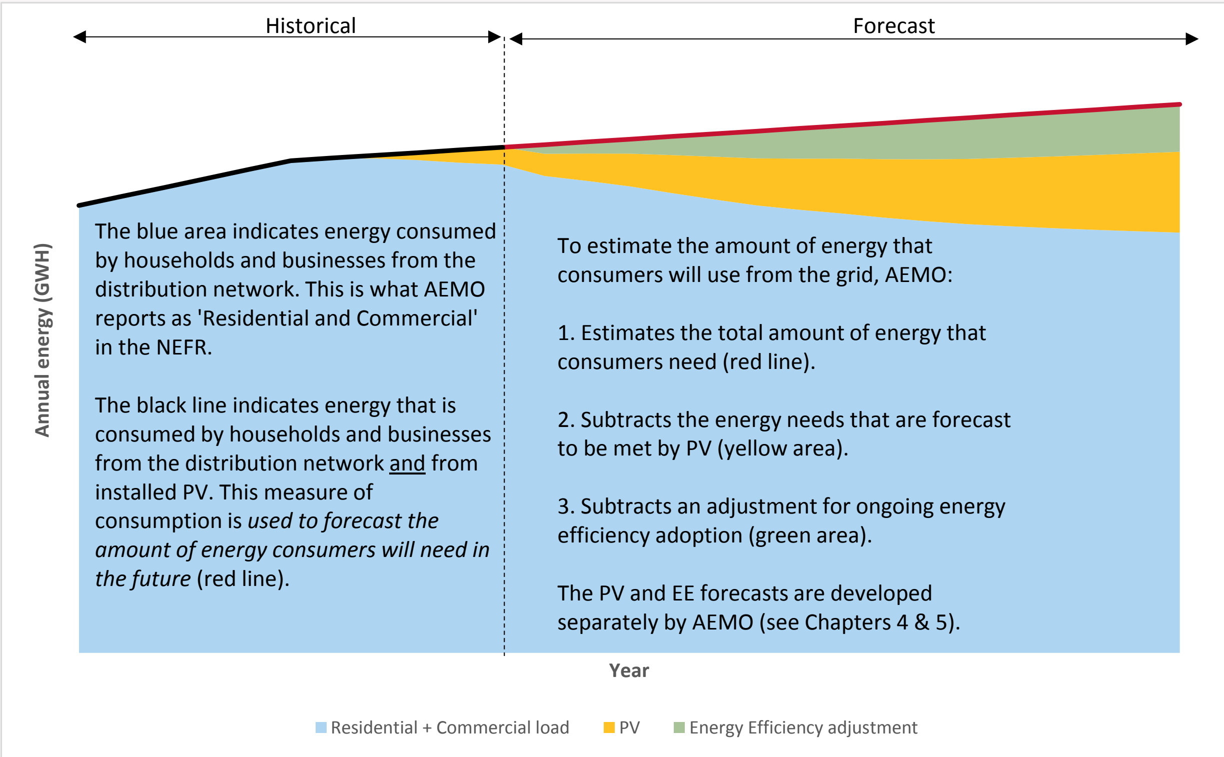
The data is region specific so unique models were developed for each region. AEMO used quarterly data for modelling, commencing September, December, March, and June. Results were then aggregated to financial year.

Calculating consumption data

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

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

Figure 1: Defining and calculating residential and commercial data



The historical residential and commercial data used in the 2014 NEFR differs to that used in the 2013 NEFR. One of the ongoing modelling improvements made was to increase the number of industrial customers for which AEMO produced individual forecasts. The 54 additional customers allocated to the industrial sector in the 2014 NEFR were previously included in the residential and commercial sector. These customers have now been removed from the residential and commercial component, resulting in reduced residential and commercial forecasts. In addition, consumption data in 2014 is based on operational rather than native demand.

Calculating income data

Historical and forecast income data was provided by Independent Economics.

The 2013 NEFR used a different income variable per NEM region. In some regions, SFD was used; in others, GSP was used. Frontier Economics' 2013 review recommended creating economic variable driver that combined both SFD and GSP. AEMO used Principal Component Analysis (PCA) to create this single income variable for the 2014 NEFR, as per the 2014 Action Plan.[4]

PCA calculates linear weights that are used to combine the two data series to create a single variable. These weights maximise the variance explained with the variables, creating a single variable that is representative of the trends in both SFD and GSP. The benefit of PCA is that it does not require *a priori* knowledge of the appropriate weights, and instead relies on variation within the data to select the weighting.

[4] Available at http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Other/planning/NEFR/2014/2014%20Supplementary/2014_NEFR_Action_Plan_Implementation_FINAL.ashx

AEMO used a combination of statistics, coefficient analysis, and residual analysis to assess whether using PCA was preferable to using a single income variable. AEMO found that the choice of variable made very little difference to the model estimation but chose to proceed with PCA as it:

- Increases the amount of income information in the model without increasing the number of variables.[5]
- Allows a consistent variable to be used in each NEM region.

Calculating price data

Historical and forecast price data was provided by Frontier Economics. Based on coefficient and residual analysis, AEMO assessed TPE as the most appropriate price variable in all regions.

Calculating population data

Historical and forecast population data was provided by Independent Economics. Consumption and income data were converted to per capita parameters before modelling.

Calculating weather data

Historical average daily temperature data was provided by the Bureau of Meteorology. AEMO used this data to estimate historical heating degree days (HDD) and cooling degree days (CDD)[6] for each region. In the 2013 NEFR, AEMO based the regional HDD and CDD on capital city weather station data. For the 2014 NEFR, as per the 2014 Action Plan, AEMO used a weighted average of several weather stations in each region.

During the modelling process, HDD and CDD were found to be significant in New South Wales, Victoria, and South Australia. HDD was not significant in Queensland and CDD was not significant in Tasmania[7] so these variables were omitted from the final models.

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

Other variables

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

Table 2: Summary of final variable selection

	Electricity consumption	Income	Price	Temperature
Variable	**Y** = Energy/population * 1000	**I** = PCA (SFD and GSP)/population * 1000	**P** = TPE	**HDD** and **CDD**
Unit	kWh/capita	$/capita	c/kWh	Degree days

Consumption, price and income variables were converted to natural logs to improve ease of coefficient interpretation.

5 Increasing the number of variables would compromise the degrees of freedom, affecting the integrity of statistical tests used for model assessment.
6 HDD and CDD are a measure of how much (in degrees) and for how long (in days) the outside air temperature is lower/higher than a threshold temperature.
7 This is because there are few heating degree days for Queensland and few cooling degree days for Tasmania.

2.1.2 Model development

The model used in the 2014 NEFR is based on the 2013 NEFR model. It is developed in two stages, which allows AEMO to produce long-run and short-run coefficients.[8] A summary of the methodology is provided below; for more details refer to the 2013 NEFR Methodology.[9]

There are two changes in the 2014 NEFR methodology:

- Using an intercept correction as per the 2014 Action Plan to correct an upward forecast bias.
- Using a Maximum Price Model in modelling the consumer response to the proposed carbon price repeal.

These are further detailed below.

Estimating the long-run relationship: Dynamic Ordinary Least Squares

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

As per the 2013 NEFR, AEMO adopted the Dynamic Ordinary Least Squares[10] (DOLS) approach. This involves estimating the cointegrating[11] long-run equation and adding sufficient leads and lags[12] of the first differences[13] of the explanatory variables. The specification of the DOLS equation is shown below in Equation 1.

Equation 1: Dynamic Ordinary Least Squares

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

AEMO adopted this approach because it:

- Enables a valid and consistent approach to be applied across all NEM regions.
- Provides an efficient estimator for the long-run relationship in the presence of variables with differing and higher orders of integration. Additionally, if a Newey-West[14] correction is applied, it is reasonable to apply standard tests on the coefficients.
- Is known to be effective when working with small datasets where endogeneity[15] may be present.

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

[8] Coefficients can be used to describe the change in energy that can be expected due to a change in a given variable. Estimating long-run and short-run coefficients allows AEMO to analyse the long-term and short-term impact of a change in a variable.
[9] AEMO. *Forecasting Methodology Information Paper*. Available at http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report-2013/NEFR-Supplementary-Information-2013.
[10] As proposed by Saikkonen (1991).
[11] Based on work undertaken for the 2013 NEFR, the variables used in the forecast models may be cointegrated, indicating a long-run relationship between price and income which can be used to forecast energy consumption.
[12] Leads and lags are transformations of existing time series data that are added to the equation to improve the fit of the model. They are created by delaying or bringing forward the data series by a specified number of time periods. AEMO determined the appropriate number of leads and lags of the differenced variables by assessing the stability of the coefficients under different leads and lags structures in DOLS. See NEFR 2013 for more info on the method used to select leads and lags.
[13] Differences are a transformation of a data series, usually adopted to deal with time series data that exhibits strong increasing (or decreasing) trends i.e. data with a non-zero mean, also known as non-stationary data. This technique allows the underlying variation in the time series to become more apparent. They are created by taking the difference of data points in consecutive observations (e.g. $income_t$ – $income_{t-1}$). When the first difference of non-stationary data achieves stationarity, as is the case for AEMO's data, then the time series is said to be integrated to order 1.
[14] 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.
[15] AEMO's data set is small and endogeneity is suspected.

Carbon price assumptions

In 2013, the Federal Government announced its intention to repeal the *Clean Energy Act 2011.* The price series produced by Frontier Economics included a decline in electricity prices from July 2014.

However, AEMO has assumed that consumers will not respond to the price decrease. AEMO's energy models are based on historical data during a period in which prices have been continually rising; they provide limited information about how consumers may respond to price decreases.

Consumer response to changes in electricity prices is asymmetric. While consumers may reduce consumption in response to price rises, they do not necessarily revert to previous levels of consumption when prices later fall, due to permanent changes in behaviour, or momentum. To reflect this, AEMO applied a Maximum Price Model which assumes that rather than responding to the carbon price repeal, customers will continue to respond to the highest prices they have experienced in recent years.

Estimating the short-run response: Integrated Dynamic Model

The short-run response estimates how much demand can deviate in the short run, from the long-run demand forecast in response to a change in a variable. As per the 2013 NEFR, AEMO adopted the Integrated Dynamic Model (IDM) approach.

The standard approach when estimating a short-run response within a cointegrating long-run equation is to place the lagged error correction (EC) term within a dynamic system, such as an error correction model (ECM). See Equation 2 below. The ECM describes how the dependent variable and explanatory variables behave in the short-run, and the speed at which the system will adjust back to the long-run equilibrium consistent with the long-run cointegrating relationship.

Equation 2: Error Correction Model with long-run estimates

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

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

Consequently, in the 2013 NEFR, AEMO adopted an Integrated Dynamic Model (IDM). The IDM integrates the long-run relationship between the variables (assuming cointegration) while allowing for short-run fluctuations consistent with the long-run equilibrium. The IDM integrates the lagged EC term (the residuals estimated from the DOLS) into the model. It also includes fourth lagged differences of all the main economic and temperature variables.

Equation 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 $\Delta 4y = y - y(-4)$, 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.

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

AEMO considers IDM as superior to a standard ECM in modelling seasonal data.[16] Advantages include:

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

Intercept correction

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

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

In the 2014 NEFR[17], AEMO tested the inclusion of an intercept correction[18] around the turning point in the historical consumption data. The intercept correction adds emphasis to recent data where a change in the consumption trend has been observed. The inclusion of the intercept correction reduced the magnitude of the overestimation in the last few periods of historical data. A statistical assessment showed that including an intercept correction was statistically significant and added more information to the model in all regions except Tasmania. Consequently, AEMO has applied an intercept correction to all regions except Tasmania. The starting point of the intercept correction varies by NEM region.

2.1.3 Model specification

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

The DOLS equation used is shown in Equation 4. The same equation was used for each region with the exception of Queensland and Tasmania, where HDD and CDD, respectively, were omitted as they were found to not be significant.

Equation 4: Dynamic Ordinary Least Squares, regional model structure

$$Log(y) = c_1 + \mathrm{c}_2 Log(I) + c_3 \mathrm{Log(P)} + c_4 \mathrm{HDD} + c_5 \mathrm{CDD} + c_6 \mathrm{S2} + c_7 S3 + c_8 S4$$

Table 3 shows the values for the estimated coefficients in each region.

[16] Based on impulse response functions for short-run demand response to innovations in the variables.
[17] The application of an intercept correction, starting in 2012, was tested in the 2013 NEFR. However, there was insufficient evidence to support including an intercept correction in the final model specification.
[18] An intercept correction is a simple method that adds a dummy variable to a particular period of time.

Table 3: DOLS coefficients

	Constant c1	Log(I) c2	Log(P) c3	HDD c4	CDD c5	S2 c6	S3 c7	S4 c8
Qld	6.83844	0.14073	-0.28362	N/A	0.00042	0.08761	0.12688	0.01533
NSW	4.05751	0.41962	-0.31291	0.00031	0.00045	0.02516	0.04159	0.01092
SA	6.31810	0.14294	-0.14055	0.00032	0.00047	0.02359	0.03890	-0.00424
Tas	6.22143	0.23181	-0.40688	0.00035	N/A	0.01931	0.05203	-0.00744
Vic	6.16080	0.17361	-0.20751	0.00025	0.00042	0.03343	0.04515	0.00633

The coefficients (c_2 – c_5) for the cointegrating long-run equation can be interpreted as follows:

- Per capita consumption has a long-run income elasticity of c_2. As the value for c_2 is positive for all NEM regions, this means that the long-run response to an increase of 1% in income per capita is a c_2% increase in electricity consumption.
- Per capita consumption has a long-run price elasticity of c_3. As the value for c_3 is negative for all NEM regions, this means that the long-run response to an increase of 1% in price is a c_3% decrease in electricity consumption.
- HDDs and CDDs are significant in explaining energy consumption in the long run, but only at the time of each heating or cooling event.

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

Using Queensland as an example:

- A 1% increase in income per capita would lead to a 0.14% increase in electricity consumption.
- A 1% increase in price would lead to a 0.28% decrease in electricity consumption.

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

The IDM equation that was used is shown in Equation 5. The same equation was used for each NEM region except Tasmania, where the intercept correction was not found to be significant.

Equation 5: Integrated Dynamic Model, regional model structure

$$\Delta_4 \mathrm{y} = c_1 + c_2\Delta_4 I_s + c_3\Delta_4 P_s + c_4\Delta_4 HDD_s + c_5\Delta_4 CDD_s + c_6\mathrm{EC}(-4) + c_7\mathrm{T}$$

Table 4 shows the values for the estimated coefficients in each region.

Table 4: IDM coefficients

	Constant c1	$\Delta_4 I_s$ c2	$\Delta_4 P_s$ c3	$\Delta_4 HDD_s$ c4	$\Delta_4 CDD_s$ c5	$\mathrm{EC}(-4)$ c6	T1
Qld	0.00683	0.11201	-0.09490	N/A	0.00034	-0.53201	-0.01943
NSW	0.00607	0.14584	-0.13741	0.00033	0.00043	-0.50524	-0.01854
SA	0.00255	0.14110	-0.01088	0.00035	0.00047	-0.81671	-0.01174
Tas	-0.00267	0.39761	-0.48674	0.00032	N/A	-1.13559	N/A
Vic	-0.00238	0.29240	-0.07866	0.00028	0.00047	-0.71982	-0.00728

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

- The instantaneous response to a 1% increase in income is a c_2% increase in electricity consumption.
- The instantaneous response to a 1% increase in price is a c_3% decrease in electricity consumption.
- The adjustment to the new long-run, following a short-run response to a change in a driver, takes place at a rate of c_6*100% after four quarters.

Using Queensland as an example:

- A 1% increase in income per capita would lead to an instantaneous electricity consumption increase of 0.11%.
- A 1% increase in price would lead to an instantaneous decrease in electricity consumption of 0.09%.
- The adjustment to the long-run, following short-run disequilibria, takes place at a rate of 53% after four quarters.

2.2 Maximum demand

This section outlines the methodology used to develop MD forecasts for residential and commercial consumption. These forecasts were prepared by Monash University's Business and Economic Forecasting Unit. Monash University prepared maximum demand reports for each NEM region and these reports are available on AEMO's website.[19]

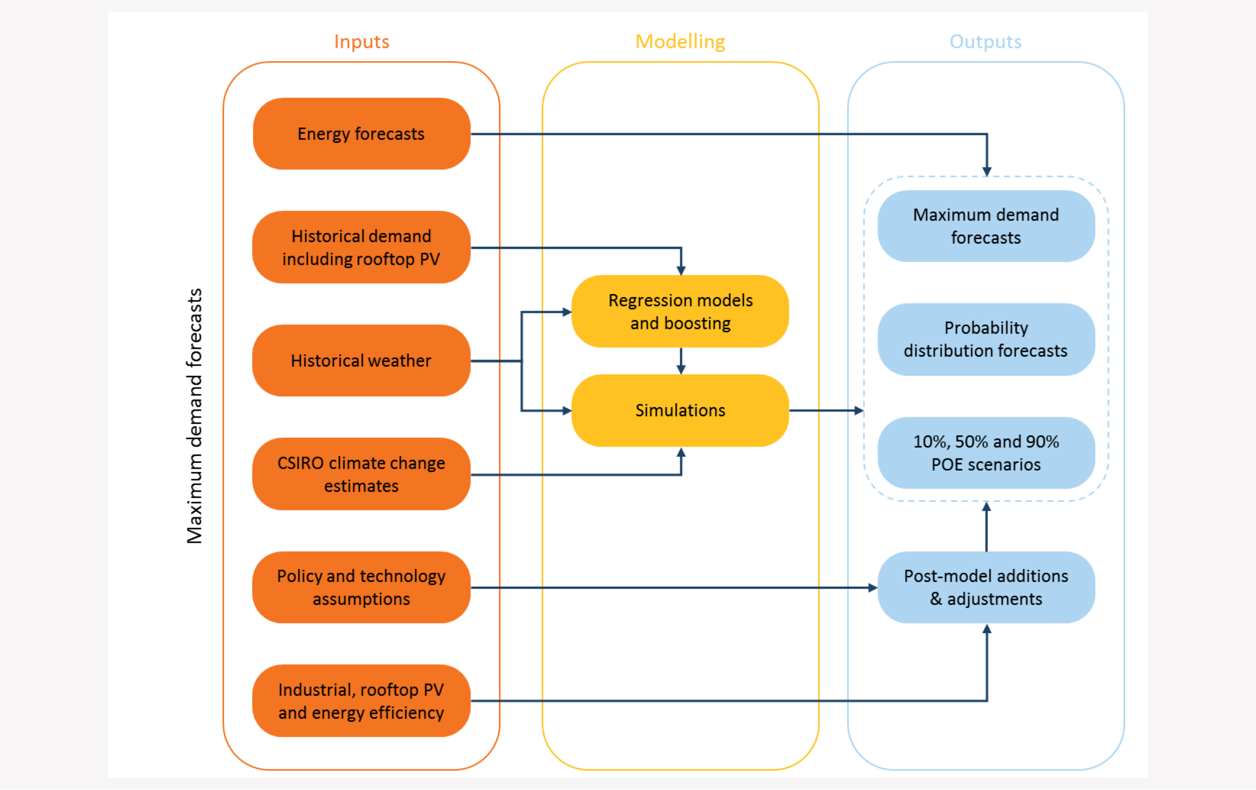
MD is the single highest demand that occurs in any half-hour period over an entire season. As this is the most extreme event that occurs in a season, and is highly dependent on weather, there is substantial uncertainty inherent in MD forecasts. For this reason a probabilistic distribution of MD is forecast,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

For each NEM region, MD 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.[20] These models include calendar-dependent effects (e.g., day of week, public holiday) and weather effects, as well as half-yearly (for each season) demographic and economic effects, based on AEMO's annual energy forecasts.

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

An overview of the MD forecast methodology used in the 2014 NEFR is shown in Figure 2.

Figure 2: Maximum demand forecast methodology diagram



[19] Monash University MD technical reports 2014. Available at http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/NEFR-Supplementary-Information.

[20] 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.

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 data used to build the models is half-hourly non-large industrial demand.[21] This demand is equivalent to potential residential and commercial consumption plus transmission network losses and generator auxiliary loads.

The semi-parametric model developed by Monash University to model demand (after a log-transform) is presented in Equation 6. It is split into two separate models, one that uses demographic, economic and cooling/heating degree day variables and another that uses the remaining half-hourly variables.

Equation 6: Short- and long-run demand model

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

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

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

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

where:

- $\bar{y}_i^{pc} = \bar{y}_i / P_i$ is the per-capita seasonal average demand.
- P_i is the population in season i.
- $h_p(t)$ models calendar effects.
- $f_p(\boldsymbol{w}_{1,t}, \boldsymbol{w}_{2,t})$ models all temperature effects using two locations within each region to represent geographical weather diversity (except for Queensland which uses three locations).
- $\boldsymbol{w}_{1,t}$, and $\boldsymbol{w}_{2,t}$ are vectors of current and past temperatures at each location.
- $z_{j,i}$ is a variable in season i that accounts for seasonal demographic, economic and degree days effects. Its impact on demand is measured by the magnitude of coefficient c_j.
- e_t and ϵ_i denotes the demand that is left unexplained by the model at 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 7 represents the normalisation of half-hourly demand.

Equation 7: 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 6.

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.

[21] Operational as-generated demand with large industrial loads subtracted.

Some specific features of the model are:

- Variable selection was done by assessing out-of-sample forecasting performance based on the root mean squared error.
- Calendar effects are modelled using variables that account for day-of-week, time-of-year, and public holidays, including days immediately before and after public holidays.
- Temperature effects $f_p(\boldsymbol{w}_{1,t}, \boldsymbol{w}_{2,t})$ are modelled using additive regression splines. A regression spline is a combination of several polynomial curves joined at points known as "knots". They are used to account for non-linear relationships between driver and predictor variables, in this case, the relationship between temperature and demand.
- Temperatures from the last three hours and the same period from the last six days are included, as are the maximum and minimum temperature in the last 24 hours and the average temperature over the last seven days.
- Warming trends based on Commonwealth Scientific and Industrial Research Organisation (CSIRO) modelling were applied to simulated future temperatures to allow for climate-change impacts.
- Separate rooftop PV model used to simulate future rooftop PV generation and its effects on demand. The rooftop PV model is a nonlinear, nonparametric function that has daily solar radiation, maximum temperature and day-of-season as driver variables.

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.[22]

Each of the 1,000 seasons of simulated temperature data allowed Monash University to obtain a single simulated value of MD. 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 MD, which were used to forecast the distribution of MD.

