FORECAST ACCURACY REPORT 2015

FOR THE NATIONAL ELECTRICITY FORECASTING REPORT

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IMPORTANT NOTICE

Purpose

The purpose of this publication is to report on the accuracy of the consumption and maximum demand forecasts in the 2014 National Electricity Forecasting Report (NEFR), which is prepared to satisfy the requirements of rule 3.13.3(q) of the National Electricity Rules (Rules), and to report any improvements made by AEMO or other relevant parties to the forecasting process.

Rule 3.13.3(u) of the Rules requires AEMO to undertake an assessment of the accuracy of consumption and maximum demand forecasts in the Electricity Statement of Opportunities. However, as the relevant forecasts are now only published in the NEFR, that publication is the subject of this Report.

AEMO has published this Forecast Accuracy Report in accordance with rule 3.13.3(u) of the Rules. It is based on information available to AEMO as at September 2015 although AEMO has endeavoured to incorporate more recent information where practical.

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OVERVIEW

The Australian Energy Market Operator (AEMO) produces this Forecast Accuracy Report for the Reliability Panel each year. The report assesses the accuracy of the operational consumption[1] and maximum demand (MD) forecasts in AEMO's 2014 National Electricity Forecasting Report[2] (NEFR) for each region in the National Electricity Market (NEM).

The accuracy of AEMO's operational consumption and MD forecasts depends on AEMO's forecast models, and also relies on forecast input data, including economic forecasts.

AEMO evaluated the accuracy of the forecasts reported in the 2014 NEFR by comparing forecast consumption against actual for 2014–15. It also evaluated the performance of the 2014 and 2015 residential and commercial forecast model. AEMO used a more rigorous statistical test this year to assess its MD model.

The operational consumption forecast was higher than actual consumption for South Australia and Victoria and lower for Queensland, New South Wales and Tasmania. The 2015 residential and commercial models were found to have improved since 2014, with the exception of Tasmania.

For maximum demand, the 2014-15 summer forecast was higher in the 2015 NEFR than the 2014 NEFR for Queensland and New South Wales. South Australia demand was lower in the 2015 NEFR. 2014 NEFR and 2015 NEFR forecasts were closely aligned for Victoria and Tasmania.

Operational consumption forecast accuracy

Generally, variances for operation consumption were between 0.03% and -2.7%, with the exception of Queensland which had a variance of -6.2%. The primary drivers of the variances between forecast and actual for each state are listed in Table 1.

Table 1 Variance between 2014 NEFR forecasts for 2014-15 and actual consumption[3]

Region	Operational consumption variance	Reasons for the variance
Queensland	-6.2%	• Higher than expected large industrial consumption. • Higher than expected residential and commercial consumption (excluding the impact of rooftop PV output).
New South Wales	-2.7%	• Higher than expected residential and commercial consumption (excluding the impact of PV output). • Higher than expected large industrial consumption. • Higher than expected rooftop PV output, reducing residential and commercial consumption from the grid.
South Australia	0.7%	• Lower than expected large industrial consumption
Victoria	0.03%	• Lower than expected residential and commercial consumption.
Tasmania	-0.6%	• Higher than expected industrial consumption.

The residential and commercial model

While operational consumption includes all residential and commercial, large industrial load, and transmission losses, only the residential and commercial forecast is modelled in the NEFR. Large industrial load forecasts are developed through interviews, and transmission loss values are calculated as a fixed percentage of operational consumption.

1 Operational consumption includes all residential and commercial, large industrial load, and transmission losses.
2 AEMO. Available: http://www.aemo.com.au/Electricity/Planning/Forecasting/NEFR-Archive/~/media/Files/Other/planning/NEFR/2014/2014%20Updates/NEFR_final_published_Nov_2014.ashx.
3 Calculated as follows: Variance % (actual base) = 100% x (Forecast-Actual)/Actual.

To assess the accuracy of the residential and commercial models for the 2014 NEFR, AEMO compares the 2014 model forecasts with and without actual driver data; this effectively differentiates model error from driver projection error. Actual driver data includes actual values for weather, population, gross state product, state final demand, and electricity price projections

In the 2014 Forecast Accuracy Report, AEMO noted that South Australia and Tasmania exhibited a high level of model variance when using actual driver data. This was addressed in 2015 by capturing the asymmetric price response to electricity prices by modelling the impact of price increases and decreases differently using different price variables.

Table 2 shows that when actual driver data is used in the 2014 NEFR model, forecast accuracy in only Queensland and Victoria improves. When actual driver data is used in the 2015 NEFR model, forecast accuracy for all regions improves, with the exception of Tasmania. Adequately capturing consumer behaviour and the relationship between price and consumption continues to be a problem in Tasmania and is something that will be further explored in the 2016 NEFR.

Table 2 2014 and 2015 NEFR residential and commercial forecasts using actual driver data [4]

Residential and commercial consumption	Qld		NSW		SA		Vic		Tas	
	GWh	Variance	GWh	Variance	GWh	Variance	GWh	Variance	GWh	Variance
2014-15 actual	33,945		53,309		10,362		35,917		3,606	
2014 NEFR forecast for 2014-15	32,538	-4.1%	52,105	-2.3%	10,244	-1.1%	36,236	0.9%	3,622	0.4%
2014 NEFR forecast using actual driver data for 2014-15	33,104	-2.5%	56,191	5.4%	10,210	-1.5%	36,098	0.5%	3,634	0.8%
2015 NEFR forecast using actual driver data for 2014-15	33,247	-2.1%	51,796	-2.8%	10,372	0.1%	36,139	0.6%	3,714	3.0%

Maximum demand

MD forecasts are based on probability of exceedance (POE) in the NEFR models. In this context, POE refers to how likely it is that a particular demand value is exceeded. For example, a summer 10% POE represents a value that is expected to be exceeded once every 10 years during summer.

The change between forecasts can be assessed by comparing how a certain POE value has changed in the most recent historical year. This is more of an assessment of the short-term forecasting accuracy of the maximum demand model and depends on the economic and weather driver variables that feed into the model. It is not an assessment of the performance of the POE distribution.

Table 3 shows the variance between the 2014 and 2015 NEFRs for the 10% POE in the 2014-15 summer. This is a forecast value for the 2014 NEFR and an “actual” value for the 2015 NEFR. Here, actual is used to indicate that actual economic and weather data has been used to calculate the 10% POE.

The 2014-15 summer forecast was higher in the 2015 NEFR than the 2014 NEFR for Queensland and New South Wales. South Australia demand was lower in the 2015 NEFR. 2014 NEFR and 2015 NEFR forecasts were closely aligned for Victoria and Tasmania.

[4] 2014 and 2015 NEFR forecasts include both residential commercial consumption and PV production but excludes energy efficiency. This adjustment enables the comparison of the forecasts with actuals.

Table 3 Operational demand variance[5] between the 10% POE forecast in the 2014 NEFR and 2015 NEFR

Region	Variance	Reasons for the variance
Queensland	-7.0%	Higher than expected LNG demand. Higher than expected residential and commercial demand due to the warm QLD summer.
New South Wales	-5.8%	Higher than expected residential and commercial demand due to the warm NSW summer.
South Australia	2.9%	Lower than expected large industrial demand.
Victoria	0.8%	Close agreement between models.
Tasmania	1.5%	Close agreement between models.

POE distributions

The maximum demand forecasts that AEMO produces are probabilistic. This means that instead of forecasting a single point for demand, AEMO forecasts a probability distribution with quantiles from 1% to 99% at 1% intervals. It is from this distribution that the 10%, 50% and 90% POE values are taken.

AEMO assesses MD forecast accuracy by looking at MD values over a 13-year historical period[6]. In general, MD values over that period should fall between the 10% POE and 90% POE distribution. MD values may fall outside of the 10% POE and 90% POE values but this is expected to occur less often.

To assess probabilistic forecasts, different score functions can be used. Quantile scoring, mean absolute excess probability (MAEP) and the Kolmogorov–Smirnov (K-S) statistic are used within this Report. They are defined in section 2.2.1. Statistical measures such as these allow for AEMO's maximum demand model to be quantitatively assessed against other maximum demand models under the same forecast conditions.

For each score, a lower number represents better performance. The scores from one state cannot be directly compared to another due to differences in the underlying demand behaviour. For example, New South Wales has much higher demand than South Australia and a considerably wider spread between POEs that results in higher quantile scoring scores, even when the model is performing well. Similarly, non-industrial scores (2014 NEFR) should not be compared against operational scores (2015 NEFR). Instead, scores allow for a different forecasting model's results for a particular region and demand type to be compared against AEMO's results for that same region.

The scores for the 2014 NEFR non-industrial MD backcasts are shown in Table 4 for each region's peaking season. AEMO moved to modelling operational demand as a whole in the 2015 NEFR. The scores for the 2015 NEFR operational MD forecasts are shown in Table 5 for each region's peaking season.

Table 4 Statistical scores for 2014 NEFR non-industrial MD forecasts

NEM region	Quantile Score	MAEP	K-S statistic
Queensland	88.0	8.9%	31.3%
New South Wales	202.2	9.5%	27.6%
South Australia	55.1	6.1%	18.7%
Victoria	177.7	5.1%	11.9%
Tasmania	11.3	9.5%	22.5%

[5] Calculated as follows: Variance % (actual base) = 100% x (Forecast-Actual)/Actual.
[6] Excluding Tasmania which is assessed over 9 years of historical data.

Table 5 Statistical scores for 2015 NEFR operational MD forecasts

NEM region	Quantile Score	MAEP	K-S statistic
Queensland	68.6	10.3%	26.9%
New South Wales	208.7	13.0%	30.6%
South Australia	51.2	6.2%	16.2%
Victoria	179.0	14.0%	39.0%
Tasmania	10.6	13.7%	33.9%

Improvements since the 2014 NEFR

The econometric model was changed for the 2015 NEFR, to provide better analysis of the decline in electricity prices in some regions in recent years. This reflects the greater importance being placed on recent consumption patterns in forecasting future trends. In the 2014 NEFR, AEMO used the same underlying model for each region. For the 2015 NEFR, given changing trends and drivers in each region[7], AEMO adjusted the underlying model to be more sensitive to region-specific trends. Where there was enough historical data, the model incorporated asymmetric price effects, allowing the forecasts to capture the different consumer behaviour linked to price increases and price decreases.

To improve accuracy in the maximum demand modelling, operational demand was forecast as a whole in 2015. In previous years, AEMO only modelled non-industrial maximum demand with a point forecast added on for industrial. In addition to this change, variable selection was allowed to vary with time of day. Maximum demand forecasts were also reconciled with the annual consumption forecasts in a more sophisticated manner.

Refer to the Forecasting Methodology Information Paper for further details[8].

Forecast variances and AEMO's key focus areas for 2016

AEMO's 2015 NEFR Action Plan, to be published in November 2015, will outline AEMO's priorities for improvement in the 2016 NEFR.

[7] Actual driver data includes actual values for weather, population, gross state product, state final demand, and electricity price projections.
[8] Available at http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Electricity/Planning/Reports/NEFR/2015/2015%20NEFR%20forecasting%20methodology%20information%20paper.ashx. Viewed 31 August 2015.

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CHAPTER 1. INTRODUCTION

The NEFR provides AEMO's independent electricity consumption forecasts for each region. The NEFR is published in June each year along with a range of supplementary documents, including the Forecasting Methodology Information Paper.[9] AEMO has prepared operational consumption and MD forecasts since 2012.

This Report assesses the accuracy of the operational consumption and MD forecasts in the 2014 NEFR for each region.

The forecasts have been assessed using the medium NEFR scenario. AEMO has assessed the accuracy of the forecasts by comparing year-to-date forecasts (2009-10 to 2014-15) with actual values. This means that AEMO compares the 2014-15 financial year forecasts in the 2014 NEFR with the actual results for 2014-15.

[9] AEMO. Available at: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Electricity/Planning/Reports/NEFR/2015/2015%20NEFR%20forecasting%20methodology%20information%20paper.ashx. Viewed: 31 October 2015.

CHAPTER 2. METHODOLOGY

2.1 Annual energy

2.1.1 Accuracy measures

AEMO assessed the accuracy of the forecasts based on the following measures:

- The variance percentage is calculated using the formula below and all variances use actuals as the base

$$\frac{forecast - actual}{actual} * 100\%$$

- In-sample forecasts assess how well the models forecast against actual residential and commercial consumption. These are essentially what the forecast outcomes would have been if they had started from 2003-04, with the actual economic and weather drivers known. Any forecast errors from earlier years will influence the forecasts in later years, thereby capturing the evolution of the relationship between forecasting variables over the 10-year period.
- The accuracy of the residential and commercial consumption models are assessed using actual driver data for 2014-15 which differentiates model error from driver projection error. Drivers include weather[10], population[11], gross state product[12], state final demand[13] and electricity price projections[14].

2.1.2 Back assessment

To evaluate the accuracy of the 2014 NEFR forecasts, operational and native consumption[15] forecast variances are presented for each region. Variances use actual consumption as the base. The back assessment compares the 2014 NEFR one-year-ahead forecasts against actual 2014-15 consumption. It also examines the variances of previous one-year-ahead forecasts for operational consumption only.

2.1.3 Backcast

Backcasting is used to evaluate the performance of AEMO's 2014 and 2015 NEFR residential and commercial models.

AEMO produced in-sample dynamic forecasts from 2003-04 to 2013-14 to assess how well the models forecast against actual residential and commercial consumption. These are essentially what the forecast outcomes would have been if they had started from 2003-04, with the actual economic and weather drivers known.

The models' forecasting performance for 2014-15 is also assessed by breaking down past forecasting errors into key driver (combined weather, economic, and demographic) projection errors, and model errors. This shows the forecast variance resulting from the models in isolation. It does not however show the forecast variance resulting from updates in individual drivers, such as the impact of weather.

The 2014 Forecast Accuracy Report used out of sample forecasts to assess the accuracy of the 2013 and 2014 consumption models by removing actual consumption for 2013-14. This meant that the data that was used to assess the model was not used to determine the model co-efficients. This approach was not used in 2015. The 2015 NEFR sought to capture the asymmetric price response to electricity prices by modelling the impact of price variations differently using different price variables. Given the limited historical data available for this approach, at

[10] Bureau of Meterology, Climate Data Online. Available at http://www.bom.gov.au/climate/data/index.shtml. Viewed 14 September 2015
[11] Australian Bureau of Statistics, December 2014, Australian Demographic Statics, cat no 3101, ABS, Canberra
[12] Deloitte Access Economics, June 2015, Business Outlook, Deloitte Access Economics, Sydney
[13] ibid
[14] Frontier Economics, April 2015, Electricity market forecasts: 2015. Available at http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/NEFR-Supplementary-Information, Viewed: 27 October 2015.
[15] Operational consumption plus contribution from small non-scheduled generation. Refer to the 2015 NEFR. Available at: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report Viewed: 8 October 2015.

this stage, performing an out-of-sample forecast to assess the model was not possible due to the distorting influence each quarter of historical data had on the calculation of the co-efficients.

2.1.4 Improvements since the 2014 NEFR

As noted above, the econometric model was changed for the 2015 NEFR, to provide better analysis of the decline in electricity prices in some regions in recent years. This reflects the greater importance being placed on recent consumption patterns in forecasting future trends. In the 2014 NEFR, AEMO used the same underlying model for each region. For the 2015 NEFR, given changing trends and drivers in each region, AEMO adjusted the underlying model to be more sensitive to region-specific trends. Where there was enough historical data, the model incorporated asymmetric price effects, allowing the forecasts to capture the different consumer behaviour linked to price variations.

Refer to the Forecasting Methodology Information Paper for further details.

2.2 Maximum demand

2.2.1 Accuracy measures

Backcasting is used to evaluate the performance of AEMO's 2014 and 2015 NEFR MD models. Using backcasts it is possible to observe where the actuals are falling in relation to the POE values. These figures are shown in each of the following chapters. It is also possible to calculate several statistical scores to assess model performance. These scores can then be used to compare different models to quantitatively determine how well they perform in relation to one another.

Since MD forecasts are essentially probability distributions, it is necessary to use a suitable statistical measure to assess the model's performance. Three measures were used to assess the performance of AEMO's maximum demand forecasts:

- Quantile scoring
- The Kolmogorov-Smirnov (K-S) statistic
- Mean absolute excess probability (MAEP)

Quantile scoring assess the entire probability distribution and is calculated using the pinball loss function. It is a commonly used score for probabilistic forecasting and has been used in forecasting competitions[16]. For a given quantile[17], $^{a}/_{100}$ and quantile forecast, q_a, the pinball loss function is calculated as

$$L(q_a, y) = \begin{cases} \left(1 - \frac{a}{100}\right)(q_a - y), & \text{if } y < q_a, \\ \frac{a}{100}(y - q_a), & \text{if } y \geq q_a, \end{cases}$$

where y is the actual observed value and $a \in \{1,2,\ldots,99\}$. To obtain the quantile score, the pinball loss function score is averaged over all quantiles and forecast years. In other words, for a particular state, season and year, the $L(q_a, y)$ score is calculated for all POEs and the actual observed maximum demand for that year. This is then done for all remaining historical years. Once all of the $L(q_a, y)$ scores have been calculated, they are averaged to obtain the quantile score for that state and season. When comparing different models against each other, a lower quantile score implies better performance.

The K-S statistic is the largest difference between the empirical distribution function (EDF) of the historical POEs and the expected cumulative distribution function (CDF) (see Figure 1). This statistic can be used to perform hypothesis testing, but is better used as another measure by which to assess forecast accuracy. It can be stated formally as

$$KS = \max_{\text{p}} |G(p) - p|$$

[16] For instance, GEFCom 2014. See http://robjhyndman.com/hyndsight/gefcom2014/.
[17] The relationship between a quantile, a, and POE is $a = 100 - POE$.

where $G(p)$ is the percentage of times that an actual maximum demand values is greater than a certain quantile value. The difference between $G(p)$ and p is called the excess percentage.

Figure 1 shows the K-S statistic calculation for New South Wales. The “expected” line gives the CDF of a uniform distribution while the “historical POE” line gives the EDF of the historical actual POE values. The EDF jumps for each historical actual POE value that exceeds the POE level. The largest distance between the two lines is marked by the arrows and represents the K-S statistic, D.

MAEP is another score that can be used to assess maximum demand forecasts. It is similar to the K-S statistic in that it compares $G(p)$ to p. Instead of only looking at the maximum difference between these two values, the MAEP calculates the total area between the two plot lines. It is defined as

$$MAEP = \int_0^1 |G(p) - p| dp.$$

The shaded area in Figure 2 shows the MAEP for New South Wales. MAEP scores assess the excess percentage for all percentiles whereas the K-S statistic only gives a measure of the worst-performing point.

Figure 1 Example of K-S statistic calculation for New South Wales

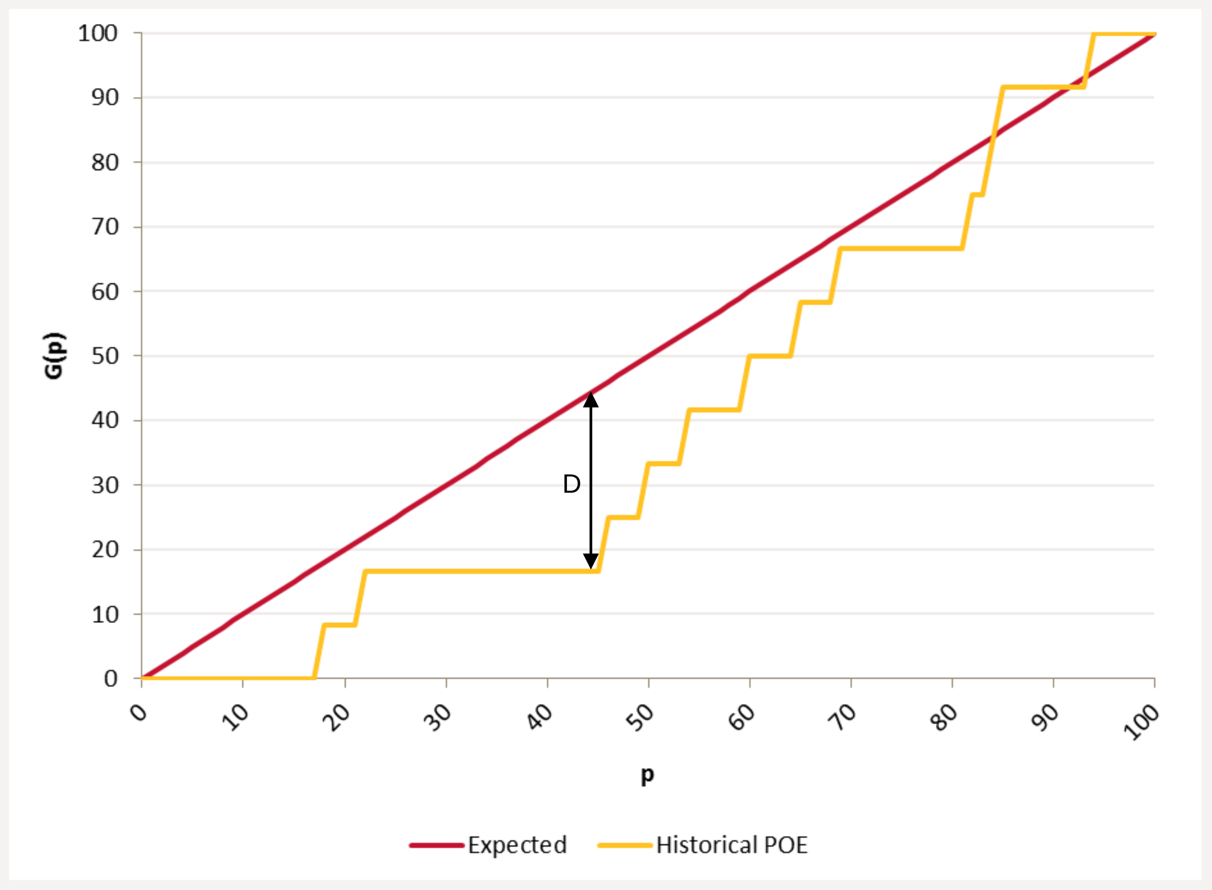
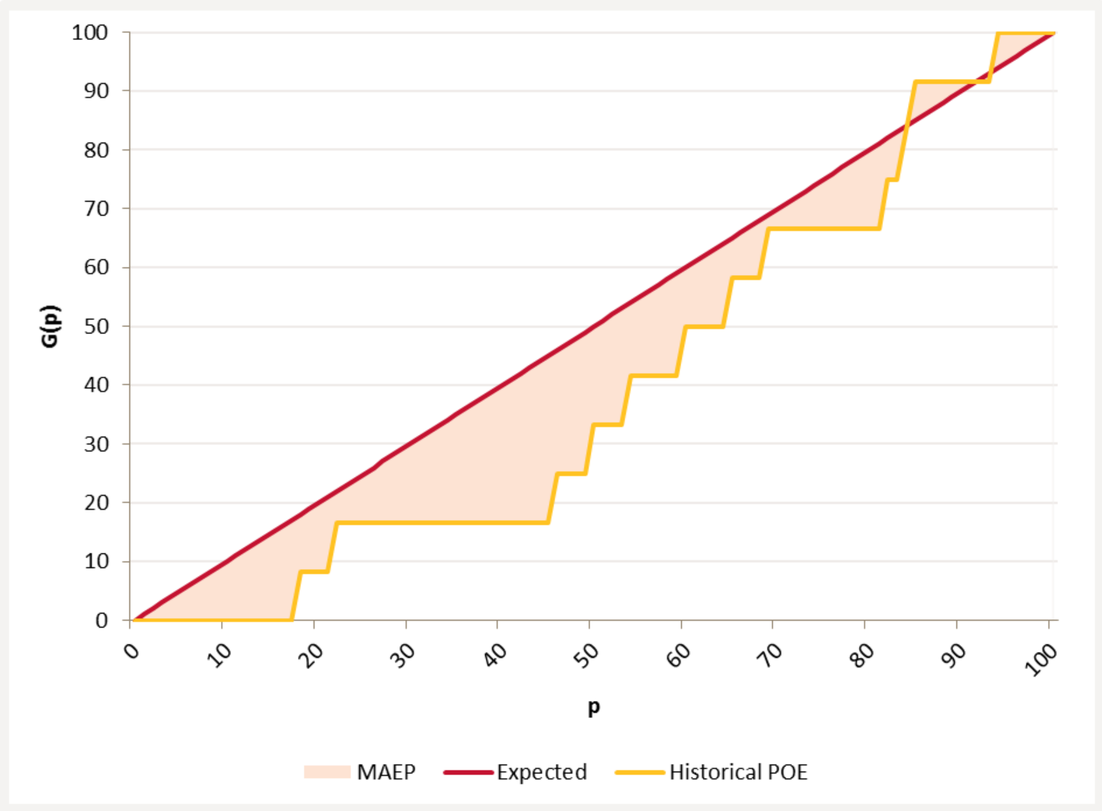