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

For each season, each of the 1,000 simulated MDs was re-constituted with the underlying seasonal average demand (as in Equation 7). 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 MD forecasts were obtained by taking the appropriate percentile of the 1,000 simulated MDs for each season. A 10% POE MD forecast has a 1-in-10 chance of being met or exceeded in any season. A 50% POE forecast has a 1-in-2 chance of being met or exceeded, and a 90% POE forecast has a 9-in-10 chance of being met or exceeded.

[22] 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.

2.2.3 Methodology improvements since 2013

As per the 2014 Action Plan, Monash University implemented the following improvements to the modelling and forecasting work:

- Conducted structural break analysis to test if the normalised demand (conditional on temperature and calendar effects) changes over time. No statistical evidence of structural change in the demand distribution was found over the historical data years. This means that no evidence was found for changing load factors or residual distributions and so no further action was required.
- Used a boosting algorithm (an automatic step in the model) to improve the model fitting performance by removing the need to manually adjust for extreme temperature bias after the model is developed. Evaluations of the model with and without boosting shows that this significantly improves forecast accuracy.
- Developed a separate model to produce rooftop PV distributions. This model is used to simulate future rooftop PV generation to account for future demand that will be met by rooftop PV.

CHAPTER 3 – LARGE INDUSTRIAL LOAD

3.1 Forecasting large industrial load

This chapter outlines the methodology used to develop the annual energy and MD forecasts for large industrial loads. The large industrial load forecast comprises a relatively small number of customers who account for a relatively large proportion of consumption in each NEM region.

Customers 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 plants.

The half-hourly demand for these customers is not typically temperature sensitive, although desalination and water pumping loads are affected by rainfall. While significant changes to large industrial consumption can substantially affect regional consumption, such changes are rare. They typically occur when plants open, expand, close, or partially close.

Given the relatively small number of customers, AEMO forecasts each individual customer's electricity consumption and forecasts are aggregated for confidentiality.

3.2 Data sources

AEMO forecasts large industrial electricity consumption based on the following data sources:

- Information/questionnaire responses from large industrial customers.
- Information from the relevant distribution network service providers (DNSPs) or transmission network service providers (TNSPs).
- Publicly available information or announcements.
- Historical data from AEMO's Metering Settlements and Transfer Solution (MSATS) system.

3.3 Approach used for the 2014 NEFR

Step 1: Selecting large industrial customers

As per the 2014 NEFR Action plan the selection of large industrial customers was expanded from 2013 to include:

- All transmission-connected loads.
- All distribution loads with MD greater than 10 MW.
- Key customers identified by TNSPs and DNSPs (including past customers and new customers with potential of significant change).

Electricity consumption associated with several committed LNG trains was also included in the large industrial segment for 2014 NEFR. Their electricity consumption forecasts were completed by AEMO's external consultant, Jacobs. Details are available in the 2014 NEFR supplementary information.[23]

[23] Available at: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/NEFR-Supplementary-Information.

Step 2: Information gathering

Questionnaire

AEMO distributed a questionnaire to all large industrial customers identified in Step 1 requesting information about their historical and forecast electricity consumption.

Each customer was asked to provide three annual energy and MD estimates:

- High: Reflecting increased electricity consumption from the network following favourable economic conditions such as high GDP. This would see increased production, increased operations/additional shifts, decreased onsite generation and increased demand for exports.
- Medium: Reflecting the most likely forecast levels of electricity consumption and MD.
- Low: Reflecting decreased electricity consumption from the network following non-favourable economic conditions (e.g., low GDP). This would see lower production levels, lower output and shifts, increased onsite generation, and decreased demand for exports.

Consultation

After receiving the questionnaire responses, AEMO contacted each customer directly to discuss the information and further clarify any likely changes to future operations. Individual company information collected from these interviews and questionnaires is confidential so the total from all customers was aggregated into regional forecasts.

Where the information provided was insufficient, AEMO sought additional information from the relevant TNSP or DNSP, and confirmed findings with the customer.

Step 3: Analysis

AEMO reviewed all information obtained to ensure consistency across responses and incorporate any additional public announcements. Responses were then mapped to the appropriate NEFR high, medium, or low scenario.

Estimating 2013-14 electricity consumption

The 2013-14 electricity consumption was estimated from nine months of actual data from July 2013 to March 2014, combined with three months of forecast data from April to June 2014, as April to June data was unavailable at the time of forecast development.

Where customers were unable to provide information, AEMO estimated consumption based on actual data plus historical data (2012-13 actuals), scaled to take into account recent trends in consumption.

Short- and medium-term forecasts

In most cases, the questionnaire responses provided enough information to construct forecasts that directly reflected the customer views over the next 10 years.

Where customers were unable to provide information, AEMO assumed that consumption in the medium scenario would continue at the 2013-14 value.

Long-term forecasts

Longer-term forecasts are inherently more uncertain. Where customers were unable to provide expected electricity consumption in the long term, AEMO consulted with them and agreed to assume that consumption forecasts for the medium scenario would continue at the last indicated value.

Forecasting for the three scenarios

Where customers were unable to provide information for the high and low scenarios, this was forecast based on information provided from external consultants, Independent Economics and Frontier Economics.

AEMO identified industry-specific indicators in consultation with industry to develop the following variances to the medium scenario:

Table 5: Variance in the low and high scenarios from the medium scenario for difference industries

Customer type	Low scenario variance from medium by 2033-34	High scenario variance from medium by 2033-34
Mining	9.7% below	8.5% above
Manufacturing	4.0% below	0% above
All others	6.0% below	6.3% above

For the low scenario, AEMO adopted a probabilistic approach to reflect the increased risk of reduced production or closure of aluminium smelters in response to less favourable economic conditions. This assumed a 50% reduction in operations across all NEM-connected aluminium smelters from 2015 to 2017, followed by closure once current arrangements with the respective state governments or electricity providers expire.

Desalination and water-supply pumping loads vary due to rainfall rather than economic conditions, so the economic scenarios were equalised to reflect this. AEMO estimated electricity consumption in the initial years of the outlook period using information about likely short-term weather conditions. Long-term electricity consumption was forecast based on information received from customers.

To determine each customer's contribution to forecast MD, AEMO reviewed several years of historical consumption at times of regional summer and winter peak. From these, AEMO calculated a diversity factor per customer, indicating the alignment between each customer's MD and peak load on the network. This was then applied to each customer's corresponding forecasts for the high, medium, and low scenarios and was aggregated to estimate their contribution to forecast MD.

To further improve forecast accuracy, the range of peak loads used to determine the diversity factor for summer and winter were based on the 10 most significant events in each season. In 2013, a single event was used.

3.4 Modelling limitations and exclusions

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

- Information provided from non-public sources is sensitive and cannot be made publicly available so AEMO's public forecasts are aggregated per NEM region.
- AEMO depends on large industrial customers proactively advising of new projects. Given some projects may be speculative and not eventuate, there is inherent uncertainty in estimating the timing and magnitude of future consumption (e.g. for LNG projects).

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

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

3.5 Methodology improvements since 2013

Changes in the large industrial load methodology from the approach used in 2013 include:

- The 2013 selection of large industrial loads was derived from a list compiled from each TNSP of all transmission-connected customers, plus additions based on large customers with significant consumption identified by TNSPs, DNSPs and AEMO. The 2014 selection was extended and based on a consumption threshold. Refer to Table 6 below for details.
- The questionnaire design was changed to obtain more information, including onsite generation capacity and demand response expectations.
- AEMO excluded specific pumped-storage loads that were included in the 2013 NEFR. Pumped-storage hydro pumping operation varies due to electricity market price volatility. Pumping loads are generally shut down at the time of peak demand and therefore do not contribute to MD. They are excluded as the energy is being stored for additional generation. In the 2013 NEFR, New South Wales pumped-storage hydro pumping was included in the large industrial segment, but Queensland pumped-storage was not.
- Where limited or no data was provided from customers, AEMO forecast electricity consumption in the high and low scenarios based on information provided from the economic consultants using industry-specific indicators to calibrate the high and low scenarios relative to the medium scenario. In 2013, industry-specific indicators were not used.
- The range of peak loads used to determine the diversity factor for summer and winter maximum demand was been increased to cover the 10 most significant events in each season. In 2013 a single event was used.
- Energy efficiency (EE) savings were applied to the forecasts based on the EE work carried out as part of the NEFR (see Chapter 5). In 2013, no EE savings were applied to the large industrial segment.

Table 6 below shows the difference in the number of customers included in the large industrial segment in the 2013 and 2014 NEFRs.

Table 6: Large industrial load numbers per NEM region in the 2013 and 2014 NEFRs

Region	Number of customers			% of 2012-13 annual energy (GWh)		
	2013 NEFR	2014 NEFR	Movement	2013 NEFR	2014 NEFR	Movement
NSW	13	23	10	17%	19%	2%
Qld	6	25	19	22%	27%	5%
SA	9	16	7	16%	22%	6%
Tas	4	14	10	53%	57%	4%
Vic	7	15	8	18%	20%	2%
Total NEM	39	93	54	19%	22%	3%

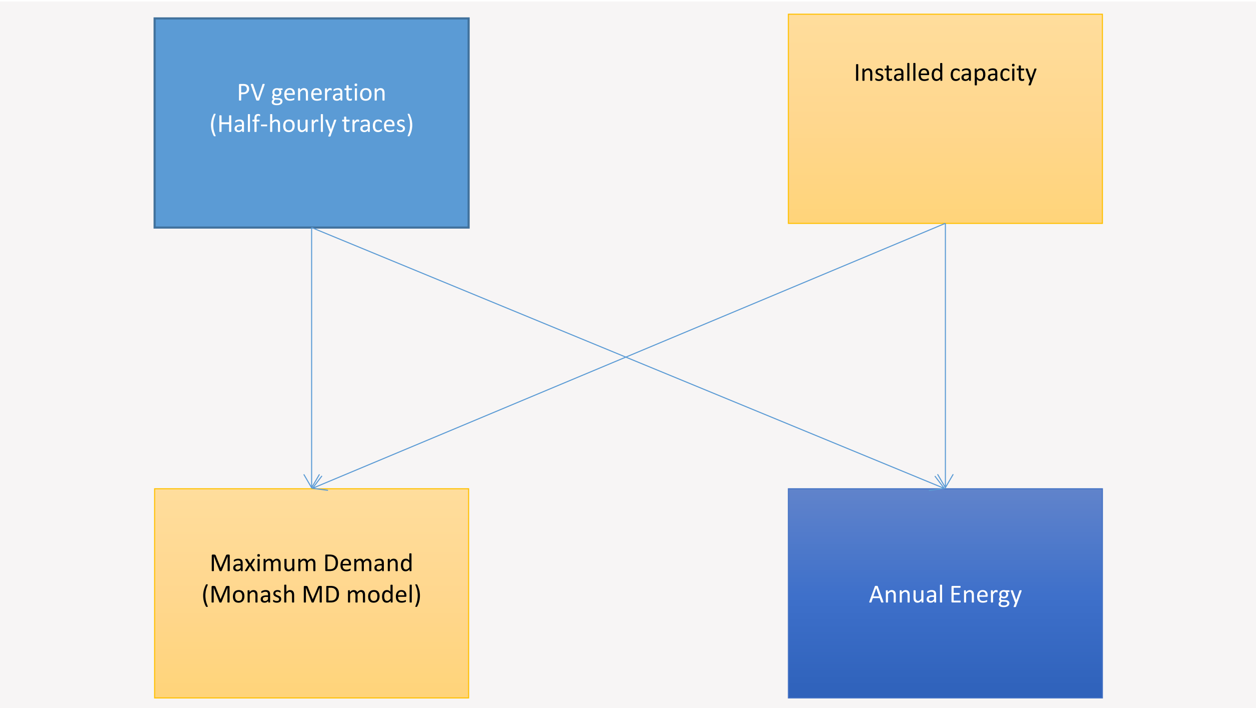
CHAPTER 4 – ROOFTOP PV

4.1 Introduction

This chapter provides the methodology used to develop the 2014 NEFR rooftop PV forecasts.

Similar to previous editions of the NEFR, the rooftop PV forecast for both annual energy and MD rests on two fundamental components: installed capacity forecasts and half-hourly traces of rooftop PV generation. This is shown below in Figure 3.

Figure 3: Overview of rooftop PV methodology



The yellow blocks highlight areas where there have been major improvements to the model. In particular:

- The installed capacity forecast now uses system prices and installation information from the Clean Energy Regulator (CER) and demographic information from the 2011 Australian Bureau of Statistics (ABS) Census. Furthermore, the methodology now better accounts for historical spikes in installations due to policy changes by adopting behavioural economic models.
- Half-hourly traces of rooftop PV were incorporated directly into the MD forecasts developed by Monash University. This major improvement allowed the MD models to capture the impact of rooftop PV on the MD timing, producing more accurate and informative MD forecasts.

The following sections focus primarily on the methodology used to forecast installed capacity. Detailed information on incorporating rooftop PV into the MD forecasts is provided in the supplementary reports written by Monash University and published on AEMO's website.[24]

[24] Available at: http://aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Other/planning/NEFR/2014/2014%20Supplementary/Monash_Electricity_Forecasting_Model_Technical_Report.ashx.

4.2 Data sources

The rooftop PV forecasts rely on several data sources. The main sources are provided below in Table 7:

Table 7: Main data sources used for rooftop PV forecasts

Data source	Description	Use
CER	A list of all installations registered with the CER to December 2013. This included size of installations and system costs.	This dataset was used extensively to model the uptake of rooftop PV.
DNSPs	Information about rooftop PV installations. Varying degrees of detail were provided.	AEMO cross- validated the installed capacity with CER data and found they matched closely. Given this, AEMO used the CER dataset to be consistent across all NEM regions.
Bureau of Meteorology (BOM)	Solar radiation data and temperature data.	Used to extrapolate half-hourly PV traces described in Section 4.5.

4.3 Rooftop PV scenarios

Three rooftop PV uptake scenarios were developed, each one relating to the economic scenarios developed by AEMO and Independent Economics.[25] A mapping of the economic scenarios and underlying drivers of the rooftop PV uptake scenarios are shown below in Table 8.

Table 8: Mapping of PV uptake scenarios and the economic scenarios

Driver	Low PV uptake	Moderate PV uptake	High PV uptake
Economic scenario	High centralised energy demand.	Medium centralised energy demand.	Low centralised energy demand.
Rooftop PV system costs	Increases up to 2016 then remains flat with ranges between $2.62/Watt and $2.99/Watt depending on region.	Continues falling at historical rates until 2016 then remains flat with ranges between $1.92/Watt and $2.17/Watt depending on region.	Continues declining until $1/Watt.
Government incentives	Feed-in tariff and SRES remain unchanged.		

Note that in all three uptake scenarios, the Small-scale Renewable Energy Scheme (SRES) was assumed to remain unchanged meaning that rooftop PV consumers will continue receiving a rebate for installing rooftop PV systems via the sale of small-scale technology certificates (STC).

However, if the current Renewable Energy Target (RET) review[26] removes or modifies the SRES, the out-of-pocket expenses borne by customers will likely increase; this is reflected to some extent by the low uptake scenario.

25 Available at:http://aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Other/planning/NEFR/2014/2014%20Supplementary/Independent_and_Frontier_Economic_and_Energy_Market_Forecasts_final.ashx.

26 More information available at https://retreview.dpmc.gov.au/.

AEMO assumes that some form of feed-in tariff will remain via retailers even though governments might remove or reduce a mandated feed-in tariff in the future. For example, the Queensland Government removed its guaranteed 8-c feed in tariff on 30 June 2014 but consumers still have some ability to negotiate a feed-in tariff via retailers.

4.4 Installed capacity forecast

This section describes the methodology used to develop the rooftop PV installed capacity forecasts. These reflect the maximum 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 MD forecasts.

AEMO developed the installed capacity forecasts for each NEM region and for each uptake scenario as follows:

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

While these steps are broadly consistent with the 2013 NEFR methodology, a number of changes were made to improve resulting forecasts. Key components of each step are described in more detail below.

Step 1: Modelling the payback period

AEMO developed a payback calculator to forecast the number of years required to repay initial rooftop PV system costs (the payback period). The payback period results were converted to installed capacity growth rates (kilowatts per month), which were then applied to existing installed capacity to generate the forecasts.

Table 9 below outlines the parameters modelled in the payback period calculator and the values used.

Table 9: Payback period calculator parameters and assumptions

Parameter	Description	Value
Feed-in tariff	Rate (cents per kWh) 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.	4 kW
System cost per watt	The estimated average installed cost per watt of a solar rooftop PV panel before a rebate is provided, for systems at the average system size.	\$2.60 – \$2.40 depending on the NEM region[27]
Percentage of energy exported	Represents the energy exported to the grid as a percentage of the energy generated by 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 postcode zone[28]
STC price	The estimated market price for STCs.	\$35.00
STC multiplier	A factor between 1 and 5 that enables additional STCs to be created per installation.	1.0 per current legislation[29]

[27] As at December 2013, in nominal dollars.
[28] The calculation of STC numbers is available at http://ret.cleanenergyregulator.gov.au/ArticleDocuments/205/solar-stc-calculations-1212.pdf.aspx.
[29] See http://www.comlaw.gov.au/Details/F2014C00241, Subdivision 2.3.3

Parameter	Description	Value
STC deeming period	The deeming period defines the number of years for which system owners can access the annual rebate.	15 years, with a decrease beginning in 2017 and reaching one in 2030 as per current legislation[30]
Abolishment year of STC rebate	The year when the STC rebate for new systems is expected to be abolished. After this, no rebate would be provided for new rooftop PV systems.	2030
Retail electricity price[31]	The nominal electricity price to be paid by consumers for electricity consumed from the grid.	Varies by NEM region.

Step 2: Modelling the uptake rate as a function of the payback period

For the 2014 methodology, AEMO redeveloped the relationship between the uptake rate and payback period used in 2013.

Analysis of monthly historical uptake rates showed that large increases occurred shortly before changes to feed-in tariffs or the STC multiplier. This was observed in all NEM regions. The analysis confirmed that historical monthly uptake was related to both the payback period (driving underlying growth) and changes in financial incentives (driving short-term growth).

To account for the short-term increases in the forecasts, AEMO developed a method that artificially decreases the payback period in the months leading up to a change in STC multiplier or feed-in tariff. In so doing, AEMO was able to more accurately reflect the underlying demand for rooftop PV which is then used to forecast future installed capacity.

Prospect Theory

In the context of AEMO's rooftop PV uptake modelling it can be useful to consider the following hypothetical situation.

A decision can be made between a rooftop PV installation happening either now or later, and a feed-in tariff decrease occurs somewhere in between those two dates. From a consumer's perspective, the incentive to capture the higher feed-in tariffs by bringing forward the installation of a system can be seen as a potential financial gain relative to the alternative of waiting and missing out on the opportunity to secure a higher rate. Although these patterns were clearly evident from the historical data, previous modelling did not attempt to account for this.

With this in mind, AEMO adapted a component of Prospect Theory[32] to capture the additional installations being brought forward in time.

Prospect Theory is a behavioural economic theory that describes the way people choose between alternatives. Broadly, it states that people make decisions based on the perceived value of losses and gains rather than the final outcome, and that losses and gains of the same value are not treated equally. At the core of the theory is the value function which relates an actual loss or gain to a perceived loss or gain.

Figure 4 shows a typical curve of a value function, and indicates that a loss (relative to present status) equates to a greater perceived loss. Similarly, gains (relative to present status) equate to perceived gains that are not actually that high.

[30] See http://www.comlaw.gov.au/Details/F2014C00241, Subdivision 2.3.3

[31] Retail electricity prices and forecasts were produced by Independent Economics and Frontier Economics. More information can be found in the Economic and Energy Market Forecasts (economic outlook) on AEMO's website. http://aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/NEFR-Supplementary-Information.

[32] *Prospect Theory: An Analysis of Decision under Risk*, by Daniel Kahneman and Amos Tversky, *Econometrica,* 47(2), pp. 263-291, March 1979.

This implies that losses are valued more strongly than gains, and suggests that people are more sensitive to losses. In the rooftop PV context, a consumer would perceive an exaggerated loss if they missed out on the higher feed-in tariff. If the perceived loss was large enough, the consumer would decide to bring forward the installation of the rooftop PV system to secure the higher feed-in tariff.

AEMO applied the value function to the relative losses that were derived from STC multiplier and feed-in tariff changes to give estimated perceived losses on a monthly basis. These were then considered to act as additional financial incentives for bringing forward installations. They were then incorporated into the payback calculation to produce an adjusted payback period (for modelling purposes).

The perceived losses and adjusted paybacks were calculated for the three months leading up to changes in financial incentives. This date range was set to capture a build-up of the installation rate in those months preceding the change. The adjusted payback was lower than the regular payback, linking these “pre-change” periods to greater rooftop PV uptake rates.