Figure 2 Example of MAEP score calculation for New South Wales



2.2.2 2014-15 summer MD forecast

An examination of where the actual MD values sit on the MD distribution provides some detail on the validity of the MD model. Given a large sample size, it would be expected that half of the points would lie below the 50% POE and half would lie above this line. Furthermore, it would be expected that 10% of points would lie above the 10% POE line and 90% would lie above the 90% POE line. Given the small sample size of seasonal historical MDs, this exact outcome is not expected, however, a general adherence to this pattern is expected.

AEMO obtained an estimate of the 10% POE for the 2014-15 summer (2014 winter for Tasmania) using the estimated historical 10% POE from the 2014 forecasting models. This was compared to the forecast 10% POE from the 2014 NEFR to determine the relative accuracy of the 2014 NEFR forecasts for one season ahead. Note that 10% POE is particularly relevant for planning purposes, so the accuracy of this forecast is important.

Analysis is provided for both operational demand (as generated) and native demand (as generated) at the time of MD, including the underlying reasons for the variance. Note that the historical MD distribution is based on the non-industrial MD POE distribution (produced by the model) and the actual large industrial demand at the time of MD.

The following potential sources of forecast variance exist outside of the 2014 NEFR MD model:

- Large industrial load forecasts.
- Energy efficiency offset forecast.
- Energy forecasts.
- Economic forecasts.

The 2015 NEFR MD model includes industrial loads and thus models all of operational demand. In addition, since the MD forecasts are better reconciled with the annual consumption forecasts, the economic and energy forecasts are taken into consideration. Energy efficiency adjustments are still treated as a post-model adjustment and so are a potential source of forecast variance that falls outside of the MD model.

2.2.3 Key improvements to the 2014 MD forecast methodology

AEMO, in conjunction with Monash University, made the following improvements to the 2014 model:

- Included industrial demand in the MD model to allow for operational demand to be modelled as a whole.
- Allowed variable selection for the demand model to vary with time of day. This improved accuracy by allowing the demand model to be tuned to morning, afternoon and evening periods rather than only the afternoon period.
- Separate models for working days and non-working days. Hierarchical modelling such as this is known to improve accuracy.
- More sophisticated reconciliation with AEMO's annual consumption forecasts.
- For further information refer to the Monash technical forecasting reports[18].

[18] Refer to: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/NEFR-Supplementary-Information

CHAPTER 3. QUEENSLAND

3.1 Annual consumption

The 2014-15 annual consumption forecast for Queensland shows under-forecasting, with most of the variance in the residential and commercial sector.

3.1.1 Back assessment

The 2014 NEFR forecasts for 2014-15 operational and native consumption were lower than actual consumption (refer to Table 6). The operational consumption forecast was 6.2% below actual. The native consumption forecast was 6.3% below actual.

Key reasons for this variance are:

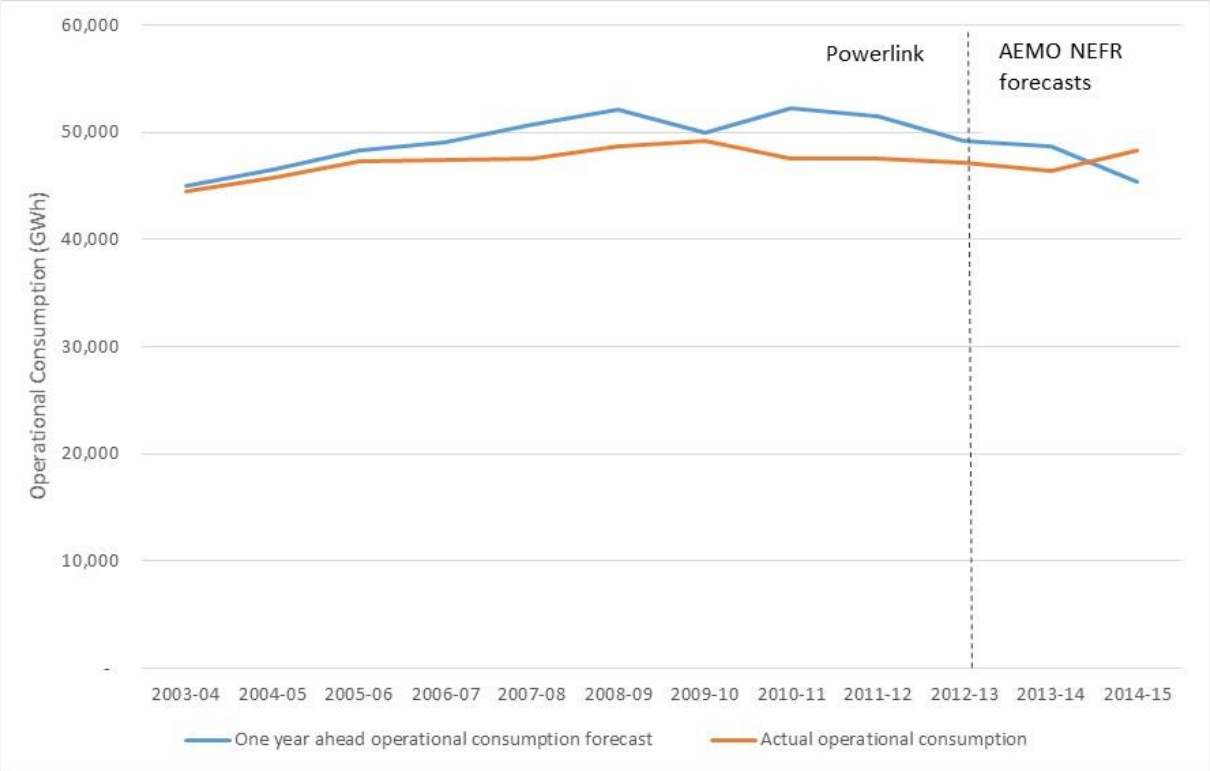
- Higher than expected large industrial consumption.
- Higher than expected residential and commercial consumption (excluding the impact of rooftop PV output).
- Higher than expected transmission losses.
- Lower than expected rooftop PV output, increasing residential and commercial consumption from the grid.

Table 6 2014 NEFR forecast of 2014-15 annual consumption, Qld

	Operational consumption	Native consumption
Forecast (GWh)	45,362	46,846
Actual (GWh)	48,356	49,991
Variance (GWh)	-2,994	-3,145
Variance (%)	-6.2%	-6.3%
Variance components	**Operational consumption**	**Native consumption**
Residential and commercial (excluding PV impact) (GWh)	-1,942	-2,093
PV production (GWh)	267	267
Large industrial (GWh)	-1,162	-1,162
Transmission losses (GWh)	-157	-157

Figure 2 shows the variances of previous one-year-ahead forecasts for operational consumption only, demonstrating a clear tendency to over-forecast until 2013-14.

Figure 3 One-year-ahead annual consumption forecast variance, Qld



3.1.2 Backcast

Table 7 presents the dynamic in-sample forecast results from the 2014 and 2015 NEFR residential and commercial models.

In the 2014 NEFR, AEMO tested the inclusion of an intercept correction around the turning point in the historical consumption data to reduce the magnitude of the overestimation in the last few periods of historical data. In the 2015 NEFR, AEMO reassessed the intercept correction based on the performance of the 2014 forecasts over the last year. In Queensland, AEMO's forecast had underestimated consumption, so the intercept correction was removed to give a better "fit".

The actual residential and commercial data used in the 2015 NEFR differs from the actual data from the 2014 NEFR due to the reallocation of large customers from the residential and commercial sector to the industrial sector.[19]

Table 7 shows that both the 2014 and 2015 NEFR residential and commercial consumption forecasts track accurately against actual residential and commercial consumption. Neither model shows a tendency to over- or under-forecast, and on the whole, differences between the forecast and actual values generated by the two NEFR models are minimal.

[19] Refer to the Forecasting Methodology Information Paper for further detail: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Electricity/Planning/Reports/NEFR/2015/2015%20NEFR%20forecasting%20methodology%20information%20paper.ashx. Viewed 31 August 2015.

Table 7 2014 and 2015 NEFR dynamic in-sample residential and commercial forecasts, Qld

Financial year end	2014 NEFR residential and commercial consumption			2015 NEFR residential and commercial consumption		
	Actual (GWh)	In-sample forecast (GWh)	Variance (%)	Actual (GWh)	In-sample forecast (GWh)	Variance (%)
2003-04	33,638	33,594	-0.1%	31,214	31,320	0.3%
2004-05	34,873	34,648	-0.6%	32,405	32,186	-0.7%
2005-06	36,342	36,100	-0.7%	33,851	33,484	-1.1%
2006-07	36,041	36,070	0.1%	33,543	33,832	0.9%
2007-08	36,016	36,238	0.6%	33,386	33,714	1.0%
2008-09	37,271	36,948	-0.9%	34,703	34,705	0.0%
2009-10	37,608	37,405	-0.5%	34,746	34,432	-0.9%
2010-11	36,437	36,650	0.6%	33,503	33,231	-0.8%
2011-12	36,657	36,792	0.4%	33,488	33,398	-0.3%
2012-13	36,880	36,765	-0.3%	33,014	33,277	0.8%
2013-14				32,709	32,828	0.4%

Table 8 presents the forecast results from the 2014 and 2015 NEFR models using actual driver data.

The variance between the 2014-15 actual and 2014 NEFR forecast residential and commercial annual consumption is -4.1%. When actual driver data is used, the degree of variation increases to -2.5% in the 2014 NEFR model and -2.1% in the 2015 NEFR model.

This indicates that when driver projection error is accounted for, the variance between forecast and actual consumption declines.

Table 8 2014 and 2015 NEFR residential and commercial forecasts using actual driver data, Qld

	Residential & commercial consumption (GWh)	Variance (GWh)	Variance
2014-15 Actual	33,945		
2014 NEFR forecast for 2014-15	32,538	-1,407	-4.1%
2014 NEFR model using actual driver data for 2014-15	33,104	-841	-2.5%
2015 NEFR model using actual driver data for 2014-15	33,247	-698	-2.1%

3.2 Maximum demand

3.2.1 2014 model assessment

Figure 4 shows the historical distribution produced by the 2014 MD model for non-industrial demand. It shows that the historical seasonal MD values tend to fall within the 90% to 10% POE values. Approximately one-third of the actuals lie below the 50% POE and approximately two-thirds lie above (refer to Table 9). With annual maximum demand there are too few data points to reject or accept the model based on where actuals have fallen, but this allows for an intuitive, high-level check of the POE backcasts.