The value function is a two-part function and is expressed as follows:

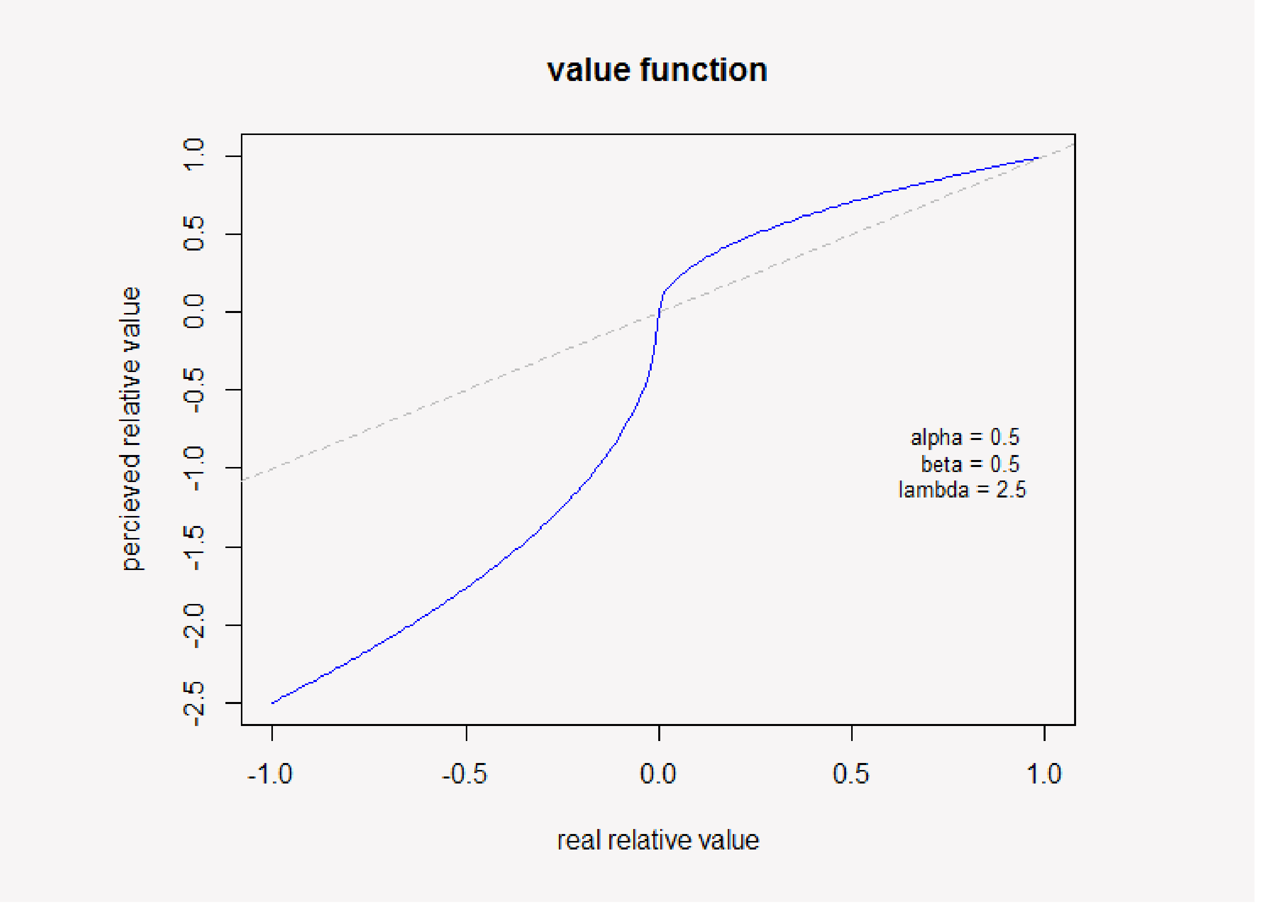
Equation 8: The value function

$$V(x) = x^{\alpha} \quad \text{for } x \geq 0$$

$$V(x) = -\lambda(-x)^{\beta} \quad \text{for } x < 0$$

where $V(x)$ is the perceived value of x, x is a relative gain or loss, and α, λ, and β set the shape of the curve. AEMO applied $\alpha = 0.5$, $\lambda = 2.5$, and $\beta = 0.5$. Figure 4 plots the function.

Figure 4: The value function



AEMO developed a linear relationship linking the adjusted payback period to monthly rooftop PV system uptake for each NEM region using historical data extending back to January 2012. Data before this date was considered to be less relevant for current and future uptake estimates given significant differences in financial incentives. The form of the linear relationships is described in Equation 9.

Equation 9: Payback–uptake relationship

$$y = ax + b$$

where y is monthly uptake, x is the adjusted payback period, a is a coefficient connecting adjusted payback to monthly uptake and b is a constant reflecting uptake not sensitive to payback period. This relationship was determined for each NEM region.

Step 3: Forecast of installed capacity

Unsaturated forecast of installed capacity

The payback–uptake relationship, described in step 2, was applied to future estimates of the payback period in each NEM region. This provided the unsaturated installed capacity forecast.

AEMO developed the future payback estimates using the information summarised in Table 9. This included forecasts of retail electricity price, system costs, and financial incentives such as feed-in tariffs and the SRES.

Application of saturation levels to installed capacity forecasts

AEMO's approach to saturation of installed capacity did not change from the 2013 NEFR. The impact of saturation on the installed capacity growth is applied at the last stage of installed capacity forecast development using the following limit equation:

Equation 10: Saturation growth rate equation

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

AEMO assumed that the effects of saturation would only appear 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 threshold values were set to 40%, 50% and 60% for the low, moderate, and high uptake scenarios respectively.

Estimating saturation levels

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

AEMO's approach to estimating saturation levels for the 2014 NEFR was consistent with the 2013 NEFR in that:

- The City of Port Phillip's (Victoria) study[33] on rooftop PV saturation capacity was used as a basis for relating numbers of dwellings to saturation capacity in megawatts.
- The average residential system size per dwelling for saturation was 3.5 kW. This was calculated independently using the study and ABS dwelling data for the City of Port Phillip.
- The saturation capacity as estimated in the City of Port Phillip study was decreased by 25% to account for considerations such as building restrictions by authorities (e.g., heritage overlays), aesthetic considerations, and lack of incentive for rental properties.

[33] City of Port Philip. *Urban Solar Atlas, Port Philip solar mapping*; 2011. Available at http://www.enviroehub.com.au/index.php?nodeId=404.

- The capacity, including the 25% adjustment, was extrapolated to each NEM region based on number of dwellings.

Key changes from 2013 were:

- Before extrapolating the saturation capacity to each NEM region, AEMO linked the number of dwellings to population using a linear relationship. This was done because the 2014 NEFR economic outlook provided population growth for the forecast period, rather than number of dwellings (as per 2013). The extrapolation was a two-step process: estimate dwellings from population and then estimate the capacity limit from the dwellings. A strong relationship between population and dwellings was found, so the final extrapolated saturation capacity estimates were comparable to the 2013 estimates.
- AEMO included the following types of dwellings as available for rooftop PV installation: separate houses, semi-detached row or terrace houses, townhouses, blocks of flats, units and blocks of apartments. Dwellings such as structures attached to a building and caravans were excluded.

4.5 Historical estimates

Estimates of a historical, 30-minute interval data trace of rooftop PV generation from January 2009 to February 2014 were prepared as per the 2013 NEFR. This includes using the ROAM Consulting rooftop PV estimates[34] and the Bureau of Meteorology's solar exposure observation.[35] The process is detailed in the 2013 Forecasting Methodology Information paper.[36]

AEMO used the half-hourly trace estimates to derive monthly average estimates of rooftop PV generation for a 1 MW system, enabling estimation of annual energy production (Section 4.6).

AEMO sourced historical installed capacity data for January 2009 to January 2014 from the CER, who provided anonymous installation data for each registered system. AEMO evaluated this data against DNSP data and confirmed the CER data as reliable. As per the 2013 NEFR, the CER data was used to estimate historical installed capacity. An inherent lag exists in the CER data as installations take up to 12 months to be registered. The lag is most pronounced in the last three to four months of the dataset, so only data to September 2013 was used.

4.6 Rooftop PV energy forecasts

AEMO derived the rooftop PV forecasts for the 2014 NEFR using the installed capacity forecasts (Section 4.4) and average monthly rooftop PV energy distribution profiles (Section 4.5).

The average monthly energy distribution profiles were calculated using the average monthly aggregated energy data from ROAM Consulting. No adjustment was made to these estimates as the average energy calculated from the ROAM Consulting traces closely matched the CER generation estimates. This resulted in the predicted generation per kilowatt of installed capacity being slightly higher than in the 2013 NEFR.

The current rooftop PV energy forecasts do not assume any future improvements in EE or any technological improvements to solar panels that may affect the amount of energy generated from a given amount of installed capacity.

[34] This was done as part of the 100% renewable electricity scenarios for the Department of the Environment. For more information, see http://www.climatechange.gov.au/reducing-carbon/aemo-report-100-renewable-electricity-scenarios.

[35] According to the BOM, "Global solar exposure is the total amount of solar energy falling on a horizontal surface. The daily global solar exposure is the total solar energy for a day." For more information see http://www.bom.gov.au/climate/austmaps/solar-radiation-glossary.shtml#globalexposure.

[36] Available at: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report-2013/~/media/Files/Other/planning/NEFR/2013/Forecast%20Methodology%20Information%20Paper.pdf.ashx.

The output of a rooftop PV system will reduce as the system degrades over time. There are also expected improvements in rooftop PV efficiency over the forecast period for new installations. AEMO modelled neither of these effects explicitly and has assumed instead that the degeneration of existing systems over 10 years or more are offset by efficiency gains of new systems being installed.

4.7 Rooftop PV contribution to maximum demand

As a result of the 2014 Action Plan, rooftop PV was incorporated directly into the MD modelling developed by Monash University.

To inform Monash University's models, AEMO provided historical rooftop PV output estimates (described in Section 4.5) and historical daily solar radiation data, in addition to historical and forecast installed capacity.

Unlike previous NEFRs, which applied a static contribution factor as a post-model adjustment, incorporating half-hourly rooftop PV traces directly into the MD model allows more accurate estimates of rooftop PV's impact on MD throughout the day.

As such, AEMO was able to capture the shift in MD times in several regions due to rooftop PV's output pattern that peaks around midday and has no output at night.

Appendix C contains snapshots of the load profiles over the forecast period. AEMO has also published the data[37] behind the load profiles.

More information about Monash University's model development is available in the reports on AEMO's website.[38]

4.8 Modelling limitations and exclusions

The following items are not considered in the rooftop PV forecasts:

- Network limitations
  - As the size of installed capacity continues to rise, certain portions of the network could start facing stability issues due to the high penetration rates of rooftop PV.
  - To maintain network stability, limitations, or restrictions on system sizes might be introduced.
  - This could take the form of outright limitations or via additional costs of connection or higher network charges to support upgrades.
  - AEMO does not consider this in its modelling of rooftop PV uptake but is monitoring the market.
- The market impact of rooftop PV increasing total generating capacity in the NEM.
- Commercial installations were not included in the capacity limit
  - Commercial installations have been, until recently, a negligible portion of installed capacity.
  - AEMO has noticed a recent upward trend in commercial installations and will investigate this for the 2015 NEFR.
- Different financing methods
  - AEMO is aware of new financing methods, such as leasing, being introduced into the market. These will reduce the upfront costs of installing a rooftop PV system.
  - In most cases, these have targeted commercial installations but extension to the residential sector is possible. AEMO is monitoring this development.

[37]Available at http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/NEFR-Supplementary-Information.
[38] Available at http://aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Other/planning/NEFR/2014/2014%20Supplementary/Monash_Electricity_Forecasting_Model_Technical_Report.ashx.

- Storage
  - At present, AEMO assumes no storage is combined with PV systems.
  - AEMO is continually monitoring market trends in storage, including prices, policy, and uptake.
- PV panel degradation and efficiency improvements
  - AEMO modelled neither system degradation nor system efficiency gains and assumed the offsetting effect one would have on the other would make a negligible impact on the forecasts.

4.9 Methodology improvements since 2013

The following table summarise the changes from the 2013 methodology:

Table 10: Summary of methodology differences for rooftop PV forecasts

Item	2013 Methodology	2014 Methodology
Installed capacity	Used payback versus uptake relationship. Based on public CER data. Implicitly assumes commercial installations.	Calculated an adjusted payback period to account for rush in installations due to policy changes. Based on anonymous data of all rooftop PV installations in the NEM from the CER. Explicitly excludes commercial installations.
Saturation rates	Based on Port Phillip study and extended to all NEM regions.	Combined Port Phillip study with ABS census data to reflect more accurate dwelling proportions in each NEM region.
Average energy	Scaled down to match a subset of PVoutput.org data.	No scaling applied as ROAM traces were found to match CER estimates quite closely.
Maximum demand	Constant factor used as post model adjustment. Unable to account for changes in MD times.	Half-hourly profiles incorporated in the Monash University MD model. Able to account for shifts in MD time due to half hourly rooftop PV output pattern.

CHAPTER 5 – ENERGY EFFICIENCY

5.1 Introduction

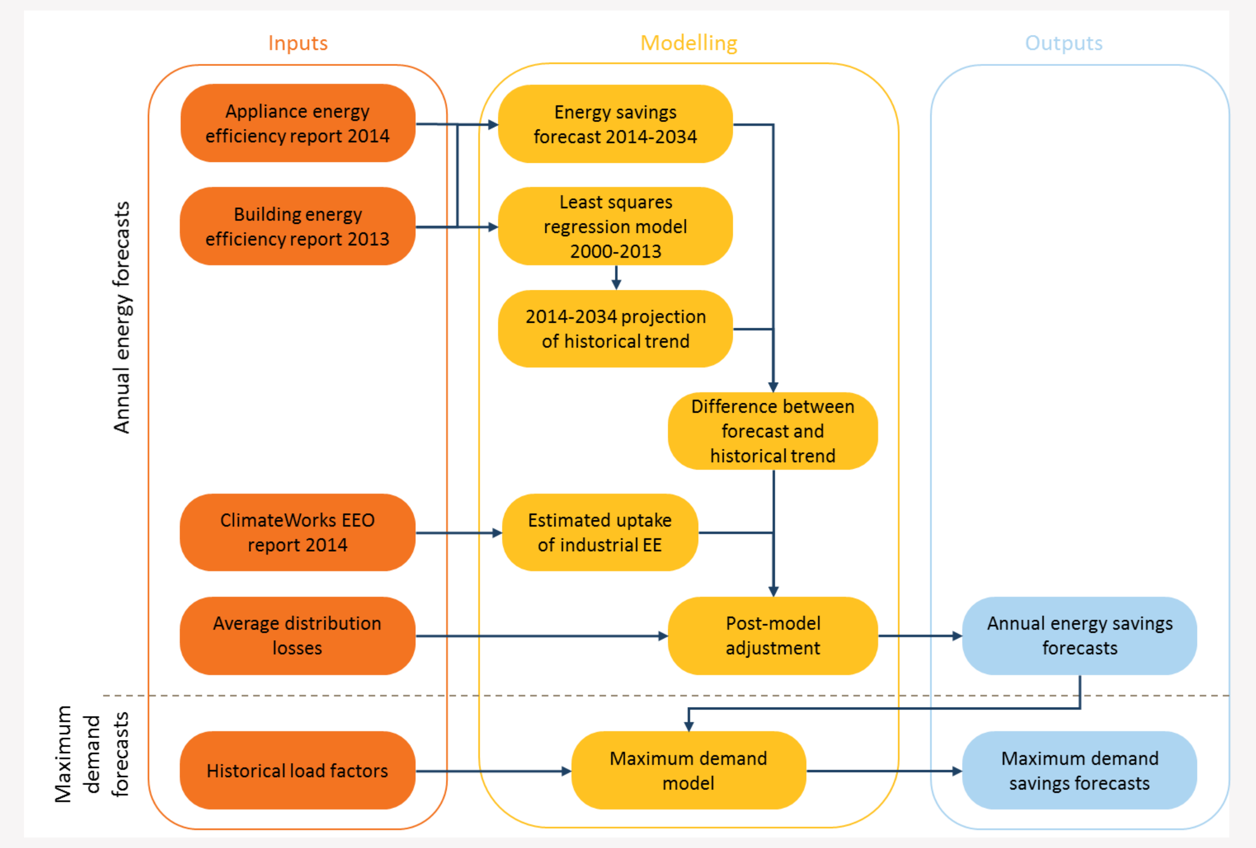
This chapter provides the methodology used to develop the 2014 NEFR energy efficiency (EE) forecasts.

Methodology changes since the 2013 NEFR improve the transparency of the forecast approach and the quality of the results. These changes are summarised in Section 5.7.

Two key changes implemented were including the impact of industrial EE measures and a new methodology to develop load factors for different POE levels when calculating EE for MD.

An overview of the EE forecast methodology used in the 2014 NEFR is shown in Figure 5.

Figure 5: Energy efficiency forecasting methodology



5.2 Energy efficiency uptake scenarios

This section describes the three EE uptake scenarios used for the 2014 NEFR forecasts. The three scenarios represent uncertainties about the number of new EE programs to be implemented in the long-term forecast period.

The slow uptake scenario assumes no additional EE programs beyond those already implemented. It assumes no additional EE savings above the existing long-term trend. This corresponds with the NEFR high scenario.

The moderate uptake scenario assumes that all EE programs already implemented and those currently being implemented remain. This incorporates assumed implementation delays for some programs (such as phasing out carbon-intensive water heaters) and uncertainty about whether some programs will be implemented (such as Residential Mandatory Disclosure). This corresponds to the NEFR medium scenario.

The rapid uptake scenario assumes implementation of additional EE programs beyond those already approved and assumes all potential savings are realised. This corresponds to the NEFR low scenario.

5.3 Data sources

AEMO estimated EE savings from three broad categories:

- Appliances.
- Buildings.
- Industrial.

The estimated savings are based on three key data sources:

- Appliances: George Wilkenfeld and Associates. *Review of Impact Modelling for E3 Work Program.* Unpublished report to the Department of Climate Change and Energy Efficiency (DCCEE), May 2014.
- Buildings: Pitt & Sherry. *Qualitative Assessment of Energy Savings from Building Energy Efficiency Measures Final Report.* Unpublished report prepared for DCCEE, February 2013.
- Industrial: ClimateWorks. *Industrial Energy Efficiency Data Analysis Project.* Unpublished report, February 2014.

These sources provide recent assessments of EE savings across programs initiated by the Federal Government. The first two sources listed used information from Regulation Impact Statements (RIS) undertaken before programs are initiated.

5.3.1 Appliance energy efficiency savings

Savings across the NEM from appliance energy rating labelling and Minimum Energy Performance Standards (MEPS)–collectively referred to in some studies as E3–are estimated by George Wilkenfeld and Associates to be 38 TWh by 2030. Over half of this comes from programs already in place.

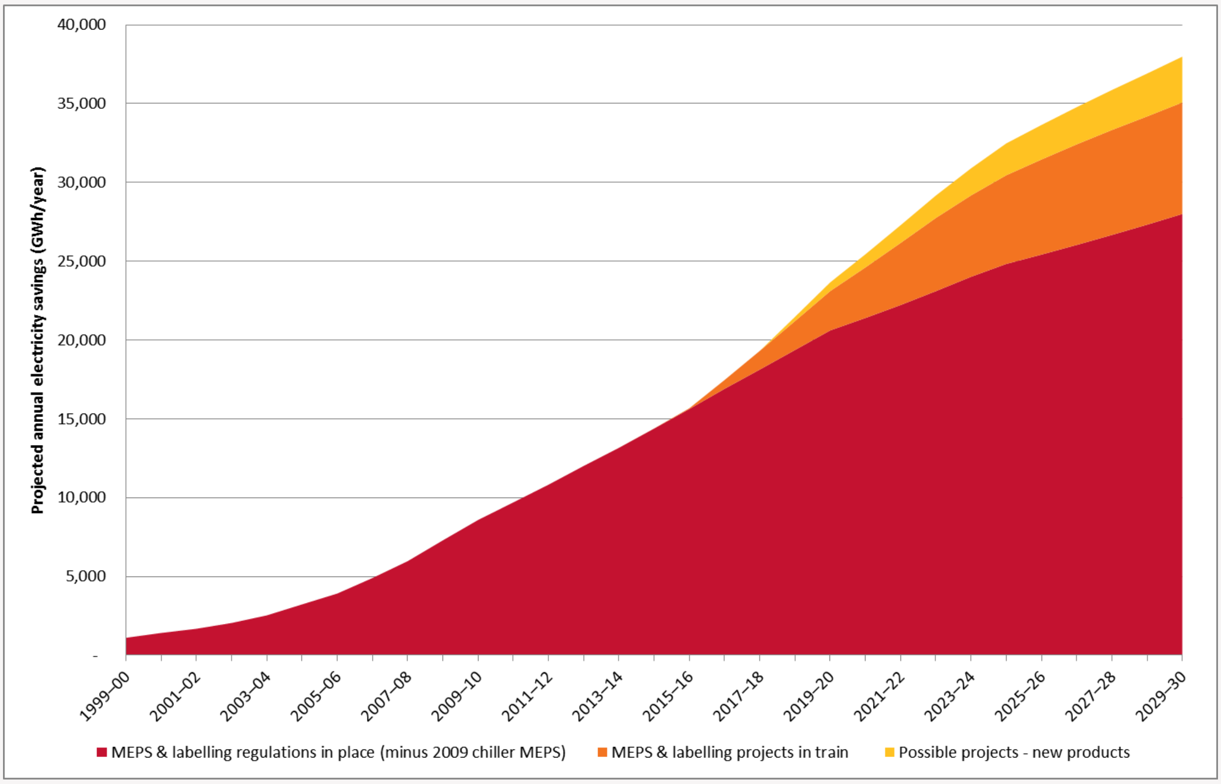
The George Wilkenfeld and Associates report does not provide a regional breakdown. AEMO determined regional values using information from a more comprehensive version of the report published in 2009[39]. Potential savings from Western Australia and Northern Territory are excluded.

The report includes forecast values to 2029-30, which AEMO extended to 2033-34 using linear extrapolation from the last five years (2024-25 to 2029-30).

Figure 6 shows the projected savings across the NEM. Stable growth between 2024-25 and 2029-30 suggests the extrapolation is a reasonable approximation of savings beyond 2030.

[39] http://www.energyrating.gov.au/wp-content/uploads/Energy_Rating_Documents/Library/Equipment_Energy_Efficiency_Program_(E3)/200901-projected-impacts.pdf

Figure 6: Projected energy efficiency savings for appliances, E3 modelling categories



Source: George Wilkenfeld and Associates (2014)

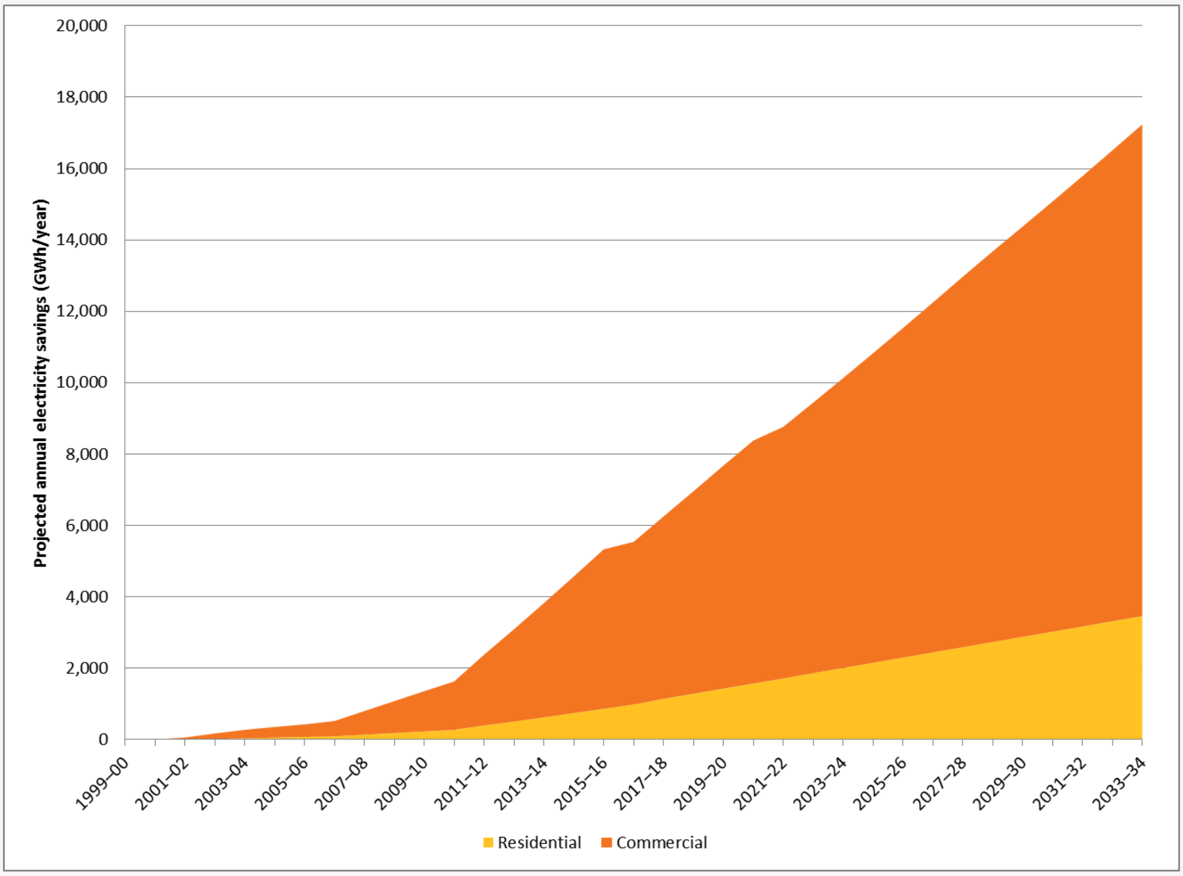
The 2009 chiller MEPS program was excluded from the appliance savings because it is also treated as an existing project in the building EE savings (as part of the baseline for the Pitt & Sherry assessment).

5.3.2 Building energy efficiency savings

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

Figure 7 shows these projected savings. Savings across the NEM from building-related EE measures are estimated to be 17 TWh by 2033.

Figure 7: Projected energy efficiency savings for buildings



Source: Pitt and Sherry (2013)

5.3.3 Industrial energy efficiency savings

The estimated industrial savings were identified using data reported under the Energy Efficiency Opportunities (EEO) program and collated by ClimateWorks. The ClimateWorks data is sourced from industry reporting potential EE savings under the EEO program.

The EEO Program is a Federal Government initiative encouraging large energy-consuming businesses to increase EE by mandating the identification of cost-effective energy savings opportunities and then invest in those opportunities.

5.4 Calculating energy efficiency impact for annual energy forecasts

5.4.1 Approach

AEMO estimated EE savings and incorporated this as a post model adjustment (PMA) to annual energy and MD. To determine residential and commercial consumption AEMO applied a PMA to the non-industrial[40] consumption for appliances and building EE. To determine large industrial load consumption, AEMO applied a PMA to account for industrial EE savings caused by equipment and building upgrades, improved process controls and measurements, improved process design and changes in behaviour and maintenance.

[40] Non-industrial defined as operational consumption minus large industrial consumption.

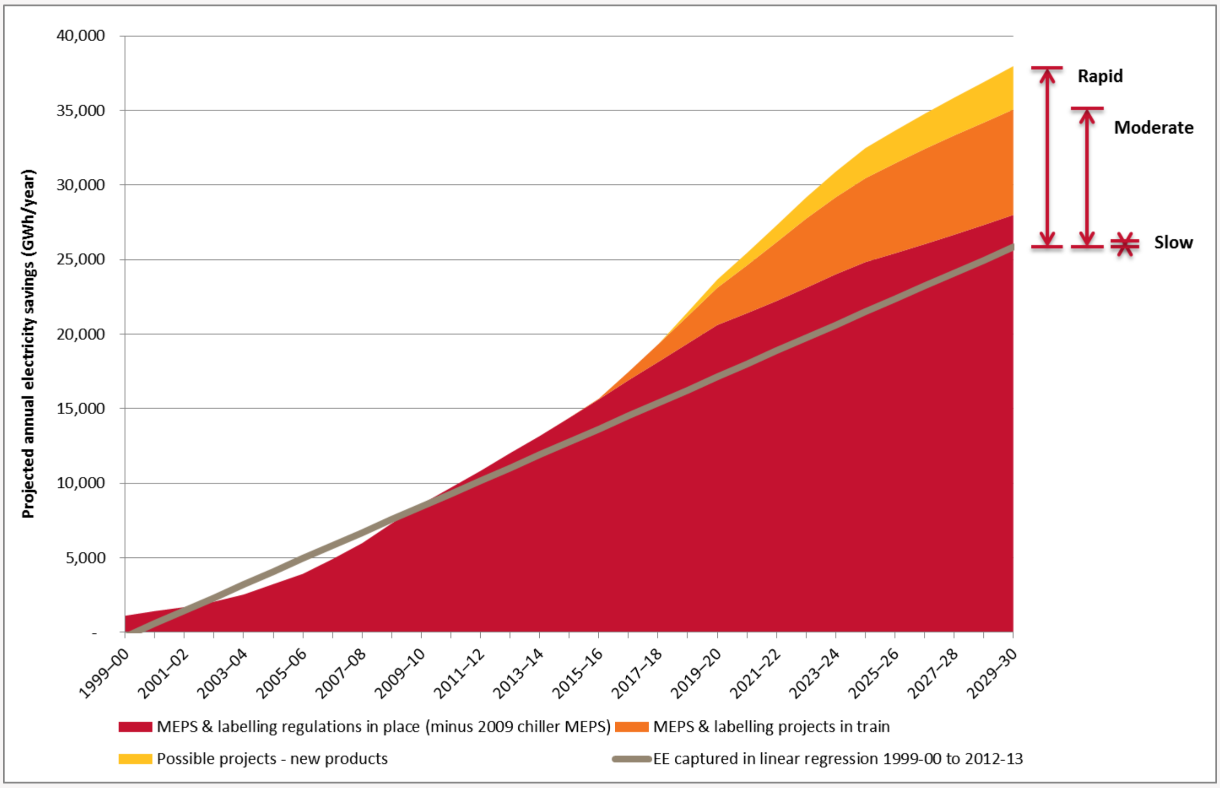
5.4.2 Calculation for appliances and building savings

AEMO developed forecasts for the three EE uptake scenarios, (rapid, moderate, and slow) defined in Section 5.1, using a three step approach:

1. Estimate the expected EE savings for annual energy using EE policy measures identified for the period 2000 to 2034.
2. Calculate the long-term efficiency trend[41] observed in the regression period (2000-13) for all NEM regions (aggregated) and project this trend to 2034. The difference between this projected trend (grey line in Figure 8 and 9) and the expected savings over the forecast period (2014-34) is the EE PMA for annual energy.
3. Disaggregate into forecasts for each region based on region-specific savings identified in 5.3.1 and 5.3.2 and account for distribution losses (detailed below).

EE forecasts for measures that target appliances and buildings are shown in Figure 8 and Figure 9 respectively.

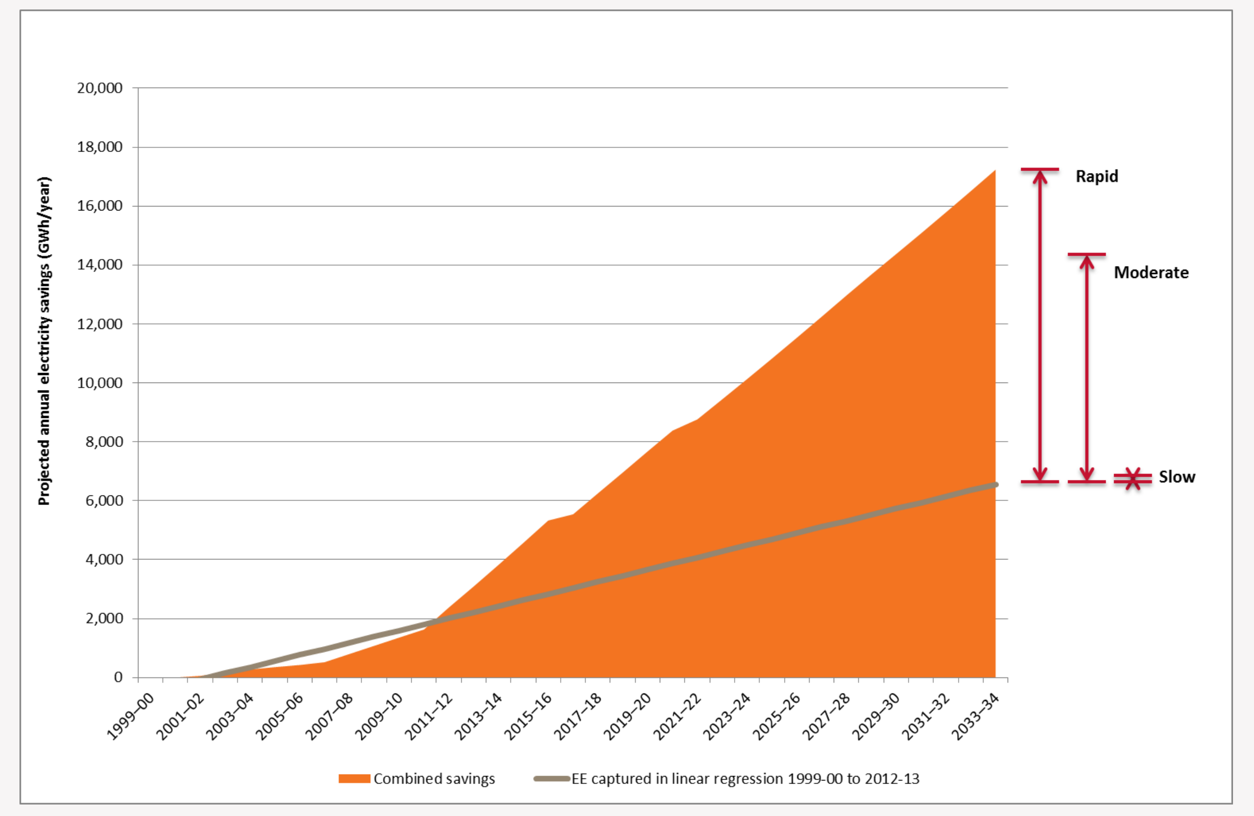
Figure 8: Energy efficiency forecasts for appliances



Source: George Wilkenfeld and Associates (2014)

[41] The long-term efficiency trend is approximated using a least-square fit for calendar years within the regression period. This calendar year-based trend is extended into the forecast period (2014-34), which uses financial years, as AEMO considers the financial year and calendar year trends to be sufficiently similar.

Figure 9: Energy efficiency forecasts for building



Source: Pitt and Sherry (2013)

The savings in the previous two figures identify electricity that is not needed due to EE savings at the end-user premises[42] i.e., if there was no EE, this electricity would be required. Since the PMA is modelled on transmission delivered consumption, distribution network losses that would have occurred when transmitting the electricity need to be accounted for.

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

The distribution losses used in this analysis are shown in Table 11. 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 11: Estimated distribution losses in Australia (% of transmitted energy)

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

[42] Households, businesses.

5.4.3 Calculation for industrial savings

AEMO developed industrial forecasts for each EE uptake scenario by identifying projects to be implemented under business-as-usual (BAU) and non-BAU conditions[43] and estimating the rate at which these projects would be implemented.

Potential industrial energy savings are identified in ClimateWorks' data. The expected implementation rate of potential projects is based on a discussion paper by ClimateWorks.[44] The moderate uptake EE scenario includes EE savings identified by industry under BAU conditions. The rapid uptake EE scenario includes BAU and non-BAU EE savings identified by industry. Distribution losses are not applied to industrial savings as the larger industrial loads are mostly transmission-connected.

Although the EEO Program was scrapped as part of the 2014 Federal Budget, AEMO has not adjusted the EE forecasts. The forecasts assume that having already identified the opportunities to reduce energy costs, these EE savings will be implemented regardless of the program status.

5.5 Calculating the energy efficiency forecasts for maximum demand

AEMO calculates the regional EE impacts on summer and winter forecast MD from the regional EE forecasts for annual energy described in Section 5.4, using daily load factors (LF).

The daily LF is the ratio of the average hourly demand savings for a particular day, to the savings at the time of that day's system MD. This is calculated as follows:

LF = [Daily energy savings (MWh)/24 hours]/savings at system MD (MW)

The LF for appliances that operate constantly, such as refrigerators, is approximately one. Appliances used heavily at the time of summer MD, such as air conditioners, generally have very low summer LFs. Other appliances, such as off-peak electrical water heaters without an override function, never contribute to MD.

AEMO uses regional summer and winter system LFs instead of individual appliance LFs to account for the diversity of appliances contributing to the forecast EE. This reduces potential overstatement of savings at times of MD, as large annual energy savings can lead to unrealistically large MD savings if the LFs are low.

In the 2013 NEFR, a single EE contribution was used at all POE levels and was based on data from only one year. AEMO's 2014 NEFR Action Plan identified that EE contribution to MD should vary at different POE levels. In the 2014 NEFR, seasonal LFs for the 10%, 50% and 90% POE levels are calculated for each region.

This is done by first deriving quadratic polynomial regression models to find the relationship between daily LFs and non-industrial MD. The load factor that corresponds to a certain POE level demand can then be calculated using these regression models.

Table 12 shows the regional 10% POE load factors used for the NEFR EE forecasts.

[43] BAU and non-BAU EE conditions have been identified by ClimateWorks using barriers analysis. See: ClimateWorks. *Inputs to the Energy Savings Initiative modelling from the Industrial Energy Efficiency Data Analysis Project*. (2012). Available: http://www.climateworksaustralia.org/sites/default/files/documents/publications/climateworks_esi_ieedap_report_jul2012.pdf. Viewed 9 July 2014.

[44] ClimateWorks. *Tracking Progress Towards a Low Carbon Economy*. (2012). Available: http://www.climateworksaustralia.org/sites/default/files/documents/publications/climateworks_tracking_progress_discussion_paper_nov2012.pdf. Viewed 9 July 2014.

Table 12: Regional 10% POE load factors for MD savings assessment

2012-13 data	Qld	NSW	Vic	SA	Tas
Annual energy (GWh)	47,160	67,627	46,508	13,319	10,033
Summer MD (MW)	8,479	13,892	9,774	3,095	1,317
Winter MD (MW)	7,469	12,213	7,966	2,408	1,599
Summer load factor	69.3%	67.7%	65.8%	70.8%	72.7%
Winter load factor	74.8%	75.8%	82.3%	72.3%	75.6%

5.6 Modelling limitations and exclusions

5.6.1 Modelling limitations

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

The two data sources[45] used for the residential and commercial forecasts include all programs being run by the Department of Industry (DOI). The EEO Program targeting industrial EE is the only program included to account for potential energy savings in industry.

As per the 2013 methodology, only savings from Federal Government measures are included. This reduces the risk of double-counting savings given that state government programs tend to target similar EE savings and bring their impact forward. Any risk of materially understating potential savings is low because state government measures are comparatively small.

The forecasts do not include rebound effects, where a portion of cost savings from EE measures are spent on additional energy services. EE savings in lighting, space conditioning (air conditioning and heating), and hot water use are likely to have rebound effects. EES (2011)[46] estimated rebound to be approximately 15%; this means that per 1 GWh of energy savings, 0.15 GWh of additional consumption would occur leading to a net EE saving of 0.85 GWh.

The effect of any interaction between electricity price response, EE, and the uptake of distributed generation such as rooftop PV is not considered in the annual energy and MD forecasts, and the potential overlap is not measured.

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

5.7 Methodology improvements since 2013

Changes made to the 2014 methodology improve the transparency of the forecast approach and the quality of the results.

The 2014 forecasts are based on two recent studies for DOI, providing consistent assumptions and information that specifically address the potential for EE savings for a range of EE programs. In addition to the studies used in the 2013 methodology, the 2014 methodology also considered industrial EE savings using EEO data obtained from ClimateWorks. Updated appliance EE data from DOI was also incorporated.

45 See Section 5.3.
46 Energy Efficient Strategies. "The Value of Ceiling Insulation", report to ICANZ, September 2011. Available http://icanz.org.au/wp-content/uploads/2013/04/ICANZ-CeilingInsulationReport-V04.pdf. Viewed 9 July 2014.

The 2013 MD savings were calculated using a single system load factor for each POE level. The 2014 approach calculates system load factors for each POE level using linear models based on daily load factor values. This means EE savings are allowed to vary at different MD levels to improve accuracy.

In 2013, load factors were based on the 2011-12 financial year only. The 2014 forecast uses data from 2006 to 2014 to obtain more realistic load factor estimates.

CHAPTER 6 – SMALL NON-SCHEDULED GENERATION

6.1 Introduction

This chapter provides the methodology used to forecast annual energy and contribution to MD for small non-scheduled generation (SNSG).[47]

Forecasts include existing SNSG projects as well as future potential SNSG projects. Forecasts for existing, operational SNSG projects are based on characteristics such as generation capacity and historical data. Forecasts for future SNSG projects (committed, advanced, and prospective) are developed based on characteristics of similar, existing SNSGs such as location and generator class (fuel source).

A list of existing SNSG projects used for the forecasts is available in Appendix B.

6.2 SNSG scenarios

SNSG forecasts are developed for three scenarios that correspond to the 2014 NEFR high, medium, and low scenarios.

Based on AEMO's generator information pages[48], company or Australian Securities Exchange (ASX) releases, and other publicly available information, AEMO categorised all SNSG projects according to the criteria below:

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

Inclusion of projects from each of these categories in each of the 2014 NEFR scenarios is listed below in table 13:

Table 13: Categories of SNSG projects included in the high, medium and low scenarios.

2014 NEFR scenario	Related SNSG scenario	Categories included
High	High uptake	A, B, C and D
Medium	Moderate uptake	A, B and C
Low	Slow uptake	A and B

[47] Defined as non-scheduled generating units that generally have a capacity of less than 30 MW.
[48] Available at: http://aemo.com.au/Electricity/Planning/Related-Information/Generation-Information.

6.3 Data sources

AEMO forecast SNSG generation based on the following data sources:

- AEMO's generation information pages.
- Publicly available information and company or ASX releases.
- Historical data.

6.4 Calculating SNSG forecasts for annual energy

SNSG installed capacity and future capacity factors are calculated using up to five years of historical data, ending December 2013. AEMO assumes that the installed capacity of existing projects remains unchanged over the 10-year outlook period unless a site has been decommissioned.

All new projects are also assumed to commence operation at the mid-point of the calendar year in which they are due for completion, at their full capacity, and likewise remain at this level over the 10-year outlook period.

Capacity factors[49] for existing projects are calculated using actual historical generation data and installed capacity information. Future output across the forecast period is then estimated using a weighted average of the historical capacity factors for each project, with emphasis placed on more recent years.

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

- Where similar projects already exist—in terms of NEM region and generator class (fuel source)—AEMO uses the total historical output from all similar, existing projects, divided by their combined rated capacity.
- Where no similar projects exist—typically a new generator class in a particular NEM region—AEMO either uses the region average for all existing SNSG projects or applies the capacity factor of similar SNSG projects from another region.

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

Finally, total generation per scenario (high, medium, low) is determined as outlined in Section 6.2.

6.5 Calculating SNSG contribution to maximum demand

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

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

A similar weighting function as for annual energy is applied when estimating contribution factors, emphasising more recent years and any developing trends.

Contribution factors for the summer and winter MD profile over the 10-year outlook period for MD were held constant, regardless of any observed trend or change in contribution levels. The summer and winter contribution factors are then applied to the each individual SNSG's annual energy forecast to develop summer and winter SNSG MD forecasts.

[49] The ratio of actual output to maximum output.

For new SNSG projects, AEMO estimates the contribution to MD factors by averaging all generators from the same NEM region and generator class (fuel source), as per the process for annual energy.

6.6 Modelling limitations and exclusions

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

While information on projects planned in the early part of the forecast period is adequate, it diminishes in quality and quantity for projects scheduled later in the forecast period.

There is no reliable information regarding SNSG project development towards the end of the forecast period. As such, no new projects are assumed, and contribution factors and capacity factors remain constant.

While this may underestimate future SNSG generation levels, a similar lack of reliable information on SNSG retirement rates mean possible overestimation of future generation from existing projects.

To address this, AEMO effectively assumes that the installation rate over the second half of the forecast period equals the retirement rate, resulting in generation profiles that do not vary beyond the initial five years of the outlook period.

6.7 Methodology improvements since 2013

The 2014 methodology incorporates changes that improve the reliability of the forecast approach and the quality of the results. Major improvements include:

- Better use of historical data to inform capacity factors and contribution to MD factors. This included using a weighted average over both time (five years historical data was used, but with more emphasis on recent years) and installed capacity (using all plant of a similar class in a given region, weighted by installed capacity).
- Using the 10 highest load intervals (half-hourly average load) over summer and winter to determine contribution factors to MD. The 2013 NEFR used the single highest interval.

CHAPTER 7 – DEMAND-SIDE PARTICIPATION

7.1 Introduction

This chapter provides the methodology used to develop the demand-side participation (DSP) forecasts presented in the 2014 NEFR Demand-side Participation.[50]

The term DSP generally covers a wide range of short-term demand responses by customers to electricity 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 DSP forecast excludes DSP from scheduled loads in the market, as these are accounted for in market clearing. However, currently 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

AEMO produces forecasts of the available DSP for winter 2014 and summer 2014-15 separately for two segments:

- DSP from large industrial loads (based on the same loads as the large industrial load forecast outlined in Chapter 3.
- DSP from non-industrial 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.

The totals are then projected into the future to produce forecasts for three possible DSP uptake scenarios: slow uptake, moderate uptake, and rapid uptake. The approach for these projections is explained in Section 7.6

All three energy consumption scenarios used for the 2014 NEFR use the moderate uptake DSP scenario, as AEMO considers this to be the most likely uptake scenario of DSP. The low and high DSP uptake scenarios are provided to support sensitivity studies for different DSP growth rates.

[50] Available at: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Other/planning/NEFR/2014/2014%20Supplementary/2014_NEFR_Demand_Side_Participation.ashx.