The statistical measures shown in Table 10 are a better means by which to assess probability forecasts. Different models can be compared against AEMO's by calculating the same scores. A lower score for each of these measures indicates better performance.

Figure 5 illustrates the calculation of the K-S statistic and the MAEP. The K-S statistic is the maximum distance between the two lines and the MAEP is the area between them.

Figure 4 2014 NEFR historical POEs for non-industrial component of MD, Qld

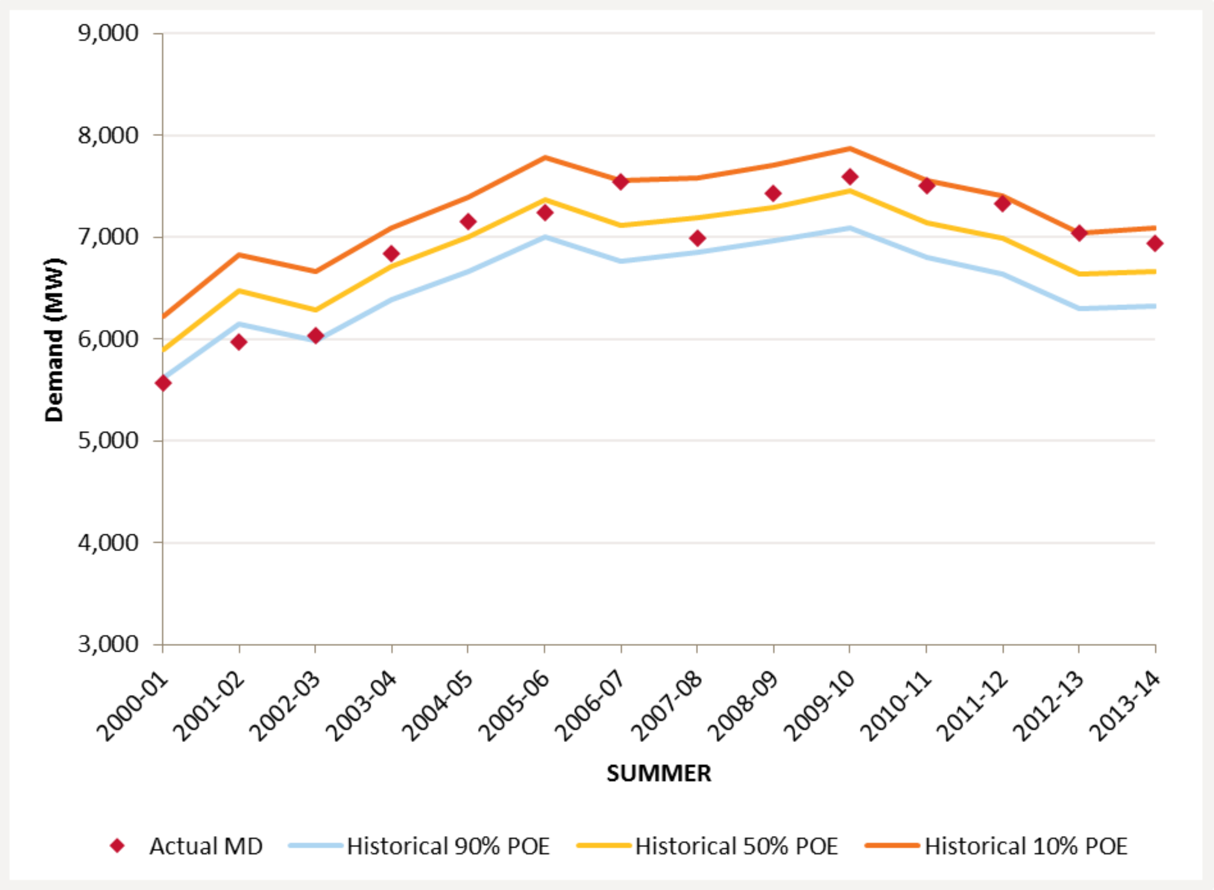


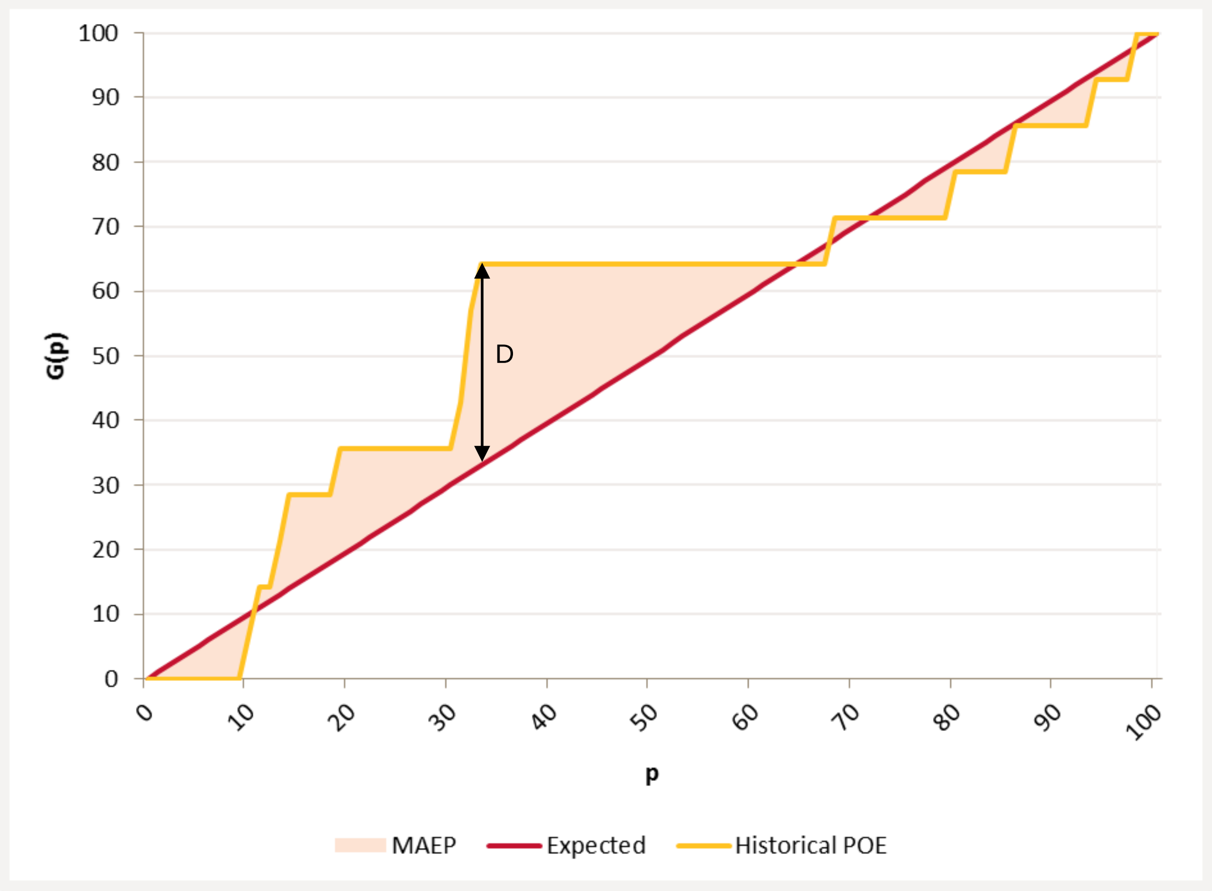
Table 9 Proportion of actual MDs exceeding 2014 NEFR Qld historical POEs for non-industrial demand

	Historical points	Percentage of actual MD above POE level
Above 10% POE	0	0%
Above 50% POE	9	64%
Above 90% POE	12	86%

Table 10 Statistical measures of summer maximum demand performance for 2014 NEFR, Qld

	Value
Quantile Score	88
MAEP	8.9%
K-S statistic	31.3%

Figure 5 2014 NEFR illustration of K-S statistic, D, and MAEP for non-industrial component of MD, Qld



3.2.2 2015 model assessment

Figure 6 shows the historical distribution produced by the 2015 MD model for operational demand. It shows that the historical seasonal MD values tend to fall within the 90% to 10% POE values. Approximately one-third of the actuals lie below the 50% POE and approximately two-thirds lie above (refer to Table 11). With annual maximum demand, there are too few data points to reject or accept the model based on where actuals have fallen, but this allows for an intuitive, high-level check of the POE backcasts.

The statistical measures shown in Table 12 are a better means by which to assess probability forecasts. Different models can be compared against AEMO's by calculating the same scores. A lower score for each of these measures indicates better performance.

Figure 7 illustrates the calculation of the K-S statistic and the MAEP. The K-S statistic is the maximum distance between the two lines and the MAEP is the area between them.

Figure 6 2015 NEFR historical POEs for operational MD, Qld

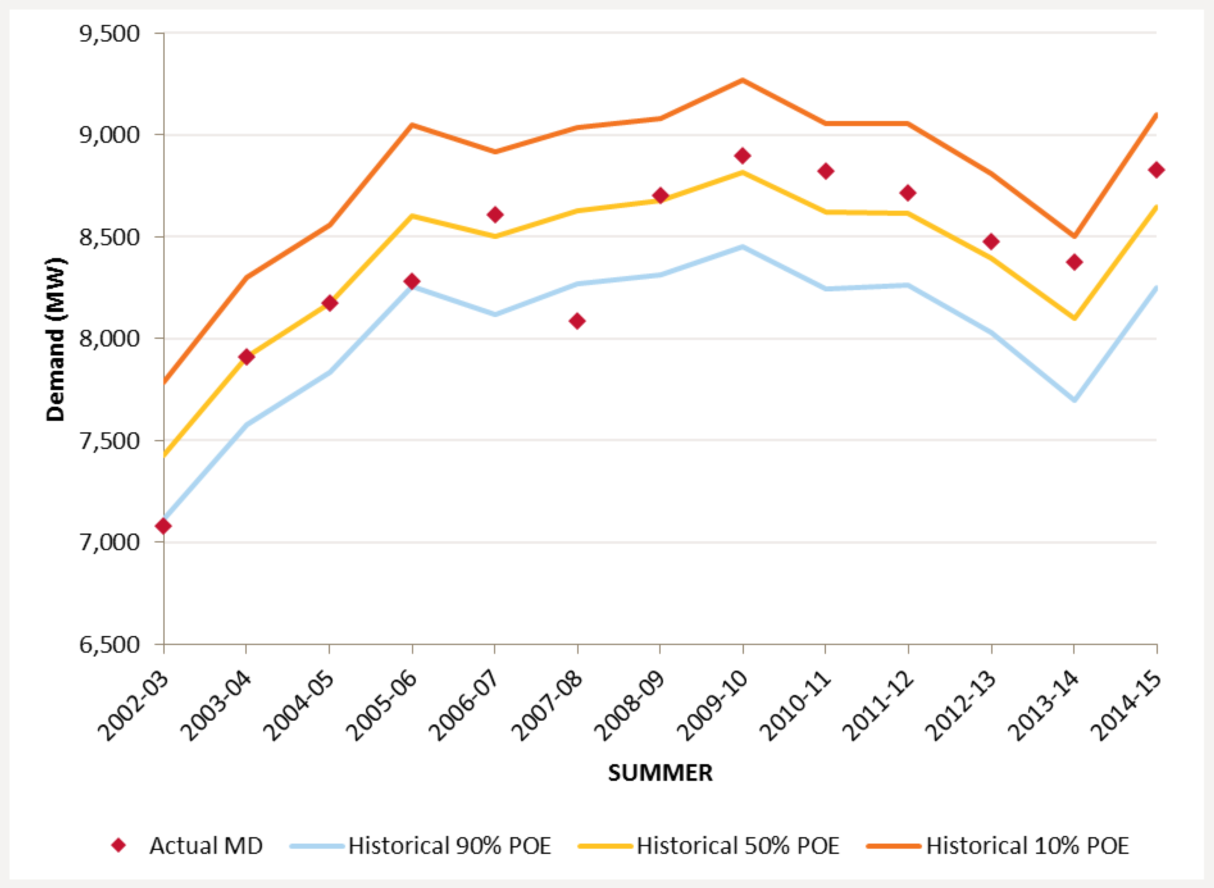


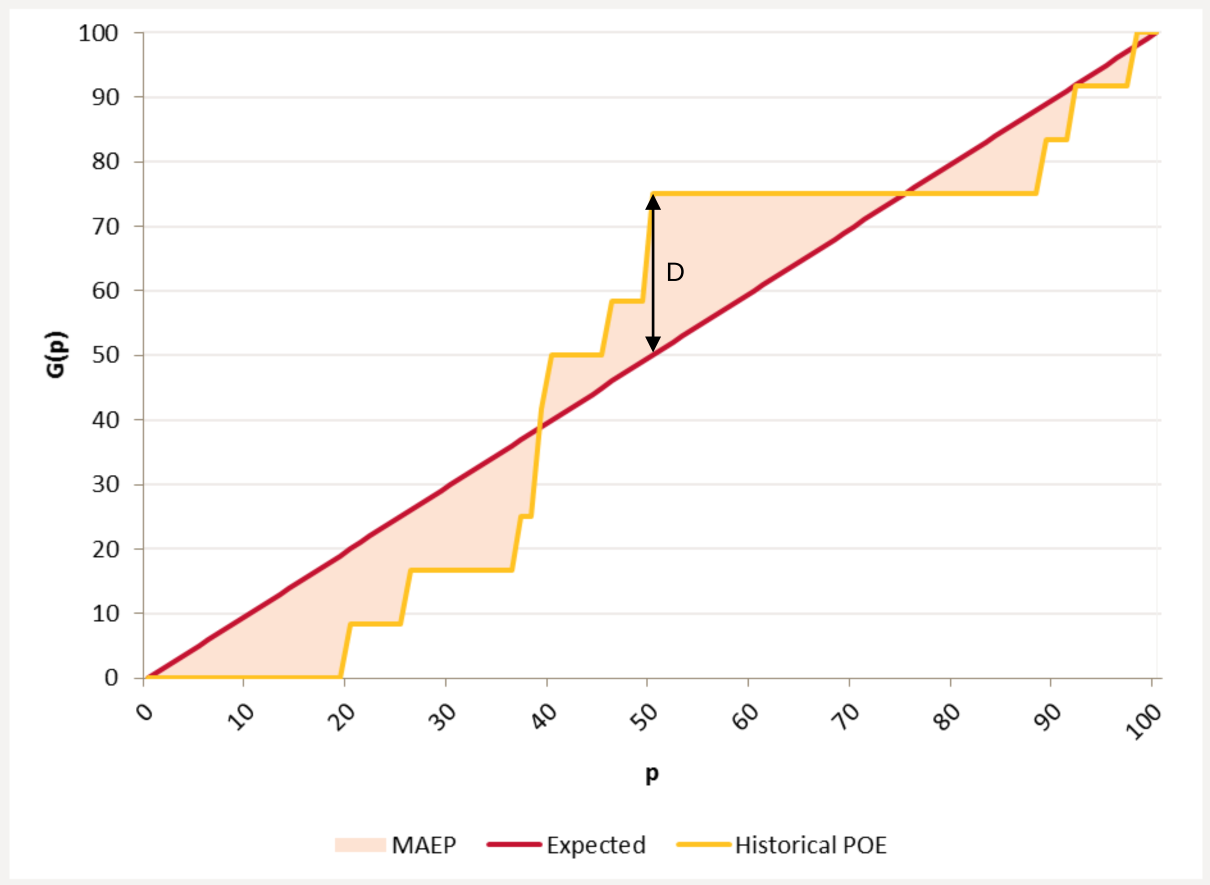
Table 11 Proportion of actual MDs exceeding 2015 NEFR Qld historical POEs for operational demand

	Historical points	Percentage of actual MD above POE level
Above 10% POE	0	0%
Above 50% POE	8	62%
Above 90% POE	11	85%

Table 12 Statistical measures of summer maximum demand performance for 2015 NEFR, Qld

	Value
Quantile Score	68.6
MAEP	10.3%
K-S statistic	26.9%

Figure 7 2015 NEFR illustration of K-S statistic, *D*, and MAEP for operational MD, Qld



3.2.3 2015 NEFR and 2014 NEFR MD model comparison

AEMO compared the 10% POE MD from the 2014 NEFR MD model using actual economic data, against the 10% POE forecast from the 2015 NEFR for the 2014-15 summer. This provides a measure of forecast accuracy for operational demand and native demand. This is shown in Table 13.

Table 13 Comparison of 2014-15 summer 10% POE from 2014 NEFR and 2015 NEFR, Qld

	Operational demand[20] (2014-15 summer)	Native demand[21] (2014-15 summer)
2014 NEFR model 10% POE forecast (MW)	8,461	8,630
2015 NEFR model 10% POE (MW)	9,100	9,271
Variance (MW)	-639	-641
Variance (%)	-7.0%	-6.9%

Higher than expected LNG demand contributed to the operational and native demand variance. The warm QLD summer caused higher than expected residential and commercial demand which also contributed to the observed variance.

[20] Excludes LNG
[21] Excludes LNG

CHAPTER 4. NEW SOUTH WALES (INCLUDING ACT)

4.1 Annual consumption

The 2014-15 annual consumption forecast for NSW shows under forecasting, with most of the variance seen in the large industrial and residential and commercial sectors.

4.1.1 Back assessment

The 2014 NEFR forecasts for 2014-15 operational and native consumption were lower than actual consumption (refer to Table 14). The operational consumption forecast was 2.7% below actual, the native consumption forecast was 2.6% below.

Key reasons for this variance are:

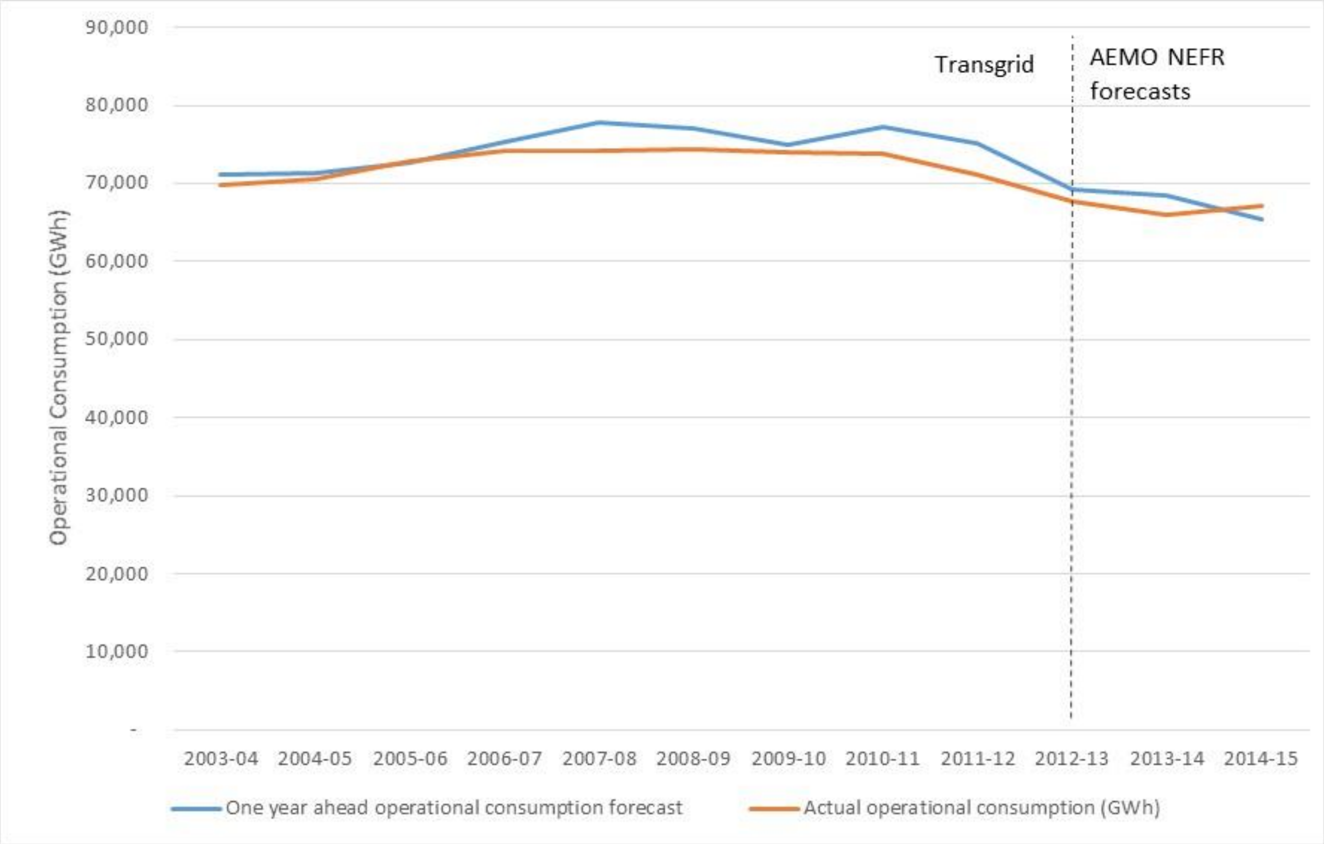
- Higher than expected residential and commercial consumption (excluding the impact of PV output).
- Higher than expected large industrial consumption.
- Higher than expected PV production

Table 14 2014 NEFR forecast of NSW annual consumption for 2014-15

	Operational consumption	Native consumption
Forecast (GWh)	65,321	66,178
Actual (GWh)	67,145	67,972
Variance (GWh)	-1,824	-1,794
Variance (%)	-2.7%	-2.6%
Variance components	**Operational consumption**	**Native consumption**
Residential and commercial (excluding PV impact) (GWh)	-858	-828
PV output (GWh)	-173	-173
Large industrial (GWh)	-976	-976
Transmission losses (GWh)	183	183

Figure 8 shows the variances of previous one-year-ahead forecasts for operational consumption only, demonstrating a tendency to over-forecast until 2014-15.

Figure 8 One-year-ahead annual consumption forecast variance, NSW



4.1.2 Backcast

Table 15 presents the dynamic in-sample forecast results from the 2014 and 2015 NEFR models.

The actual residential and commercial data used in the 2015 NEFR differs from the actual data from the 2014 NEFR due to the reallocation of large customers from the residential and commercial sector to the industrial sector.[22]

The accuracy of the NEFR models has continued to improve from one year to the next for most years. The in-sample forecasts generated by both the 2014 and 2015 NEFR models track closely against the actual values. As the results show, the forecast generated by the 2015 NEFR model is more closely aligned to the actual values. The variance between the actual and in-sample forecast in 2013-14 for the 2015 NEFR is 0.02%.

[22] Refer to the Forecasting Methodology Information Paper for further detail: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Electricity/Planning/Reports/NEFR/2015/2015%20NEFR%20forecasting%20methodology%20information%20paper.ashx. Viewed 31 August 2015.

Table 15 2014 and 2015 NEFR dynamic in-sample residential and commercial annual consumption forecasts, NSW

Financial year end	2014 NEFR residential and commercial consumption			2015 NEFR residential and commercial consumption		
	Actual (GWh)	In-sample forecast (GWh)	Variance (%)	Actual (GWh)	In-sample forecast (GWh)	Variance (%)
2003-04	55,368	55,831	0.8%	52,794	53,637	1.6%
2004-05	55,717	55,920	0.4%	53,039	53,498	0.9%
2005-06	57,882	57,942	0.1%	55,238	55,456	0.4%
2006-07	58,333	58,000	-0.6%	55,565	55,553	0.0%
2007-08	58,331	58,207	-0.2%	55,503	55,338	-0.3%
2008-09	58,746	58,736	0.0%	55,971	55,916	-0.1%
2009-10	58,055	58,132	0.1%	55,053	55,281	0.4%
2010-11	57,924	57,574	-0.6%	54,761	54,332	-0.8%
2011-12	56,130	56,156	0.0%	53,045	52,882	-0.3%
2012-13	55,429	55,574	0.3%	52,236	52,461	0.4%
2013-14				50,754	50,766	0.02%

Table 16 presents the forecast results from the 2014 and 2015 NEFR models using actual driver data.