7.3 Estimate of current DSP from large industrial loads

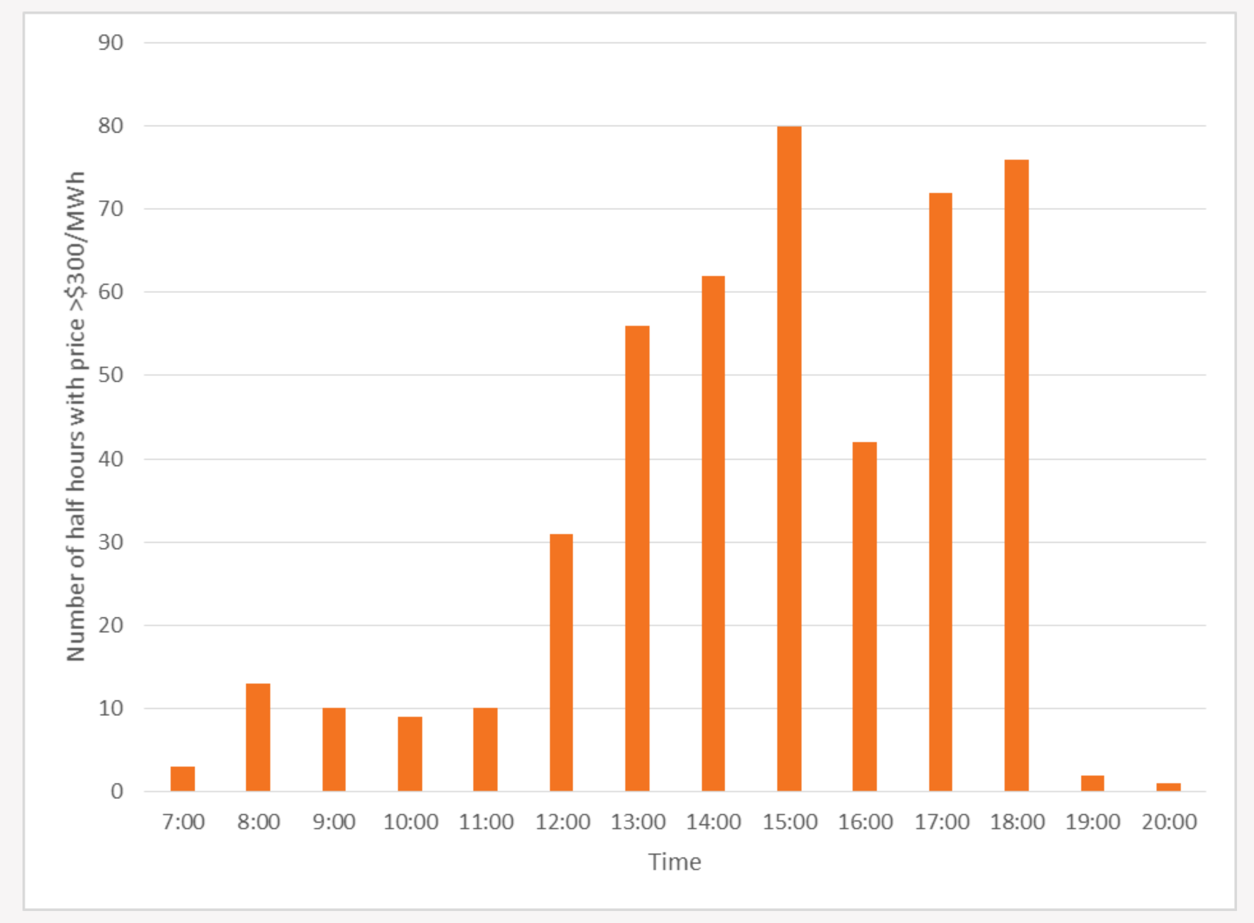
To calculate the DSPcurrently available as of 2014, AEMO calculates the expected DSP response (reduction in consumption) for large industrial loads based on half-hourly metered data from January 2000 to March 2014. The response is assessed for different regional wholesale price levels:

- Prices above $300/MWh.
- Prices above $500/MWh.
- Prices above $1,000/MWh.
- Prices above $7,500/MWh.

The response is 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, AEMO only considers the hours from 7.00 am to 8.00 pm with prices below $300/MWh as this is when high price events generally occur (as shown for Victoria in Figure 10). Night-time industrial demand tends to be slightly higher, driven by lower night-time electricity prices, so comparing against a daily average that included price events outside 7.00 am to 8.00 pm would have introduced a bias which would lead to less accurate results.

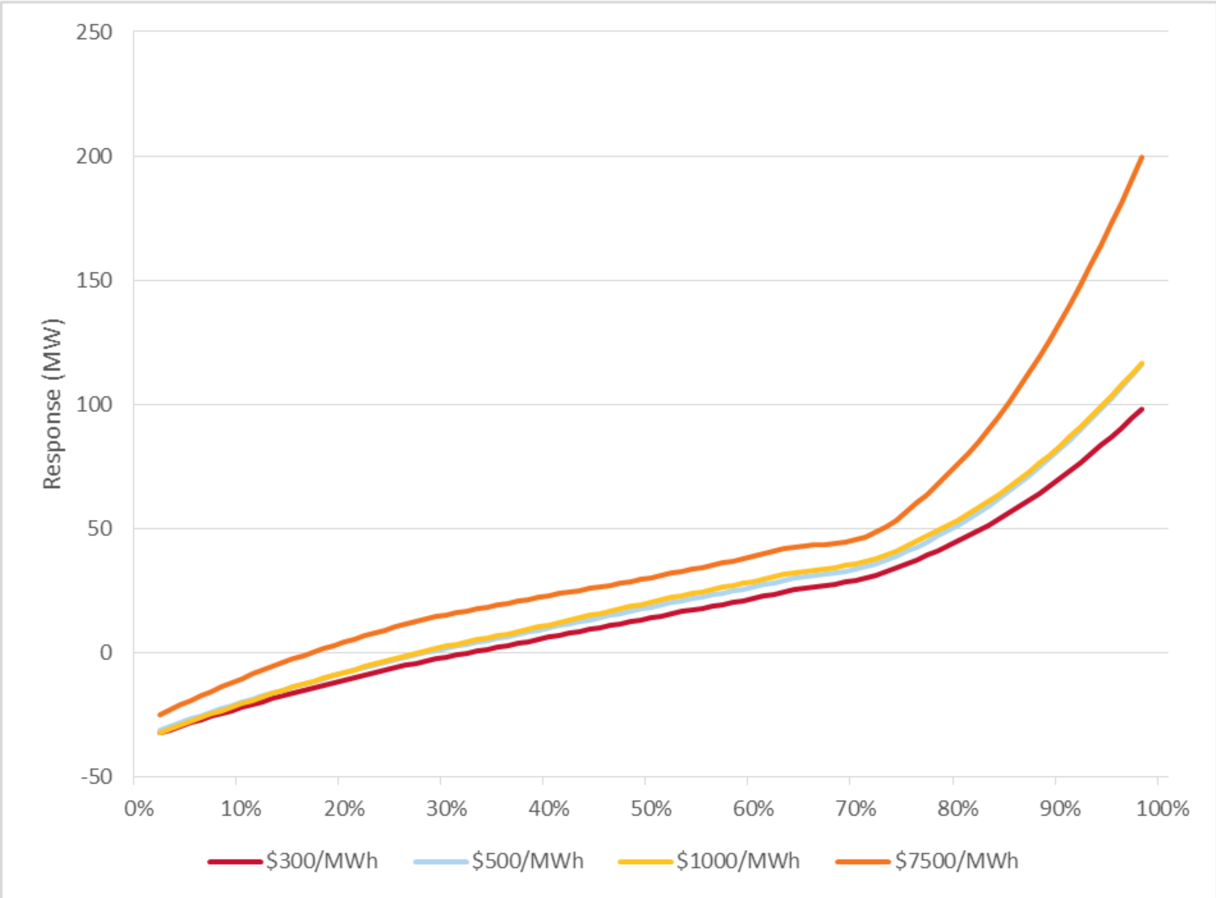
Figure 10: Time of day with prices above $300/MWh in Victoria (Jan 2000 – Mar 2014)



AEMO calculates the DSP response for each high price occasion. The number of high-price events enabled a reasonable estimate of the probability distribution of responses, as shown in Figure 11. This figure shows the historically observed probability of response in megawatts. For example, 90% of the time when prices have been at or above $1,000/MWh, the historically observed DSP response has been at most 80 MW.

This assessment shows that DSP, at least from large industrial loads, is a probable resource rather than a firm resource[51]; customer response depends on a range of factors, such as their production commitment to customers and production flexibility. For these reasons, the same customer may respond differently at different times.

Figure 11: Probability of DSP response in NSW based on historical responses[52] (Jan 2000 - Mar 2014)



Due to the limited data available because of the rarity of such events, it is not possible to reliably estimate the DSP response for prices above $7,500 using this approach. For use in reliability assessments, discussed later in Section 7.5, AEMO had to estimate DSP response during system crises—just before involuntary load shedding is required.

Prices would at that point equal the market price cap (MPC). AEMO assumes that DSP response during system crises would be equal to the response seen in the 90–98% interval of the $7,500/MWh curve Figure 11 (the 98–100% interval is excluded from the analysis as it includes outliers, including mandated load shedding).

So the lowest expected response equals the plotted value for 90% (corresponding to 10% probability of exceedance) and the highest expected response equals the value for 98%, with the midpoint (50% probability of exceedance) equal to the 94% value.

These regional estimates align with DSP forecasts for the 2013 NEFR and are consistent with actual responses seen in extreme pricing events.[53]

[51] Note 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.
[52] This excludes any historical response from the Kurri Kurri smelter.
[53] See Attachment 1 (pages 13 & 14) of AER's submission to AEMC's *Power of Choice review - Direction paper*. Available at: http://www.aemc.gov.au/Media/docs/AER---120508-af5529b8-d12f-40d9-98f1-6546921c645c-0.PDF. Viewed 7 July 2014.

Following this assessment, AEMO evaluates the impact of large industrial load on the MD forecast to see if any historical price response might have interfered with the MD forecast calculations. This avoids double-counting of price impacts already accounted for in the MD forecast. AEMO found that no DSP price response was present in the estimated MD for any NEM region and therefore the DSP forecasts should not be lowered.

7.4 Estimate of current DSP from smaller loads

As per the 2013 NEFR methodology, the DSP response from smaller loads is based on a survey undertaken by AEMO. In early 2013 AEMO surveyed network service providers (transmission and distribution), retailers, and DSP aggregators about the DSP available to them for 2013-14. Refer to the 2013 NEFR Forecast Methodology Information Paper[54] for details.

7.5 The combined DSP forecast for 2014-15

AEMO added the results from the large industrial analysis and the survey responses to produce the combined DSP forecast, which is presented in the 2014 NEFR Demand-side Participation report.[55]

7.6 Assumed growth of DSP in the future

The assumed growth of DSP in the 20-year outlook period for the 2014 NEFR is the same as the 2013 NEFR. Refer to Chapter 7 of the 2013 NEFR Forecast Methodology Information Paper[56] for details.

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 is potentially underestimated.
- To ensure confidentiality of the capabilities and bidding behaviour of individual DSP resources (retailers, NSPs, large industrial loads), 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 forecasts.
- Estimating the growth (or decline) of the DSP resource into the future is difficult due to lack of data for potential DSP growth. AEMO arrives at estimates of future DSP levels, presented in Section 7.6, by making assumptions guided by policy objectives, and verifying the estimates against achieved levels of DSP in other electricity markets.
- The DSP forecast excludes any daily or common customer response (whether voluntary or through load control enabled by tariff type).

7.8 Methodology improvements since 2013

The 2014 methodology is not significantly different from the 2013 methodology. Some minor revisions to the industrial DSP calculations were made to attempt to capture all historical DSP.

[54] Available at: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report-2013/~/media/Files/Other/planning/NEFR/2013/Forecast%20Methodology%20Information%20Paper.pdf.ashx.
[55] Available at: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Other/planning/NEFR/2014/2014%20Supplementary/2014_NEFR_Demand_Side_Participation.ashx.
[56] Available at: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report-2013/~/media/Files/Other/planning/NEFR/2013/Forecast%20Methodology%20Information%20Paper.pdf.ashx.

APPENDIX A – INPUT DATA, CHANGES, AND ESTIMATED COMPONENTS

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

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

Data for rooftop 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 elements of this data have been included or excluded in response to inconsistencies revealed by detailed analysis.

Changes to historical data compared to the 2013 NEFR are outlined below.

A.1.1 All NEM regions

The historical record of rooftop PV installed capacity was extended in the 2014 NEFR, to be as up-to-date as possible. This gave a more complete history of installed capacity. 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

SNSG was revised due to changes in methodology.

The number of large industrial loads included in this year's analysis increased by 10 compared to the 2013 NEFR. This resulted in a decrease in demand for the residential and commercial sector over the historical period.

A.1.3 Queensland

SNSG was revised due to changes in methodology.

The number of large industrial loads included in the 2014 analysis increased by 19 compared to the 2013 NEFR. This resulted in a decrease in demand for the residential and commercial sector over the historical period.

[57] Annual energy refers to operational consumption.

A.1.4 Victoria

SNSG was revised due to changes in methodology. The number of large industrial loads included in this year's analysis increased by eight compared to the 2013 NEFR. This resulted in a decrease in demand for the residential and commercial sector over the historical period.

A.1.5 South Australia

SNSG was revised due to changes in methodology.

The number of large industrial loads included in this year's analysis increased by seven compared to the 2013 NEFR. This resulted in a decrease in demand for the residential and commercial sector over the historical period.

A.1.6 Tasmania

SNSG was revised due to changes in methodology.

The number of large industrial loads included in this year's analysis increased by 10 compared to the 2013 NEFR. This resulted in a decrease in demand for the residential and commercial sector over the historical period.

A.2 Estimated components for the forecasts

A.2.1 Transmission loss forecasts

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

Transmission losses were forecast based on historical data and were normalised by the large industrial and residential and commercial annual energy. Analysis of historical data showed that the normalised transmission losses were fairly consistent over the years (Table 14). As such, AEMO forecast transmission losses by using the historical normalised transmission losses averaged over the last five years.

Table 14 shows the historical normalised transmission losses in each NEM region. Of note is that historical data was revised slightly due to changes in the calculations of the normalised transmission losses.

Table 14: Historical normalised transmission losses

	NSW	Qld	Vic	SA	Tas
2000-01	2.15%	3.79%	3.16%	2.30%	-
2001-02	2.28%	4.34%	3.00%	2.01%	-
2002-03	2.23%	3.92%	3.70%	2.31%	2.22%
2003-04	2.51%	3.78%	3.51%	2.44%	2.35%
2004-05	2.59%	3.56%	3.19%	2.32%	2.39%
2005-06	2.77%	3.36%	2.99%	2.34%	2.86%
2006-07	2.75%	3.45%	2.71%	2.10%	2.34%
2007-08	2.92%	3.39%	2.43%	1.88%	2.44%
2008-09	2.68%	3.19%	2.68%	2.21%	2.61%
2009-10	2.78%	3.24%	2.88%	2.35%	3.01%
2010-11	2.47%	3.08%	2.90%	2.32%	3.00%
2011-12	2.42%	3.11%	3.00%	2.37%	2.73%
2012-13	2.14%	3.24%	2.72%	2.40%	3.21%
5-year average	2.50%	3.17%	2.84%	2.33%	2.91%

Changes since 2013

The methodology has been changed from that in 2013.

Transmission losses were forecast using historical data averaged over the last five years, in contrary to the 10-year average used in 2013. This better captures the changes in the network and generation mix in more recent years.

A.2.2 Auxiliary loads forecast

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

Historical data

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

Analysis – Annual energy

Since auxiliary loads vary proportionally with total generation, forecasts were based on the auxiliary factor, i.e, auxiliary loads normalised by total generation:

$$\text{Auxiliary factor} = \frac{\text{Auxiliary load}}{\text{Total generation}}$$

The auxiliary factor was forecast based on the expected auxiliary loads as a percentage of total generation. The expected percentage was determined by historical data and anticipated changes in the future generation mix. Forecasts of the future generation mix were obtained from the 2013 National Transmission Network Development Plan (NTNDP).

The annual auxiliary loads were then estimated by multiplying the auxiliary factor by the total demand/generation as forecast by the annual energy model.

Analysis – Maximum demand

The auxiliary loads during MD were forecast using a different approach to that for annual energy. Analysis of historical data showed auxiliary loads varied significantly during past MD periods, suggesting that auxiliary loads correlated poorly with the generation mix for most regions.

Therefore, for the 2014 NEFR, auxiliary load forecasts during MD were based on the average auxiliary factor. This factor was calculated from the average of the auxiliary loads during the MD periods over the past five years.

Changes since 2013

The methodology has been changed from the approach used in 2013, as detailed below:

- Contrary to the 2013 forecasts which factored in carbon price, the 2014 forecasts assumed no carbon price.
- The 2013 forecasts were based on ACIL Allen’s estimates of the auxiliary load factor for each individual generator. For the 2014 NEFR, these estimates were revised for several generators, e.g., Northern Power Station in South Australia, based on more recent historical data. This improved the auxiliary load forecasts.
- Methodology for auxiliary load forecasts during maximum demand has been revised. Details can be found in the section above.
- The 2013 auxiliary factor forecasts were averaged by a specific number of years. For the 2014 NEFR, no averaging was applied to the forecasts.

Tables 15 to 17 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 15: Auxiliary load expected percentages for the annual energy demand forecasts

Annual Energy	NSW	QLD	SA	TAS	VIC
2013-14	5.31%	6.22%	3.70%	1.52%	8.02%
2014-15	5.38%	6.66%	3.39%	1.52%	8.31%
2015-16	5.00%	6.67%	2.38%	1.36%	8.18%
2016-17	4.81%	6.68%	2.39%	1.37%	7.87%
2017-18	4.58%	6.65%	2.55%	1.29%	7.78%
2018-19	4.53%	6.59%	2.29%	1.23%	7.71%
2019-20	4.41%	6.46%	2.29%	1.23%	7.49%
2020-21	4.40%	6.29%	2.28%	1.23%	7.41%
2021-22	4.41%	6.29%	2.35%	1.23%	7.44%
2022-23	4.41%	6.28%	2.34%	1.23%	7.45%
2023-24	4.42%	6.28%	2.32%	1.23%	7.46%
2024-25	4.42%	6.27%	2.31%	1.23%	7.46%
2025-26	4.45%	6.26%	2.32%	1.23%	7.47%
2026-27	4.62%	6.25%	2.35%	1.23%	7.48%
2027-28	4.61%	6.23%	2.35%	1.24%	7.49%
2028-29	4.63%	6.22%	2.30%	1.23%	7.50%
2029-30	4.63%	6.21%	2.30%	1.23%	7.50%
2030-31	4.63%	6.19%	1.58%	1.23%	7.50%
2031-32	4.62%	6.17%	1.59%	1.23%	7.51%
2032-33	4.62%	6.14%	1.58%	1.23%	7.50%
2033-34	4.62%	6.12%	1.59%	1.23%	7.50%

Table 16: Auxiliary load expected percentages for the summer maximum demand forecasts

Summer MD	NSW	QLD	SA	TAS	VIC
2014-15	4.28%	5.58%	4.10%	1.40%	5.70%
2015-16	4.28%	5.58%	4.10%	1.40%	5.70%
2016-17	4.28%	5.58%	4.10%	1.40%	5.70%
2017-18	4.28%	5.58%	4.10%	1.40%	5.70%
2018-19	4.28%	5.58%	4.10%	1.40%	5.70%
2019-20	4.28%	5.58%	4.10%	1.40%	5.70%
2020-21	4.28%	5.58%	4.10%	1.40%	5.70%
2021-22	4.28%	5.58%	4.10%	1.40%	5.70%
2022-23	4.28%	5.58%	4.10%	1.40%	5.70%
2023-24	4.28%	5.58%	4.10%	1.40%	5.70%
2024-25	4.28%	5.58%	4.10%	1.40%	5.70%
2025-26	4.28%	5.58%	4.10%	1.40%	5.70%
2026-27	4.28%	5.58%	4.10%	1.40%	5.70%
2027-28	4.28%	5.58%	4.10%	1.40%	5.70%
2028-29	4.28%	5.58%	4.10%	1.40%	5.70%
2029-30	4.28%	5.58%	4.10%	1.40%	5.70%
2030-31	4.28%	5.58%	4.10%	1.40%	5.70%
2031-32	4.28%	5.58%	4.10%	1.40%	5.70%
2032-33	4.28%	5.58%	4.10%	1.40%	5.70%
2033-34	4.28%	5.58%	4.10%	1.40%	5.70%

Table 17: Auxiliary load expected percentages for the winter maximum demand forecasts

Winter MD	NSW	QLD	SA	TAS	VIC
2014	4.29%	5.77%	4.09%	0.81%	6.76%
2015	4.29%	5.77%	4.09%	0.81%	6.76%
2016	4.29%	5.77%	4.09%	0.81%	6.76%
2017	4.29%	5.77%	4.09%	0.81%	6.76%
2018	4.29%	5.77%	4.09%	0.81%	6.76%
2019	4.29%	5.77%	4.09%	0.81%	6.76%
2020	4.29%	5.77%	4.09%	0.81%	6.76%
2021	4.29%	5.77%	4.09%	0.81%	6.76%
2022	4.29%	5.77%	4.09%	0.81%	6.76%
2023	4.29%	5.77%	4.09%	0.81%	6.76%
2024	4.29%	5.77%	4.09%	0.81%	6.76%
2025	4.29%	5.77%	4.09%	0.81%	6.76%
2026	4.29%	5.77%	4.09%	0.81%	6.76%
2027	4.29%	5.77%	4.09%	0.81%	6.76%
2028	4.29%	5.77%	4.09%	0.81%	6.76%
2029	4.29%	5.77%	4.09%	0.81%	6.76%
2030	4.29%	5.77%	4.09%	0.81%	6.76%
2031	4.29%	5.77%	4.09%	0.81%	6.76%
2032	4.29%	5.77%	4.09%	0.81%	6.76%
2033	4.29%	5.77%	4.09%	0.81%	6.76%

APPENDIX B – GENERATORS INCLUDED

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

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

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

B.1 Queensland

B.1.1 Power stations used for operational consumption 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 B	700	Steam Sub Critical	Black Coal	Scheduled
Callide C	900	Steam Super Critical	Black Coal	Scheduled
Collinsville	190	Steam Sub Critical	Black Coal	Scheduled
Condamine A	144	CCGT	Coal Seam Methane	Scheduled
Darling Downs	644.5	CCGT	Coal Seam Methane	Scheduled
Gladstone	1,680	Steam Sub Critical	Black Coal	Scheduled
Kareeya	86.4	Run of River	Water	Scheduled
Kogan Creek	744	Steam Super Critical	Black Coal	Scheduled
Mackay Gas Turbine	34	OCGT	Diesel	Scheduled
Millmerran Power Plant	852	Steam Super Critical	Black Coal	Scheduled
Mt Stuart	423.5	OCGT	Kerosene Aviation fuel used for stationary energy	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 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)	244	CCGT	Coal Seam Methane	Scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Wivenhoe	500	Pump Storage	Water	Scheduled
Yarwun[58]	154	CCGT	Natural Gas Pipeline	Scheduled

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

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Callide A4	30	Steam Sub Critical	Black Coal	Non-scheduled
Daandine	30	Compression Reciprocating Engine	Coal Seam Methane	Non-scheduled
German Creek	45	Spark Ignition Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
Invicta	50.3	Steam Sub Critical	Bagasse	Non-scheduled
ISIS Central Sugar Mill Cogen	25	Steam Sub Critical	Bagasse	Non-scheduled
KRC Cogen	5	Steam Sub Critical	Natural Gas Pipeline	Non-scheduled
Moranbah North PS	45.6	Spark Ignition Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
Moranbah PS	12.6	Compression Reciprocating Engine	Waste Coal Mine Gas	Non-scheduled
Oaky Creek	20.8	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	1.2	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non-scheduled
Somerset Dam	4	Run of river	Water	Non-scheduled
Southbank Institute of Tech	1	Compression Reciprocating Engine	Diesel	Non-scheduled
Suncoast Gold Macadamias	1.4	Steam Sub Critical	Macadamia Nut Shells	Non-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

[58] The National Electricity Market registration classifications of Anglesea Power Station Unit 1 (dispatchable unit ID: APS) and Yarwun Power Station Unit1 (dispatchable unit ID: YARWUN_1) are market non-scheduled generating units. However, it is a condition of the registration of these units that the Registered Participants comply with some of the obligations of a scheduled generator. Both units are dispatched as scheduled generating units with respect to their dispatch offers, targets and generation outputs. Accordingly, information about APS and YARWUN_1 is reported as scheduled generating unit information.