The variance between the 2014-15 actual and 2014 NEFR forecast residential and commercial annual consumption is -2.3%. When actual driver data is used, the variance increases to 5.4% in the 2014 NEFR model and to -2.8% in the 2015 NEFR model.

This indicates that once driver projection error is accounted for, the variance between forecast and actual consumption increases with the 2014 NEFR model over-forecasting and the 2015 NEFR model under-forecasting.

Table 16 2014 and 2015 NEFR residential and commercial forecasts using actual driver data, NSW

	Residential & commercial consumption (GWh)	Variance (GWh)	Variance
2014-15 Actual	53,309		
2014 NEFR forecast for 2014-15	52,105	-1,204	-2.3%
2014 NEFR model using actual driver data for 2014-15	56,191	2,882	5.4%
2015 NEFR model using actual driver data for 2014-15	51,796	-1,513	-2.8%

4.2 Maximum demand

4.2.1 2014 model assessment

Figure 9 shows the historical distribution produced by the 2014 MD model for non-industrial demand. It shows that the historical seasonal MD values tend to fall within the 90% to 10% POE values. Approximately two-thirds of the actuals lie below the 50% POE and approximately one-third lie above (refer to Table 17). With annual maximum demand, there are too few data points to reject or accept the model based on where actuals have fallen, but this allows for an intuitive, high-level check of the POE backcasts.

The statistical measures shown in Table 18 are a better means by which to assess probability forecasts. Different models can be compared against AEMO's by calculating the same scores. A lower score for each of these measures indicates better performance.

Figure 10 illustrates the calculation of the K-S statistic and the MAEP. The K-S statistic is the maximum distance between the two lines and the MAEP is the area between them.

Figure 9 2014 NEFR historical POEs for non-industrial component of MD, NSW

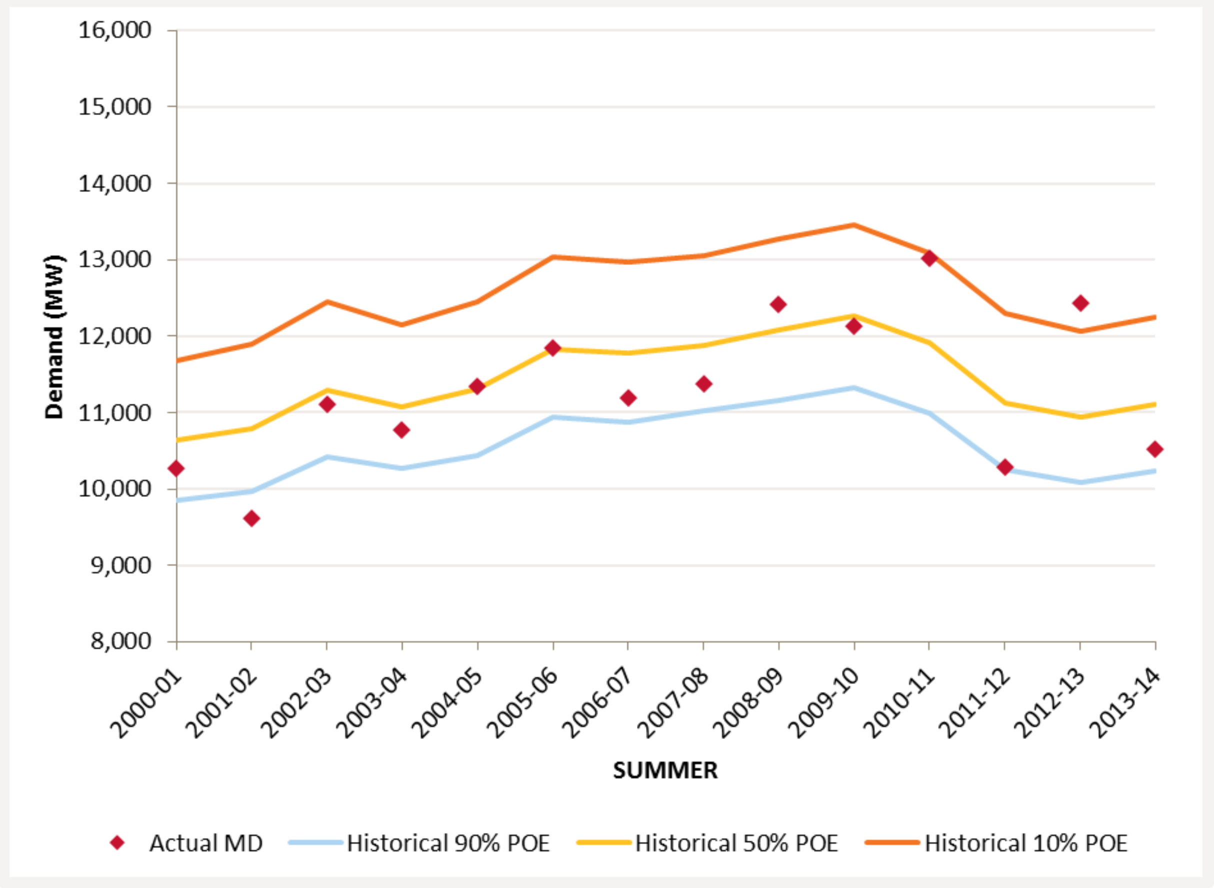


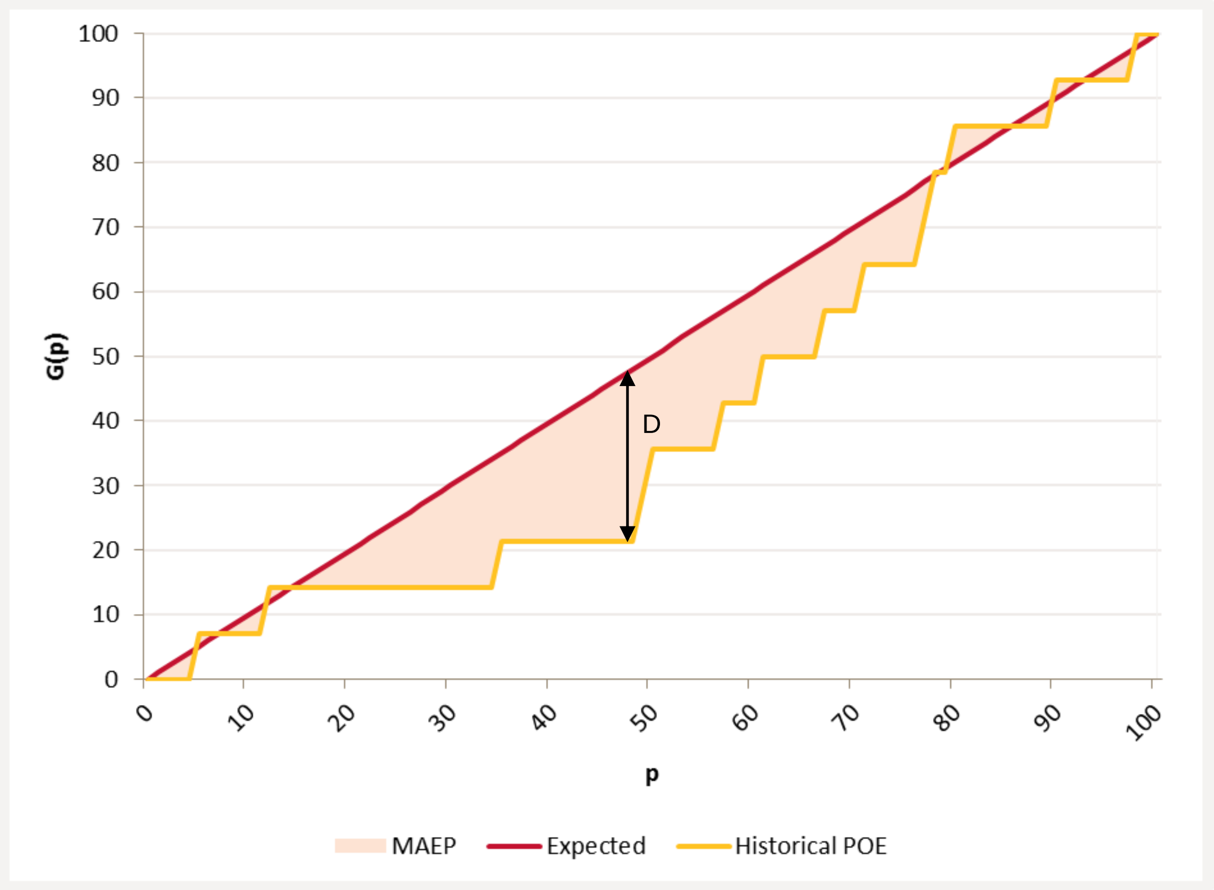
Table 17 Proportion of actual MDs exceeding 2014 NEFR NSW historical POEs for non-industrial demand

	Historical points	Percentage of actual MD above POE level
Above 10% POE	1	7%
Above 50% POE	4	29%
Above 90% POE	12	86%

Table 18 Statistical measures of summer maximum demand performance for 2014 NEFR, NSW

	Value
Quantile Score	202.2
MAEP	9.5%
K-S statistic	27.6%

Figure 10 2014 NEFR illustration of K-S statistic, D, and MAEP for non-industrial component of MD, NSW



4.2.2 2015 model assessment

Figure 11 shows the historical distribution produced by the 2015 MD model for operational demand. It shows that the historical seasonal MD values tend to fall within the 90% to 10% POE values. Approximately two-thirds of the actuals lie below the 50% POE and approximately one-third lie above (refer to Table 19). With annual maximum demand there are too few data points to reject or accept the model based on where actuals have fallen, but this allows for an intuitive, high-level check of the POE backcasts.

The statistical measures shown in Table 20 are a better means by which to assess probability forecasts. Different models can be compared against AEMO's by calculating the same scores. A lower score for each of these measures indicates better performance.

Figure 12 illustrates the calculation of the K-S statistic and the MAEP. The K-S statistic is the maximum distance between the two lines and the MAEP is the area between them.

Figure 11 2015 NEFR historical POEs for operational MD, NSW

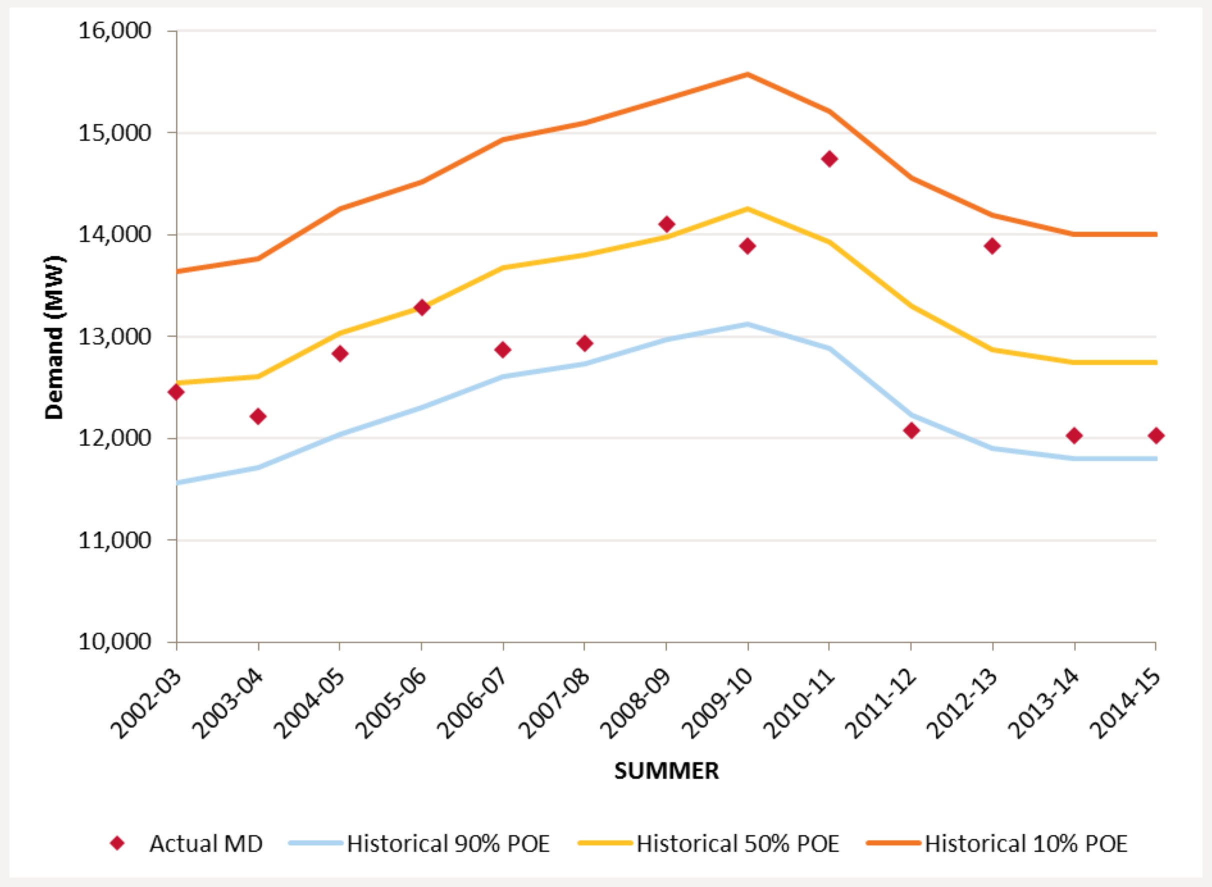


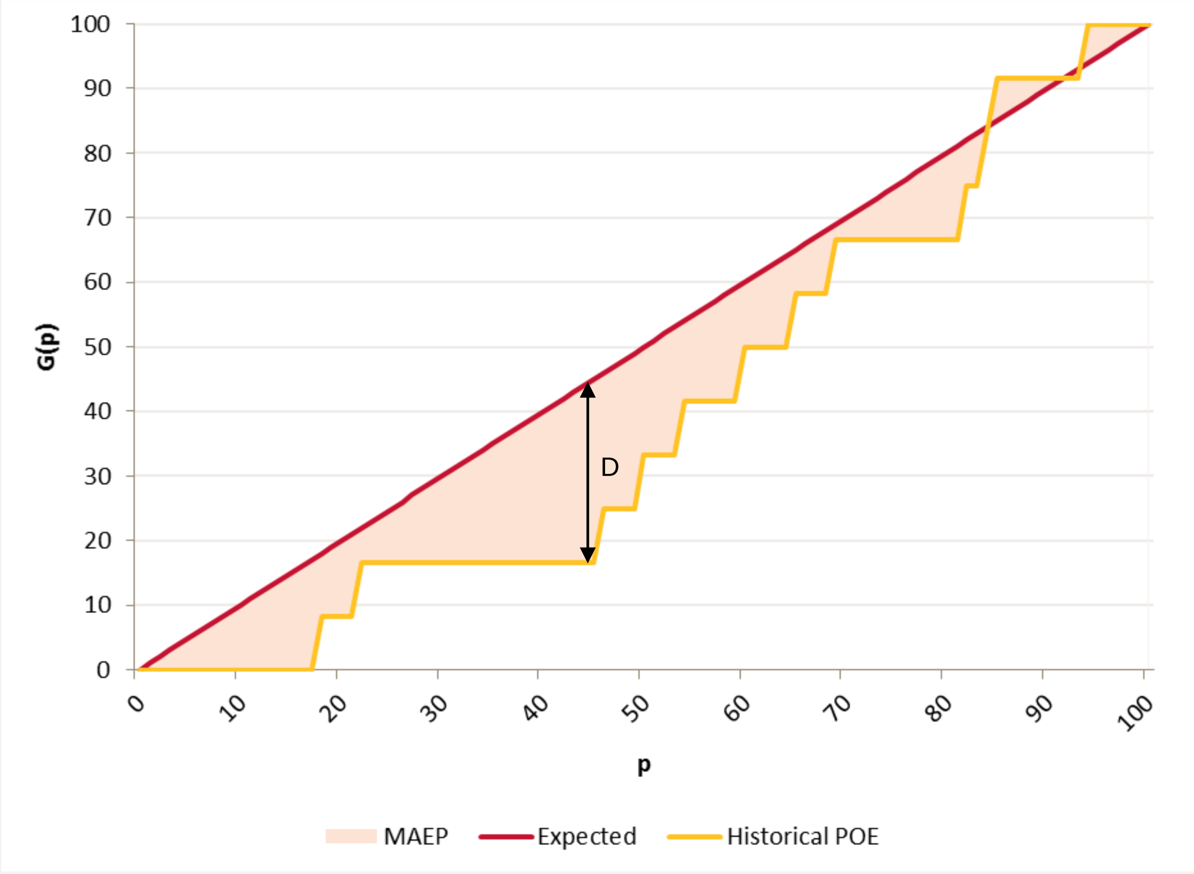
Table 19 Proportion of actual MDs exceeding 2015 NEFR NSW historical POEs for operational demand

	Historical points	Percentage of actual MD above POE level
Above 10% POE	0	0%
Above 50% POE	3	23%
Above 90% POE	12	92%

Table 20 Statistical measures of summer maximum demand performance for 2015 NEFR, NSW

	Value
Quantile Score	208.7
MAEP	13.0%
K-S statistic	30.6%

Figure 12 2015 NEFR illustration of K-S statistic, D, and MAEP for operational MD, NSW



4.2.3 2015 NEFR and 2014 NEFR MD model comparison

AEMO compared the 10% POE MD from the 2014 NEFR MD model using actual economic data, against the 10% POE forecast from the 2015 NEFR for the 2014-15 summer. This provides a measure of forecast accuracy for operational demand and native demand. This is shown in Table 18.

Table 21 Comparison of 2014-15 summer 10% POE from 2014 NEFR and 2015 NEFR, NSW

	Operational demand (2014-15 summer)	Native demand (2014-15 summer)
2014 NEFR model 10% POE forecast (MW)	13,438	13,600
2015 NEFR model 10% POE (MW)	14,265	14,428
Variance (MW)	-827	-828
Variance (%)	-5.8%	-5.7%

Contributing to the operational and native demand variance are higher than expected residential and commercial demand due to the warm NSW summer.

CHAPTER 5. SOUTH AUSTRALIA

5.1 Annual consumption

The 2014-15 annual consumption forecast for South Australia marginally exceeds the actuals. Variances are caused by lower than expected large industrial consumption.

5.1.1 Back assessment

The 2014 NEFR forecasts for 2014-15 operational and native consumption were higher than actual consumption (refer to Table 22).

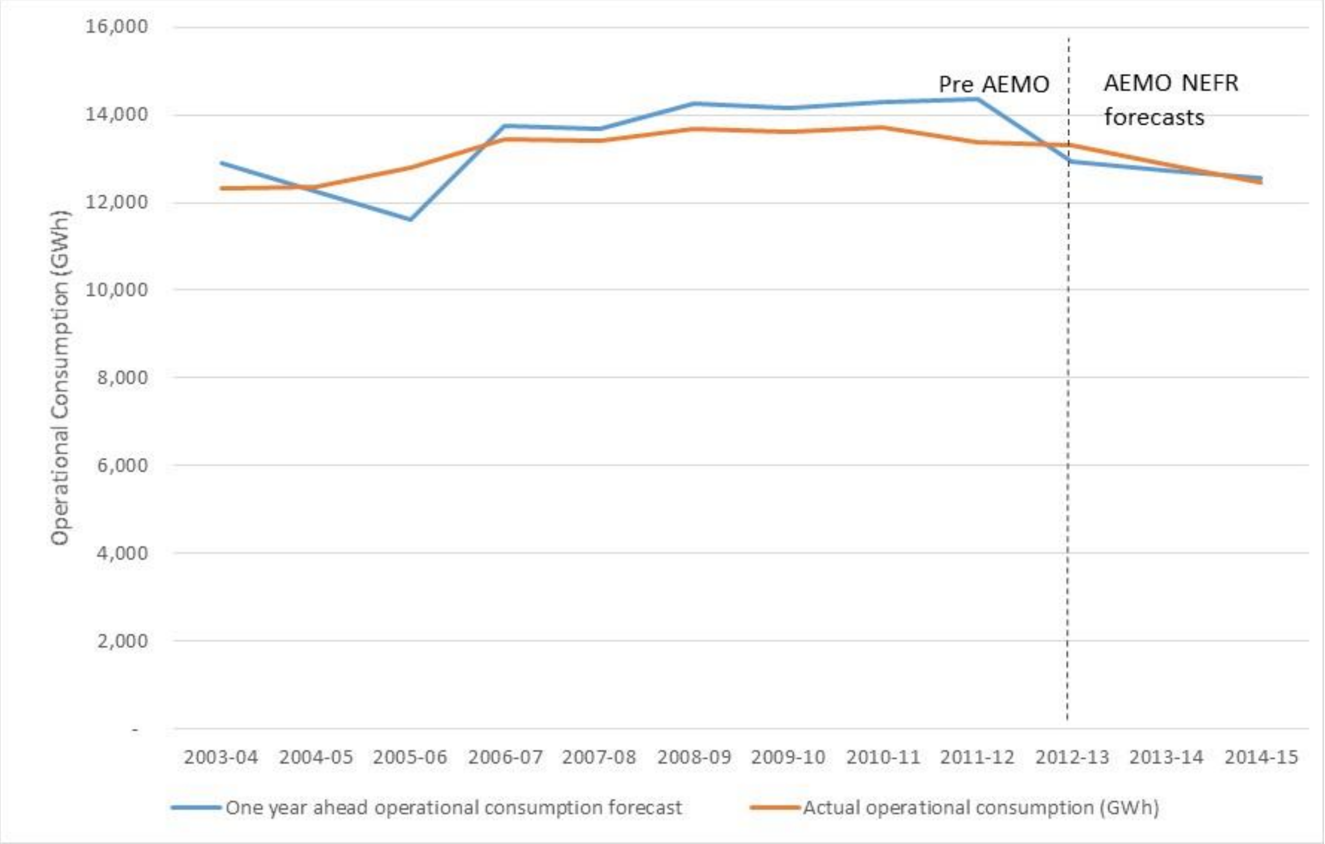
The operational forecasts were 0.7% above actuals; the native forecasts were 0.8% above. The key reason for this variance is lower than expected large industrial consumption

Table 22 2014 NEFR forecast of SA annual consumption for 2014-15

	Operational consumption	Native consumption
Forecast (GWh)	12,560	12,575
Actual (GWh)	12,468	12,476
Variance (GWh)	92	99
Variance (%)	0.7%	0.8%
Variance components	**Operational consumption**	**Native consumption**
Residential and commercial (excluding PV impact) (GWh)	-128	-121
PV output (GWh)	4	4
Large industrial (GWh)	287	287
Transmission losses (GWh)	-71	-71

Figure 13 shows the variances of previous one-year-ahead forecasts for operational consumption only.

Figure 13 One-year-ahead annual consumption forecast variance, SA



5.1.2 Backcast

Table 23 presents the dynamic in-sample forecast results from the 2014 and 2015 NEFR models.