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Whitwood Road Renewable	1.1	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non-scheduled
Windy Hill	12	Wind - Onshore	Wind	Non-scheduled
Wivenhoe Small Hydro	4.5	Hydro - Gravity	Water	Non-scheduled

B.2 New South Wales

B.2.1 Power stations used for operational consumption forecasts for New South Wales (including ACT)

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Bayswater	2640	Steam Sub Critical	Black Coal	Scheduled
Blowering	80	Hydro - Gravity	Water	Scheduled
Capital Wind Farm	140.7	Wind - Onshore	Wind	Non-scheduled
Colongra	724	OCGT	Natural Gas Pipeline	Scheduled
Cullerin Range Wind Farm	30	Wind - Onshore	Wind	Non-scheduled
Eraring	2880	Steam Sub Critical	Black Coal	Scheduled
Gullen Range Wind Farm	165.5	Wind - Onshore	Wind	Semi-scheduled
Gunning Wind Farm	46.5	Wind - Onshore	Wind	Semi-scheduled
Guthega	60	Hydro - Gravity	Water	Scheduled
Hume NSW	29	Hydro - Gravity	Water	Scheduled
Hunter Valley GT	50	OCGT	Fuel Oil	Scheduled
Liddell	2000	Steam Sub Critical	Black Coal	Scheduled
Mt Piper	1400	Steam Sub Critical	Black Coal	Scheduled
Munmorah	600	Steam Sub Critical	Black Coal	Scheduled
Redbank	143.8	Steam Sub Critical	Black Coal	Scheduled
Shoalhaven	240	Pump Storage	Water	Scheduled
Smithfield Energy Facility	170.9	CCGT	Natural Gas Pipeline	Scheduled
Tallawarra	420	CCGT	Natural Gas Pipeline	Scheduled
Tumut 359	1500	Pump Storage	Water	Scheduled
Upper Tumut	616	Hydro - Gravity	Water	Scheduled

[59] The Tumut 3 Pumps (dispatchable unit ID: SNOWYP) are not classified as scheduled load in the National Electricity Market. However, they are required to comply with some of the obligations of a Market Customer in respect of a scheduled load. The Tumut 3 Pumps are dispatched as if they were scheduled loads with respect to their dispatch bids, targets and consumption. Accordingly, information about SNOWYP is reported as market scheduled load information.

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Uranquinty	664	OCGT	Natural Gas Pipeline	Scheduled
Vales Point B	1320	Steam Sub Critical	Black Coal	Scheduled
Wallerawang C	1000	Steam Sub Critical	Black Coal	Scheduled
Woodlawn Wind Farm	48.3	Wind - Onshore	Wind	Semi-scheduled

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

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
Broadwater Power Station	38	Steam Sub Critical	Bagasse	Non-scheduled
Broken Hill GT	50	Diesel	OCGT	Non-scheduled
Brown Mountain	5.2	Hydro - Gravity	Water	Non-scheduled
Burrendong Hydro	19	Hydro - Gravity	Water	Non-scheduled
Burrinjuck PS	27.2	Hydro - Gravity	Water	Non-scheduled
Condong PS	30	Steam Sub Critical	Bagasse	Non-scheduled
Conroy's Gap	30	Wind - Onshore	Wind	Non-scheduled
Copeton Hydro	20	Hydro - Gravity	Water	Non-scheduled
EarthPower Biomass	3.9	Spark Ignition Reciprocating Engine	Biomass recycled municipal and industrial materials	Non-scheduled
Eastern Creek PS	5.1	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non-scheduled
Glenbawn Hydro	5	Hydro - Gravity	Water	Non-scheduled
Glennies Creek PS	11	Compression Reciprocating Engine	Coal Seam Methane	Non-scheduled
Grange Avenue	1.3	Compression Reciprocating Engine	Landfill Methane/Landfill Gas	Non-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	7.2	Hydro - Gravity	Water	Non-scheduled
Nine Network Willoughby	3.2	Compression Reciprocating Engine	Diesel	Non-scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Pindari Hydro	5.7	Hydro - Gravity	Water	Non-scheduled
St Georges League Club	1.5	Compression Reciprocating Engine	Diesel	Non-scheduled
Teralba	3.1	Compression Reciprocating Engine	Waste Coal Mine Gas	Non-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 Power Station A	10	Spark Ignition Reciprocating Engine	Natural Gas - Unprocessed	Non-scheduled
Wilga Park Power Station B	6	Spark Ignition Reciprocating Engine	Natural Gas - Unprocessed	Non-scheduled
Woodlawn Bioreactor	5.3	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non-scheduled
Wyangala A	20	Hydro - Gravity	Water	Non-scheduled
Wyangala B	4	Hydro - Gravity	Water	Non-scheduled

B.3 South Australia

B.3.1 Power stations used for operational consumption forecasts for South Australia

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Angaston	50	Compression Reciprocating Engine	Diesel	Non-scheduled
Canunda Wind Farm	46	Wind - Onshore	Wind	Non-scheduled
Cathedral Rocks Wind Farm	66	Wind - Onshore	Wind	Non-scheduled
Clements Gap Wind Farm	56.7	Wind - Onshore	Wind	Semi-scheduled
Dry Creek Gas Turbine Station	156	OCGT	Natural Gas Pipeline	Scheduled
Hallett 1 (Brown Hill) Wind Farm	94.5	Wind - Onshore	Wind	Semi-scheduled
Hallett 2 (Hallett Hill) Wind Farm	71.4	Wind - Onshore	Wind	Semi-scheduled
Hallett 4 (North Brown Hill) Wind Farm	132.3	Wind - Onshore	Wind	Semi-scheduled
Hallett 5 (The Bluff) Wind Farm	52.5	Wind - Onshore	Wind	Semi-scheduled
Hallett GT	228.3	OCGT	Natural Gas Pipeline	Scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
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	546	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
Port. Stanvac	57.6	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
Snowtown S2 North Wind Farm	144	Wind - Onshore	Wind	Semi-scheduled
Snowtown S2 South Wind Farm	126	Wind - Onshore	Wind	Semi-scheduled
Snuggery Power Station	63	OCGT	Diesel	Scheduled
Starfish Hill Wind Farm	34.5	Wind - Onshore	Wind	Non-scheduled
Torrens Island A	480	Steam Sub Critical	Natural Gas Pipeline	Scheduled
Torrens Island B	800	Steam Sub Critical	Natural Gas Pipeline	Scheduled
Waterloo Wind Farm	111	Wind - Onshore	Wind	Semi-scheduled
Wattle Point Wind Farm	90.8	Wind - Onshore	Wind	Non-scheduled

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

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Amcor Glass	4.0	Compression Reciprocating Engine	Diesel	Non-scheduled
Blue Lake Milling Power Plant	0.5	Compression Reciprocating Engine	Diesel	Non-scheduled
Lonsdale	20.7	Compression Reciprocating Engine	Diesel	Non-scheduled
Port Macdonell	1	Wave	Water	Non-scheduled
Seacliff Park	0.9	Hydro	Water	Non-scheduled

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Tatiara	0.5	Compression Reciprocating Engine	Diesel	Non-scheduled
Terminal Storage Mini Hydro	2.5	Hydro - Gravity	Water	Non-scheduled

B.4 Victoria

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

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Anglesea[60]	150	Steam Sub Critical	Brown Coal	Scheduled
Bairnsdale	94	OCGT	Natural Gas Pipeline	Scheduled
Bogong/Mckay	310	Hydro - Gravity	Water	Scheduled
Challicum Hills Wind Farm	52.5	Wind - Onshore	Wind	Non-scheduled
Dartmouth	185	Hydro - Gravity	Water	Scheduled
Eildon	135	Hydro - Gravity	Water	Scheduled
Energy Brix Complex (Morwell)	189	Steam Sub Critical	Brown Coal	Scheduled
Hazelwood	1600	Steam Sub Critical	Brown Coal	Scheduled
Hume VIC	29	Hydro - Gravity	Water	Scheduled
Jeeralang A	212	OCGT	Natural Gas Pipeline	Scheduled
Jeeralang B	228	OCGT	Natural Gas Pipeline	Scheduled
Laverton North	312	OCGT	Natural Gas Pipeline	Scheduled
Loy Yang A	2180	Steam Sub Critical	Brown Coal	Scheduled
Loy Yang B	1000	Steam Sub Critical	Brown Coal	Scheduled
Macarthur Wind Farm	420	Wind - Onshore	Wind	Semi-scheduled
Mortlake Units	566	OCGT	Natural Gas Pipeline	Scheduled
Mortons Lane Wind Farm	19.5	Wind - Onshore	Wind	Non-scheduled
Mt. Mercer Wind Farm	131.2	Wind - Onshore	Wind	Semi-scheduled
Murray 1	950	Hydro - Gravity	Water	Scheduled
Murray 2	552	Hydro - Gravity	Water	Scheduled
Newport	510	Steam Sub Critical	Natural Gas Pipeline	Scheduled
Oaklands Hill Wind Farm	67.2	Wind - Onshore	Wind	Semi-scheduled

[60] The National Electricity Market registration classifications of Anglesea Power Station Unit 1 (dispatchable unit ID: APS) and Yarwun Power Station Unit1 (dispatchable unit ID: YARWUN_1) are market non-scheduled generating units. However, it is a condition of the registration of these units that the Registered Participants comply with some of the obligations of scheduled generator. Both units are dispatched as scheduled generating units with respect to their dispatch offers, targets and generation outputs. Accordingly, information about APS and YARWUN_1 is reported as scheduled generating unit's information.

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Portland Wind Farm	102	Wind - Onshore	Wind	Non-scheduled
Somerton	160	OCGT	Natural Gas Pipeline	Scheduled
Valley Power Peaking Facility	300	OCGT	Natural Gas Pipeline	Scheduled
Waubra Wind Farm	192	Wind - Onshore	Wind	Non-scheduled
West Kiewa	60	Hydro - Gravity	Water	Scheduled
Yallourn W	1480	Steam Sub Critical	Brown Coal	Scheduled
Yambuk Wind Farm	30	Wind - Onshore	Wind	Non-scheduled

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

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Ballarat Base hospital	2.0	Spark Ignition Reciprocating Engine	Natural Gas Pipeline	Non-scheduled
Banimboola PS	12.2	Hydro - Gravity	Water	Non-scheduled
Berwick	4.6	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non-scheduled
Brooklyn Landfill	2.8	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non-scheduled
Codrington Wind Farm	18.2	Wind - Onshore	Wind	Non-scheduled
Hallam Hydro – South East Water	0.3	Hydro - Gravity	Water	Non-scheduled
Hallam Road	9.0	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non-scheduled
Hepburn (Leonards Hill) Wind Farm	4.1	Wind - Onshore	Wind	Non-scheduled
HRL Tramway Road	5.0	OCGT	Diesel	Non-scheduled
Longford	31.8	OCGT	Natural Gas Pipeline	Non-scheduled
Mornington Waste Disposal Facility	0.8	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non-scheduled
Qenos Cogeneration Facility	21.0	CCGT	Natural Gas Pipeline	Non-scheduled
Rubicon	13.5	Hydro - Gravity	Water	Non-scheduled
Shepparton	0.8	Spark Ignition Reciprocating Engine	Non-biomass recycled municipal and industrial waste	Non-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

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Toora Wind Farm	21.0	Wind - Onshore	Wind	Non-scheduled
Wonthaggi Wind Farm	12.0	Wind - Onshore	Wind	Non-scheduled
Wyndham Renewable Energy Facility	1.9	Spark Ignition Reciprocating Engine	Landfill Methane/Landfill Gas	Non-scheduled
Yarrawonga Hydro	9.5	Hydro - Gravity	Water	Non-scheduled
Werribee Western Treatment Plant	9.6	Spark Ignition Reciprocating Engine	Biogas	Non-scheduled

B.5 Tasmania

B.5.1 Power stations used for operational consumption forecasts for Tasmania

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

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Woolnorth Studland Bay/Bluff Point Wind Farm	140	Wind - Onshore	Wind	Non-scheduled

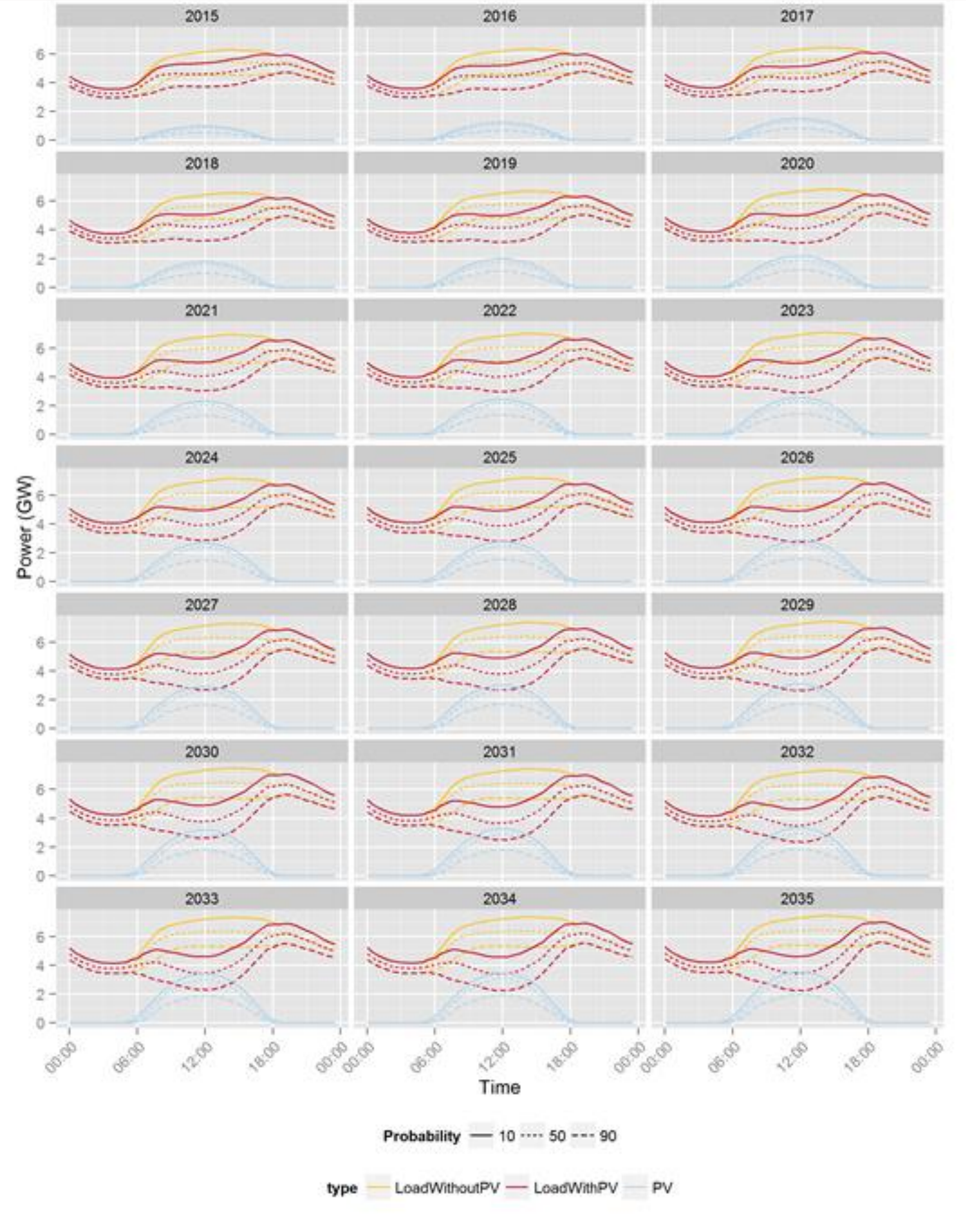
B.5.2 Power stations (existing, SNSG) used for native consumption forecasts for Tasmania – in addition to those in Table B.5.1

Power station	Installed capacity (MW)	Plant type	Fuel	Dispatch type
Butlers Gorge	14.4	Hydro - Gravity	Water	Non-scheduled
Cluny	17	Hydro - Gravity	Water	Non-scheduled
Paloona	28	Hydro - Gravity	Water	Non-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

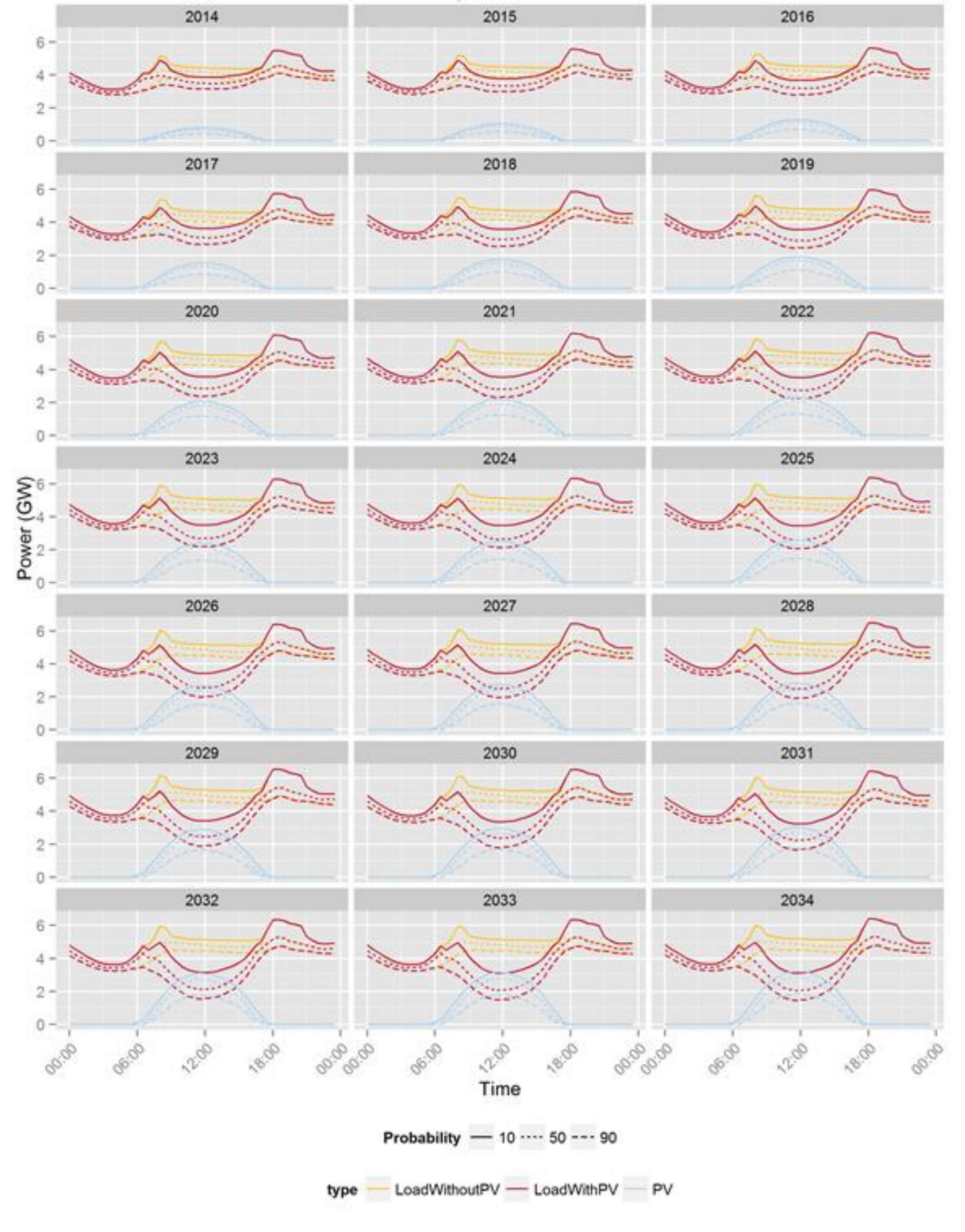
APPENDIX C – MAXIMUM DEMAND PV SNAPSHOTS

This appendix provides snapshots of the MD load profiles over the forecast period.

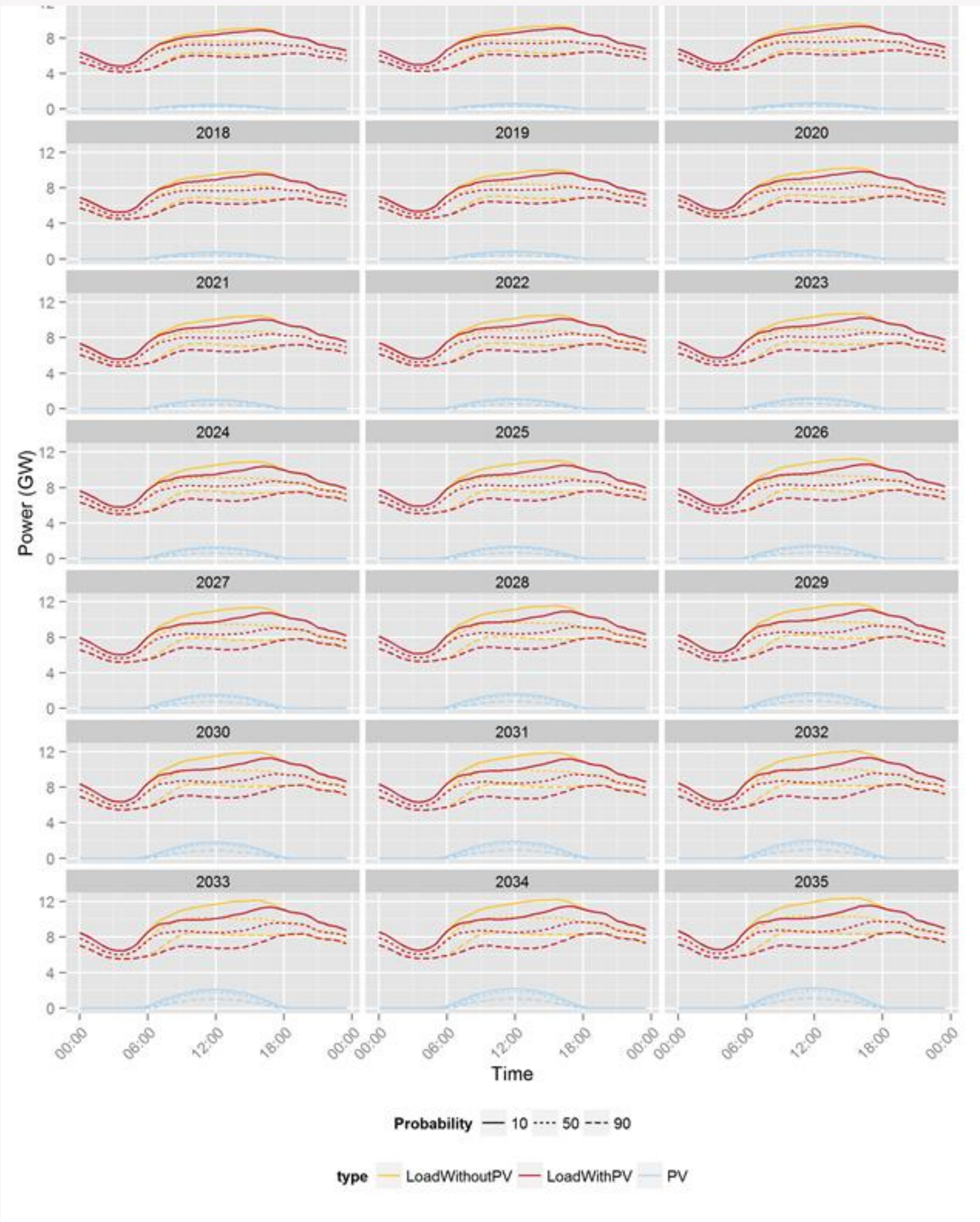
C.1 Queensland summer



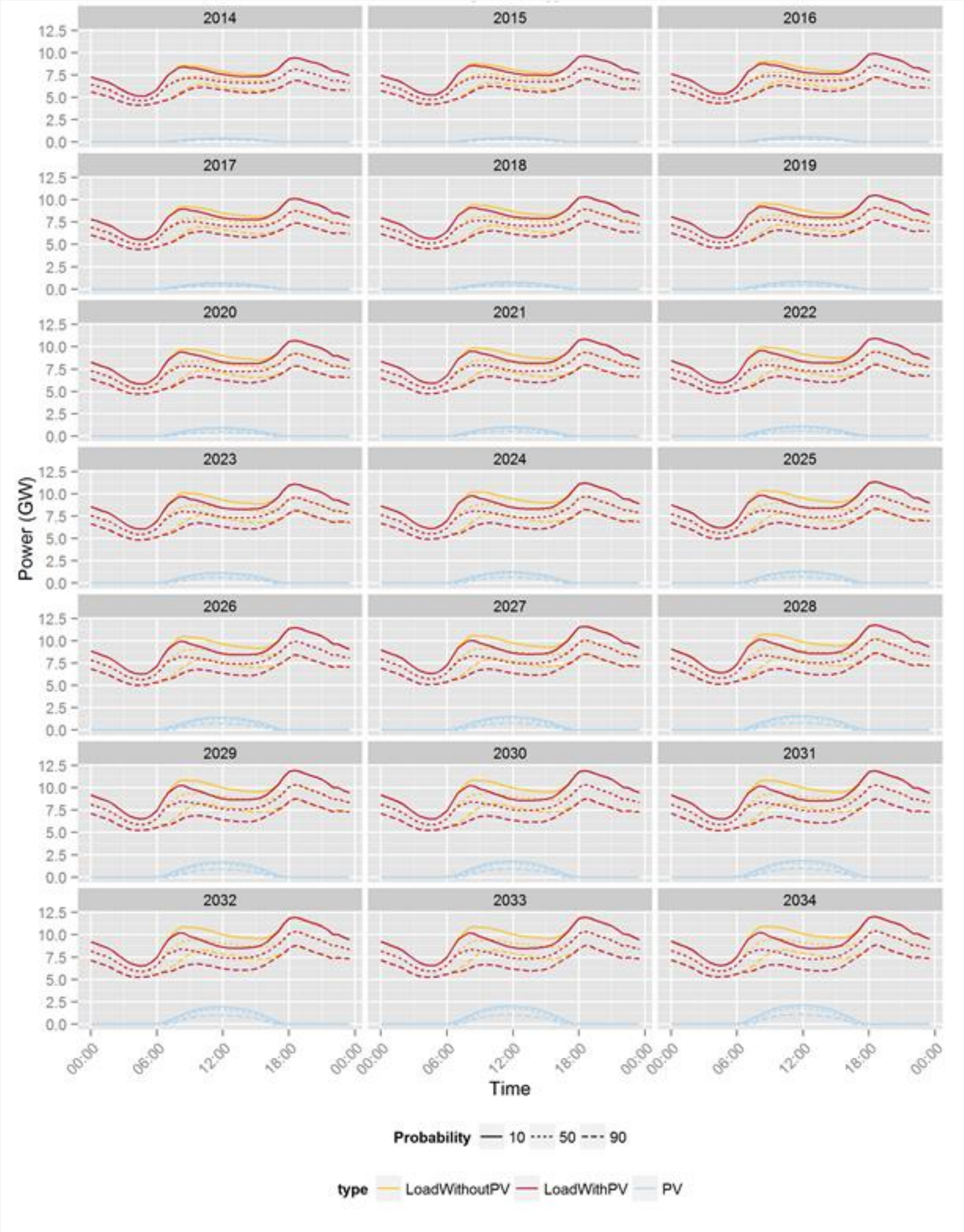
C.2 Queensland winter



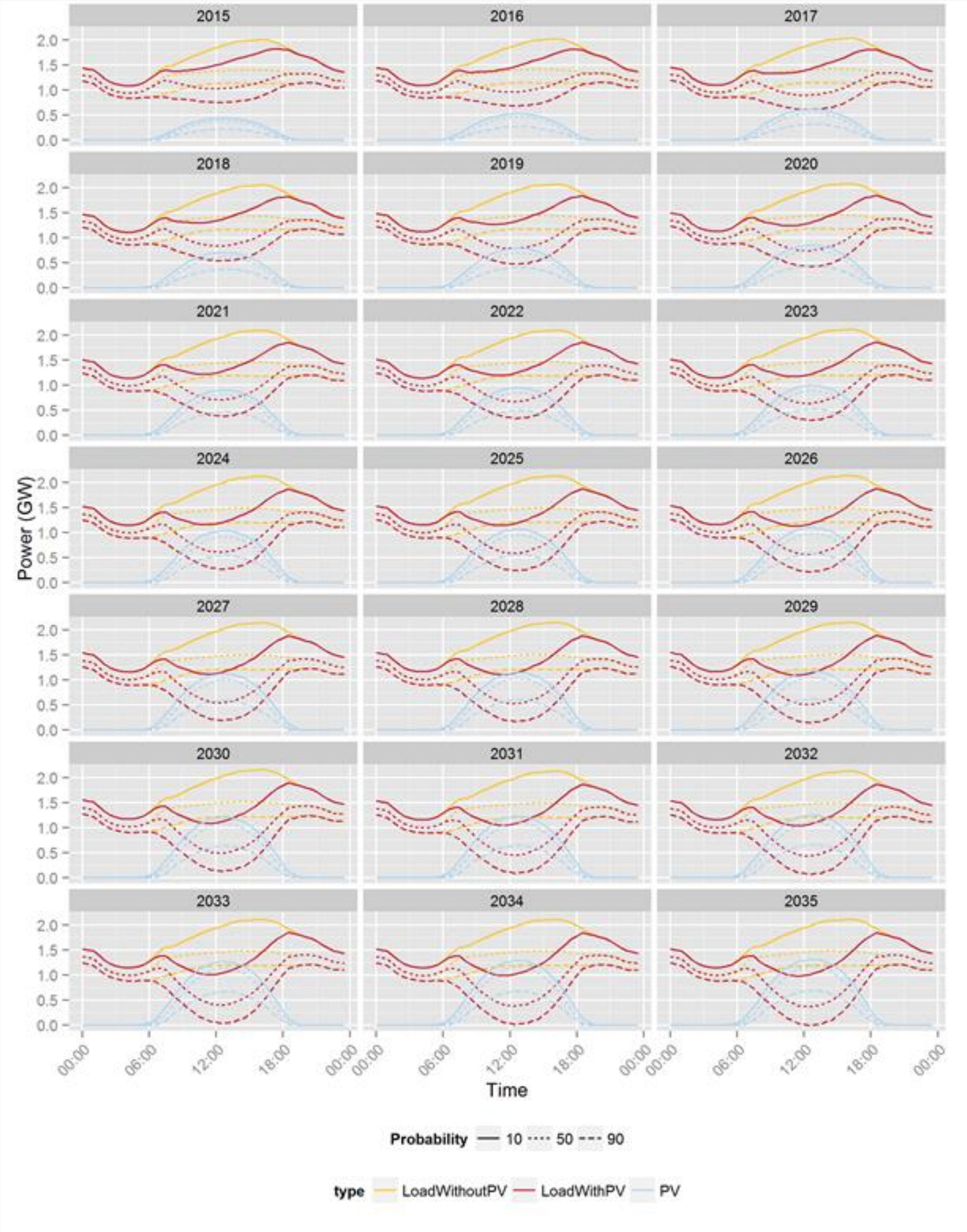
C.3 New South Wales summer



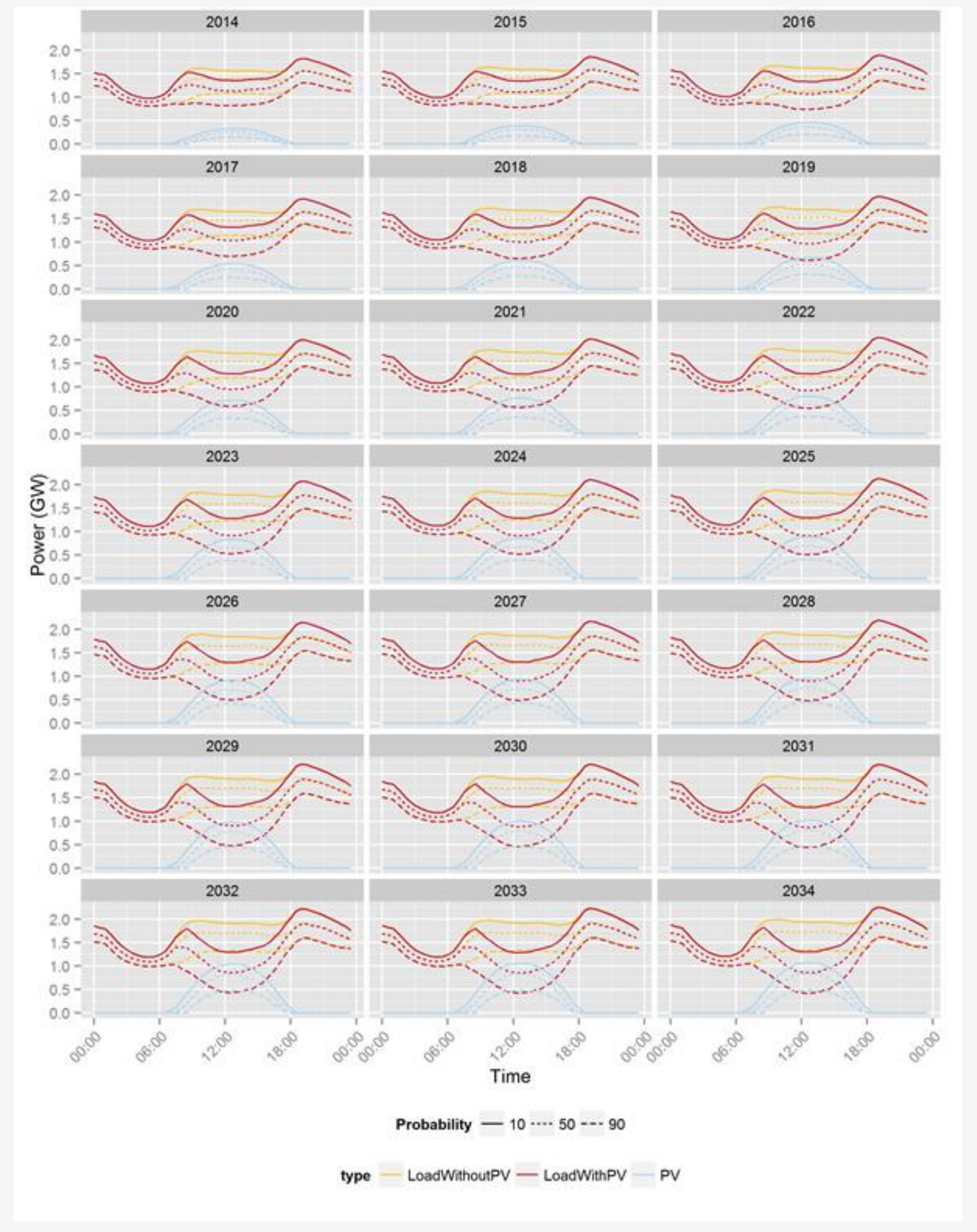
C.4 New South Wales winter



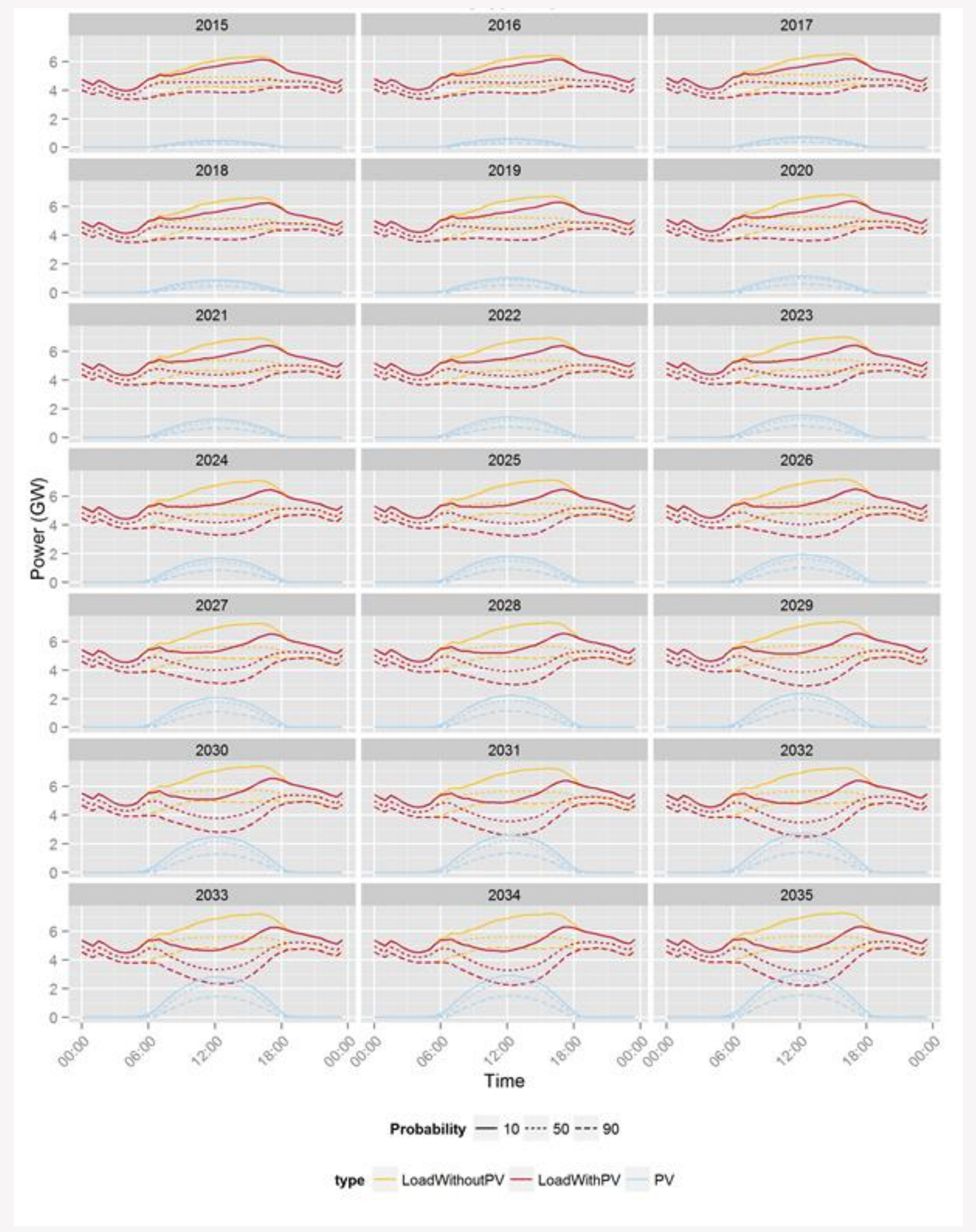
C.5 South Australia summer



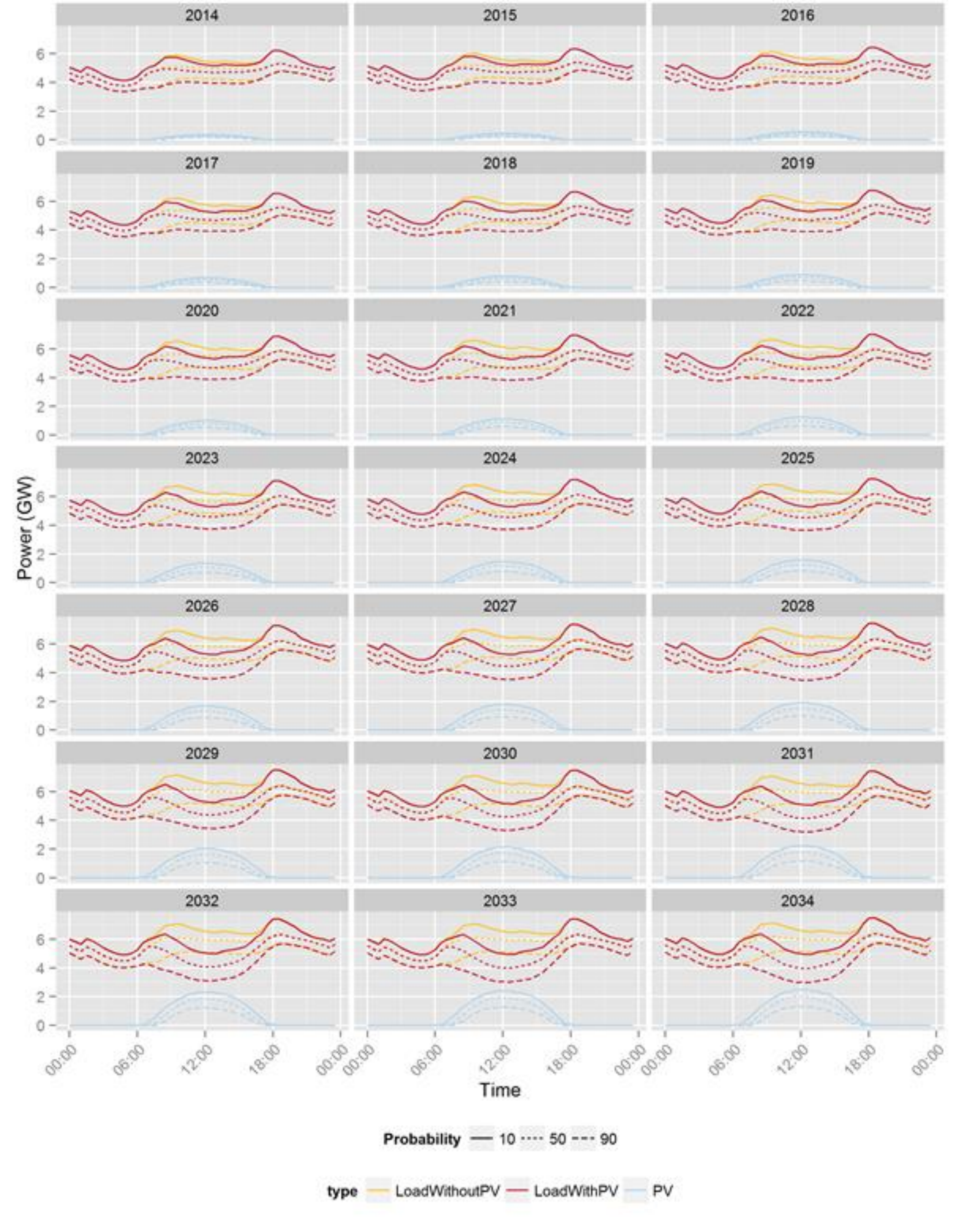
C.6 South Australia winter



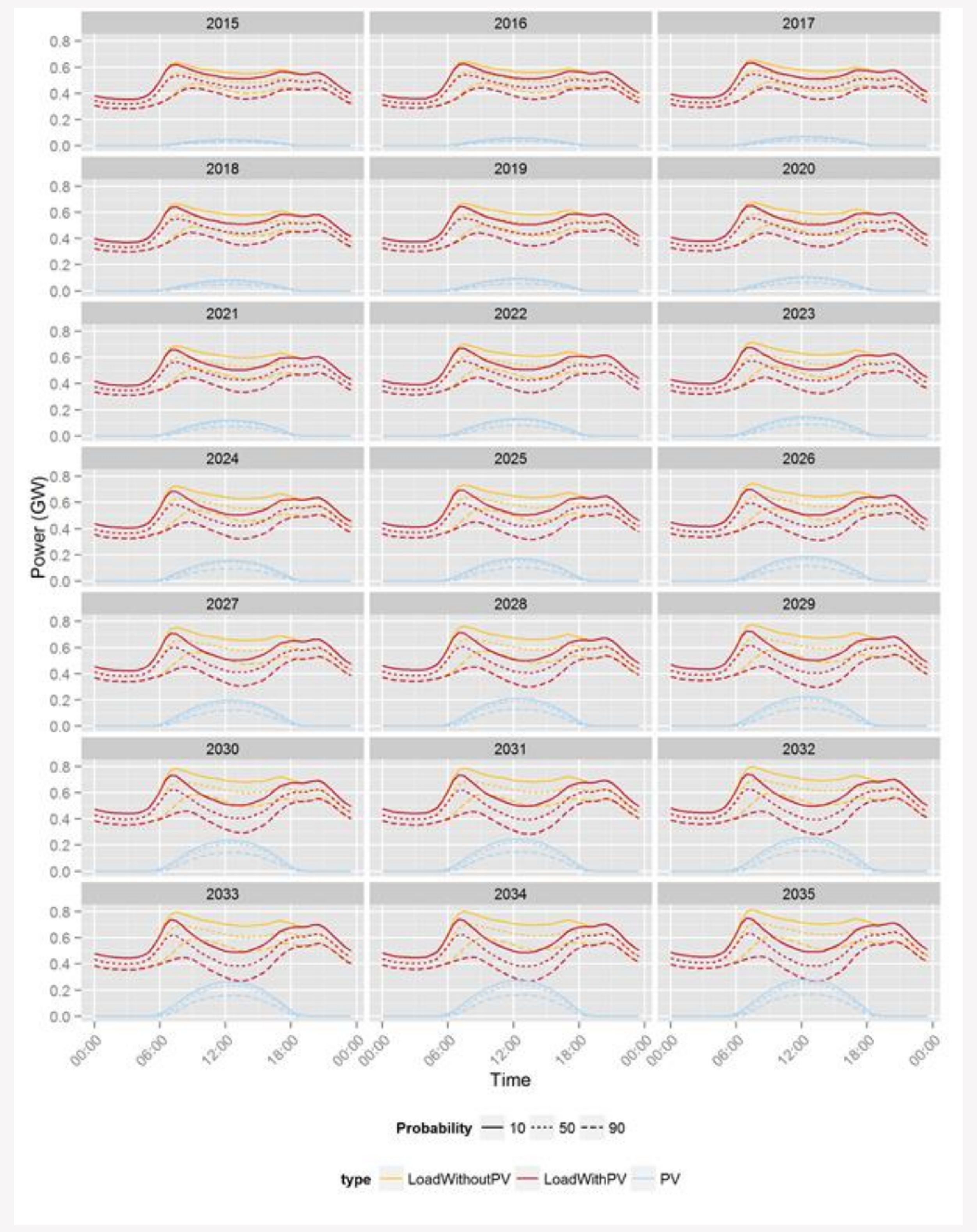
C.7 Victoria summer



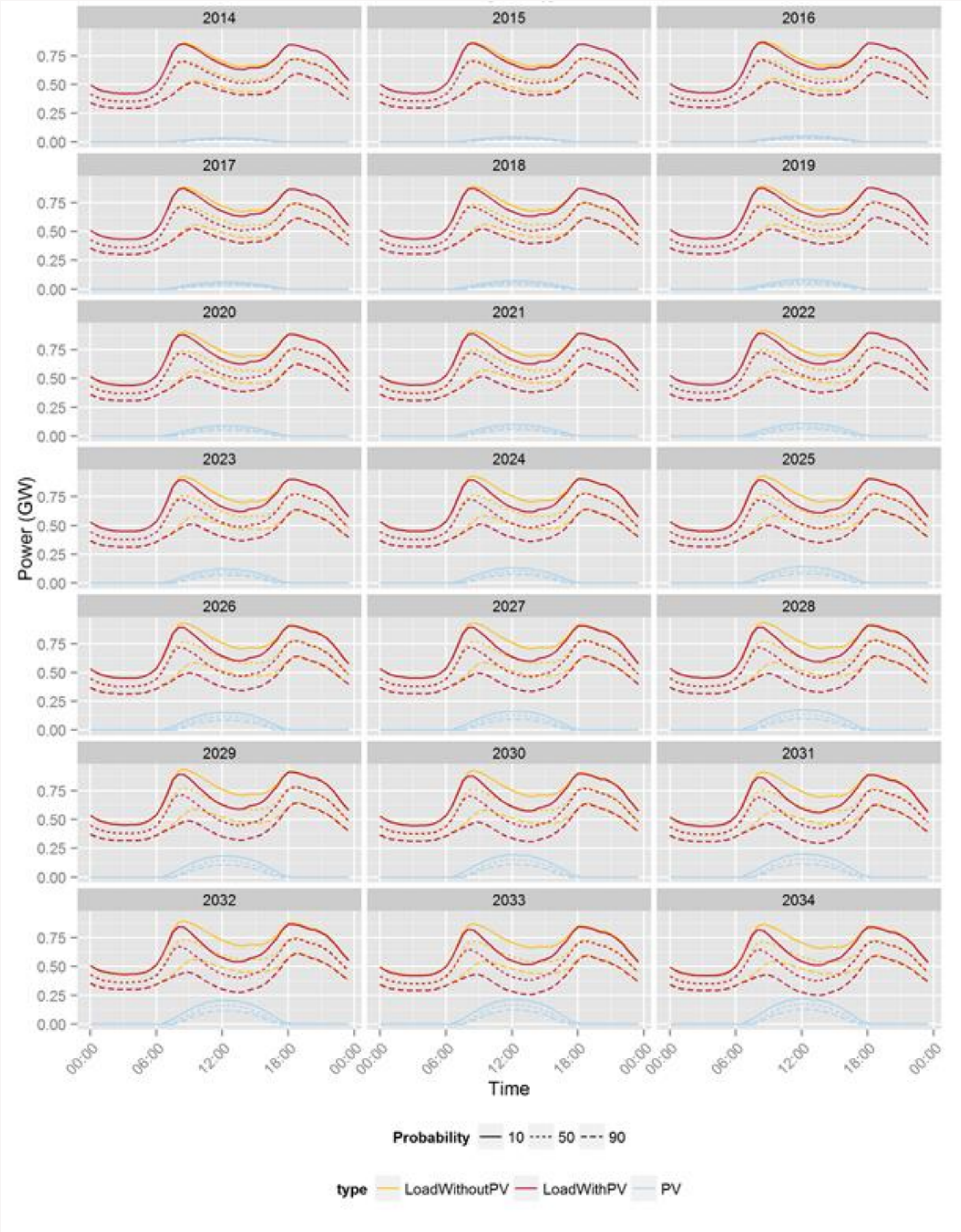
C.8 Victoria winter



C.9 Tasmania summer



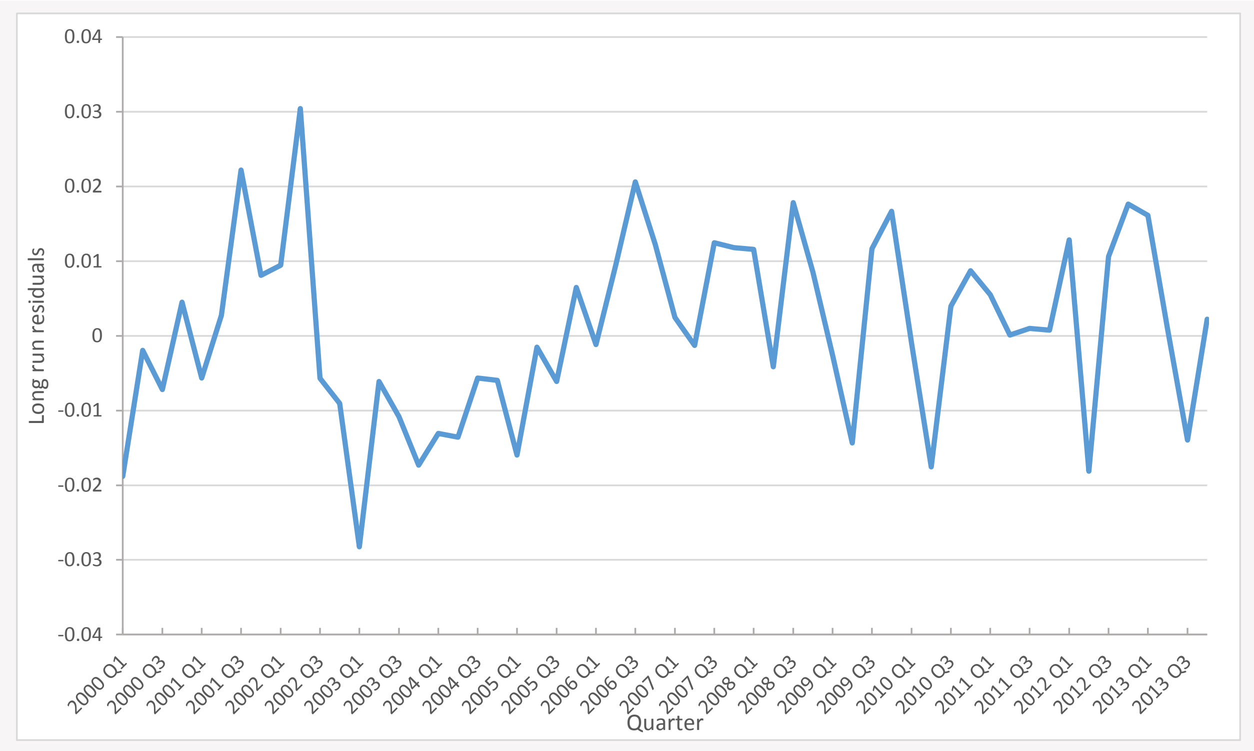
C.10 Tasmania winter



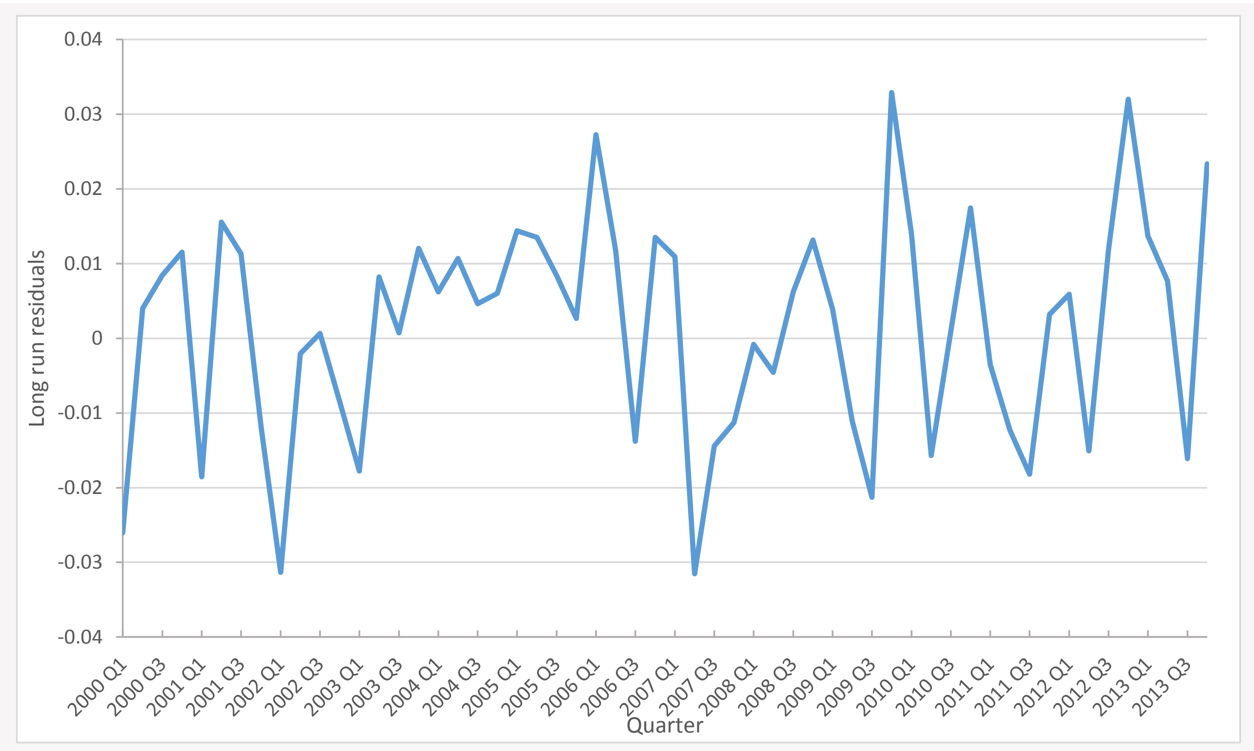
APPENDIX D – DOLS RESIDUALS

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

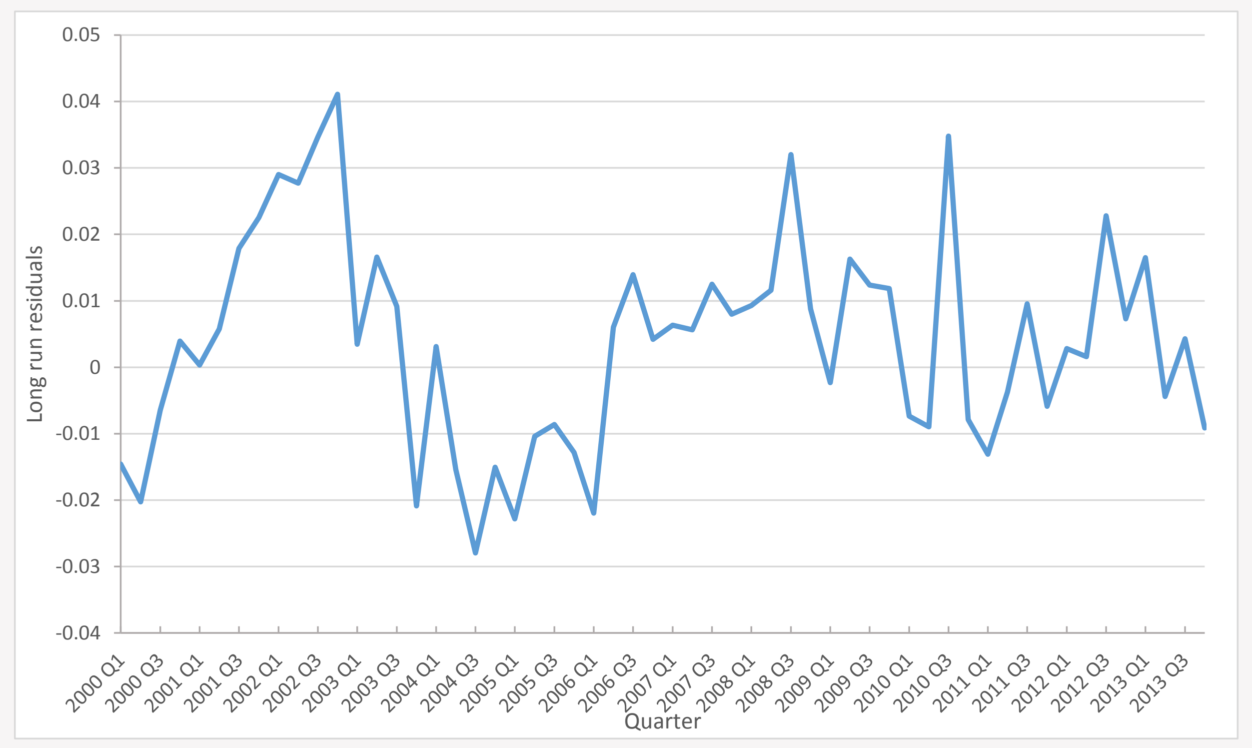
D.1 DOLS residuals for New South Wales



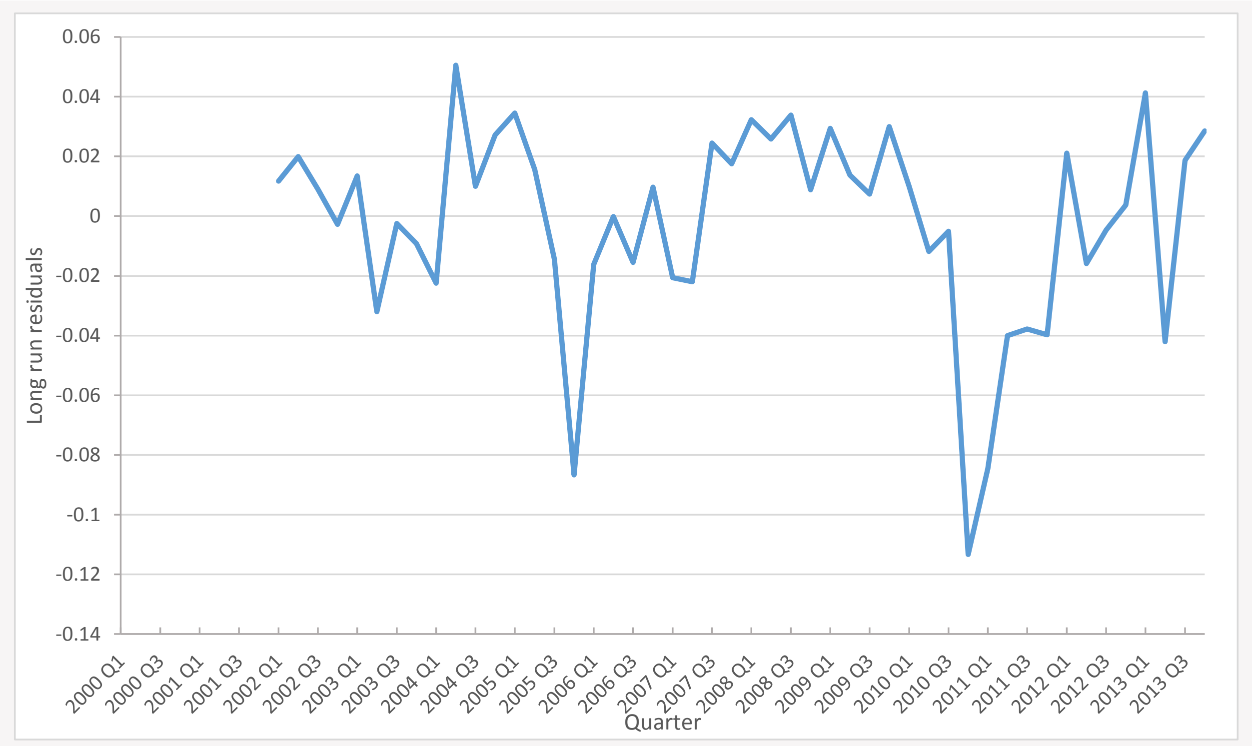
D.2 DOLS residuals for Queensland



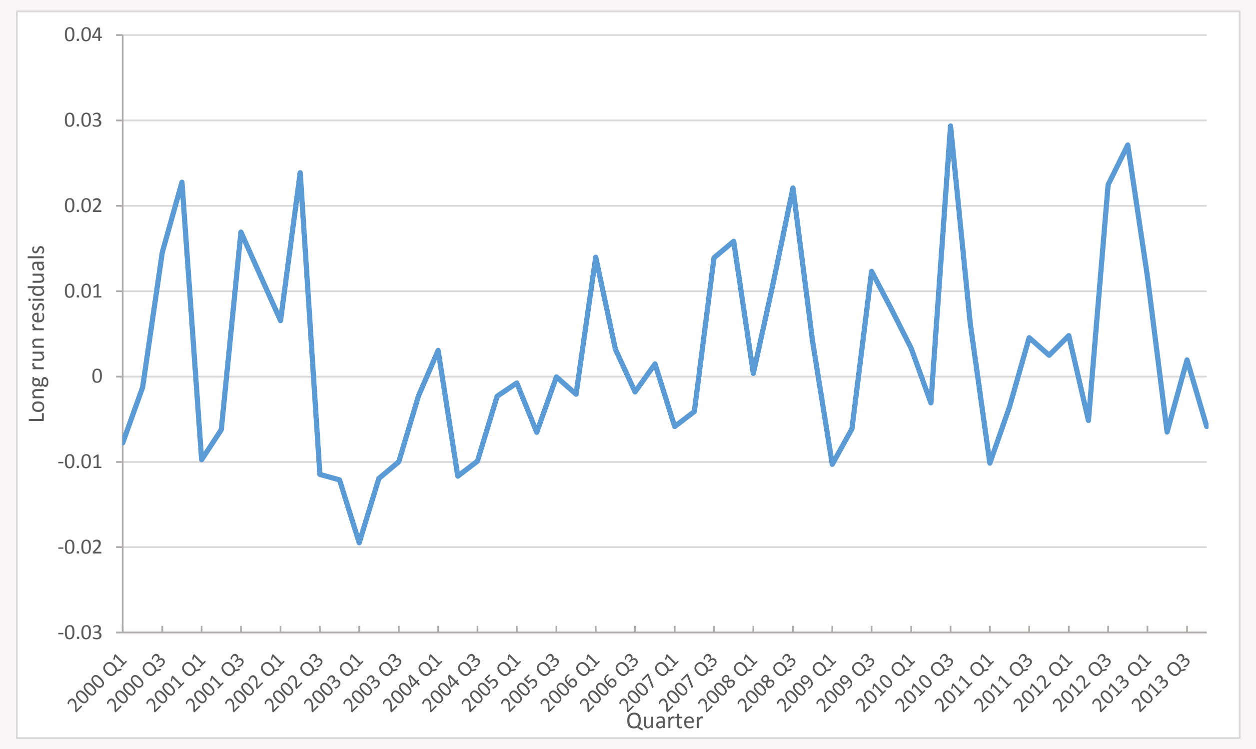
D.3 DOLS residuals for South Australia



D.4 DOLS residuals for Tasmania



D.5 DOLS residuals for Victoria



MEASURES AND ABBREVIATIONS

Units of measure

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

Abbreviations

Abbreviation	Expanded term
AEMO	Australian Energy Market Operator
BAU	Business as usual
BGP	Real Business Gas Price
BOM	Bureau of Meteorology
BPE	Real Business Price of Electricity
CER	Clean Energy Regulator
CCGT	Combined Cycle Gas Turbine
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DNSP	Distribution Network Service Provider
DOI	Department of Industry
DOLS	Dynamic Ordinary Least squares
DSP	Demand-side Participation
EC	Error Correction
EEO	Energy Efficiency Opportunities
ECM	Error Correction Model
EE	Energy Efficiency
GDP	Gross Domestic Product

Abbreviation	Expanded term
GSP	Gross State Product
IDM	Integrated Dynamic Model
MD	Maximum Demand
MEPS	Minimum Energy Performance Standards
MMS	Market Management System
MPC	Market Price Cap
NEM	National Electricity Market
NSP	Network Service Provider
OCGT	Open Cycle Gas Turbine
PCA	Principal Component Analysis
PMA	Post Model Adjustment
POP	Population
RGP	Real Residential Gas Price
RIS	Regulation Impact Statements
RPE	Real Residential Price of Electricity
SRES	Small-scale Renewable Energy Scheme
STC	Small-scale Technology Certificates
TGP	Real Total Gas Price
TNSP	Transmission Network Service Provider
TOU	Time of use
TPE	Real Total Price of Electricity