The actual residential and commercial data used in the 2015 NEFR differs from the actual data from the 2014 NEFR due to the reallocation of large customers from the residential and commercial sector to the industrial sector.[23]

The residential and commercial forecasts generated by both the NEFR 2014 and 2015 models accurately track against actual residential and commercial forecasts. Neither shows a tendency to over- or under-forecast, and on the whole, differences between the forecast and actual values are minimal. The accuracy of both 2014 and 2015 models improves in the later years.

[23] Refer to the Forecasting Methodology Information Paper for further detail: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Electricity/Planning/Reports/NEFR/2015/2015%20NEFR%20forecasting%20methodology%20information%20paper.ashx. Viewed 31 August 2015.

Table 23 2014 NEFR and 2015 NEFR dynamic in-sample residential and commercial residential and commercial annual energy forecasts, SA

Financial year end	2014 NEFR residential and commercial consumption			2015 NEFR residential and commercial consumption		
	Actual (GWh)	In-sample forecast (GWh)	Variance (%)	Actual (GWh)	In-sample forecast (GWh)	Variance (%)
2003-04	10,774	10,962	1.7%	10,041	9,121	-9.2%
2004-05	10,629	10,810	1.7%	9,981	9,735	-2.5%
2005-06	11,052	11,150	0.9%	10,314	10,291	-0.2%
2006-07	11,481	11,386	-0.8%	10,733	10,571	-1.5%
2007-08	11,666	11,623	-0.4%	10,862	10,797	-0.6%
2008-09	11,687	11,656	-0.3%	10,895	10,835	-0.6%
2009-10	11,853	11,862	0.1%	11,065	11,118	0.5%
2010-11	11,611	11,615	0.0%	10,776	10,782	0.1%
2011-12	11,513	11,544	0.3%	10,571	10,583	0.1%
2012-13	11,623	11,632	0.1%	10,524	10,513	-0.1%
2013-14				10,279	10,332	0.5%

Table 24 presents the results from the 2014 and 2015 NEFR models using actual driver data.

The variance between the 2014-15 actual and 2014 NEFR forecast residential and commercial annual consumption is -1.1%. When actual driver data is used, the magnitude of the variance increases to -1.5% in the 2014 NEFR model, but declines to 0.1% in the 2015 NEFR model. This indicates that when driver projection error is accounted for, the variance between forecast and actual consumption is reduced markedly in the 2015 NEFR, suggesting an improvement in model accuracy from 2014 to 2015.

Table 24 2014 and 2015 NEFR residential and commercial forecasts using actual driver data, SA

	Residential & commercial consumption (GWh)	Variance (GWh)	Variance
2014-15 Actual	10,362		
2014 NEFR forecast for 2014-15	10,244	-119	-1.1%
2014 NEFR model using actual driver data for 2014-15	10,210	-152	-1.5%
2015 NEFR model using actual driver data for 2014-15	10,372	10	0.1%

5.2 Maximum demand

5.2.1 2014 model assessment

Figure 14 shows the historical distribution produced by the 2014 MD model for non-industrial demand. It shows that the historical seasonal MD values tend to fall within the 90% to 10% POE values. Approximately half of the actuals lie below the 50% POE and approximately half lie above (refer to Table 25). With annual maximum demand, there are too few data points to reject or accept the model based on where actuals have fallen, but this allows for an intuitive, high-level check of the POE backcasts.

The statistical measures shown in Table 26 are a better means by which to assess probability forecasts. Different models can be compared against AEMO's by calculating the same scores. A lower score for each of these measures indicates better performance.

Figure 15 illustrates the calculation of the K-S statistic and the MAEP. The K-S statistic is the maximum distance between the two lines and the MAEP is the area between them.

Figure 14 2014 NEFR historical POEs for non-industrial component of MD, SA

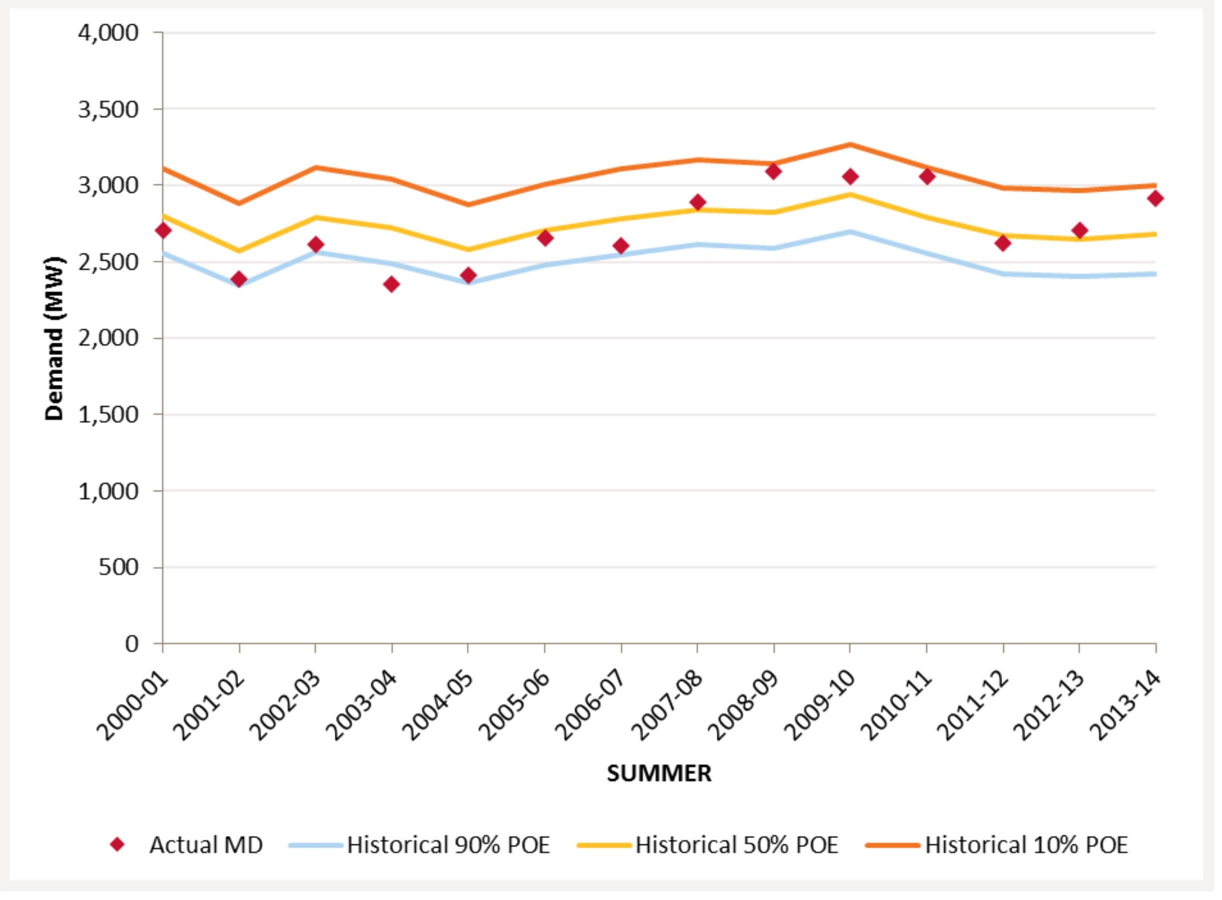


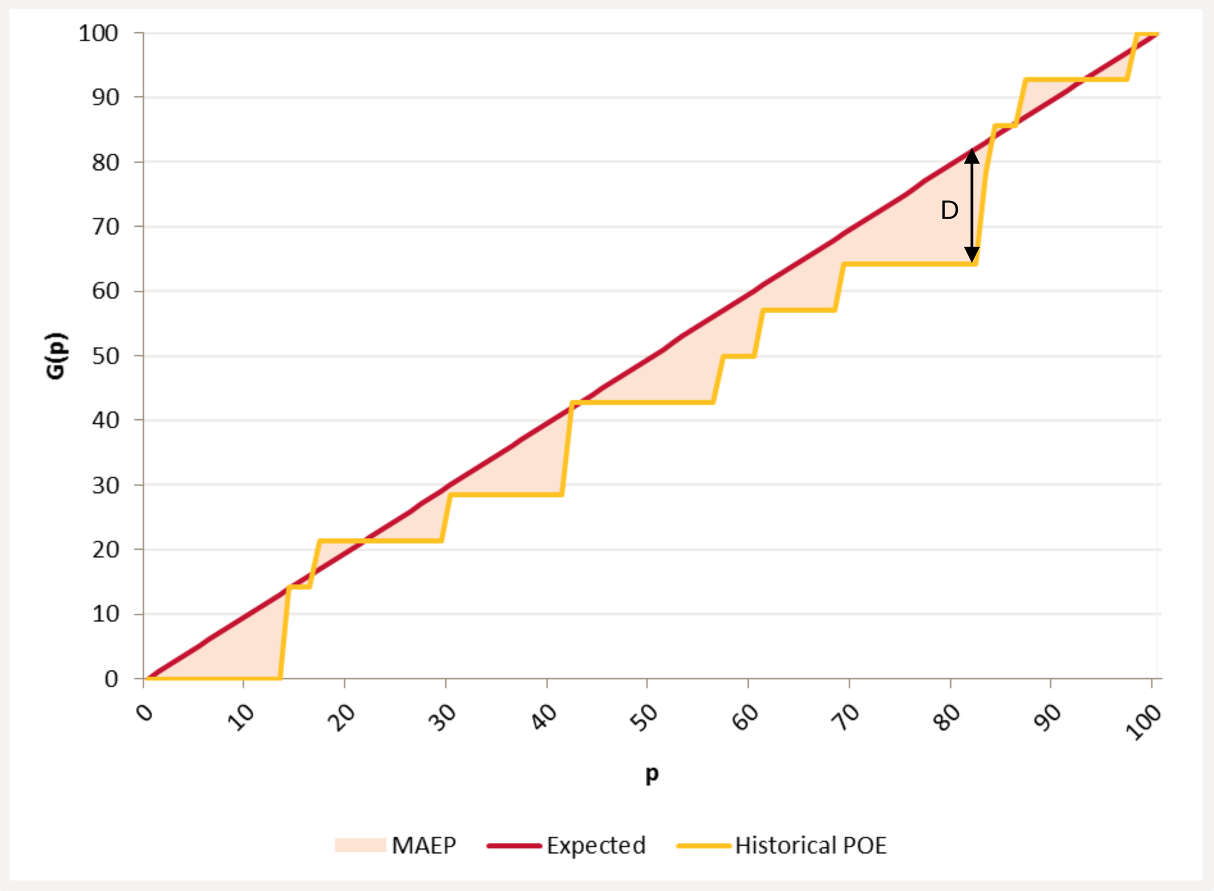
Table 25 Proportion of actual MDs exceeding 2014 NEFR SA historical POEs for non-industrial demand

	Historical points	Percentage of actual MD above POE level
Above 10% POE	0	0%
Above 50% POE	6	43%
Above 90% POE	13	93%

Table 26 Statistical measures of summer maximum demand performance for 2014 NEFR, SA

	Value
Quantile Score	55.1
MAEP	6.1%
K-S statistic	18.7%

Figure 15 2014 NEFR illustration of K-S statistic, D, and MAEP for non-industrial component of MD, SA



5.2.2 2015 model assessment

Figure 16 shows the historical distribution produced by the 2015 MD model for operational demand. It shows that the historical seasonal MD values tend to fall within the 90% to 10% POE values. Approximately half of the actuals lie below the 50% POE and approximately half lie above (refer to Table 27). With annual maximum demand, there are too few data points to reject or accept the model based on where actuals have fallen, but this allows for an intuitive, high-level check of the POE backcasts.

The statistical measures shown in Table 28 are a better means by which to assess probability forecasts. Different models can be compared against AEMO's by calculating the same scores. A lower score for each of these measures indicates better performance.

Figure 17 illustrates the calculation of the K-S statistic and the MAEP. The K-S statistic is the maximum distance between the two lines and the MAEP is the area between them.

Figure 16 2015 NEFR historical POEs for operational MD, SA

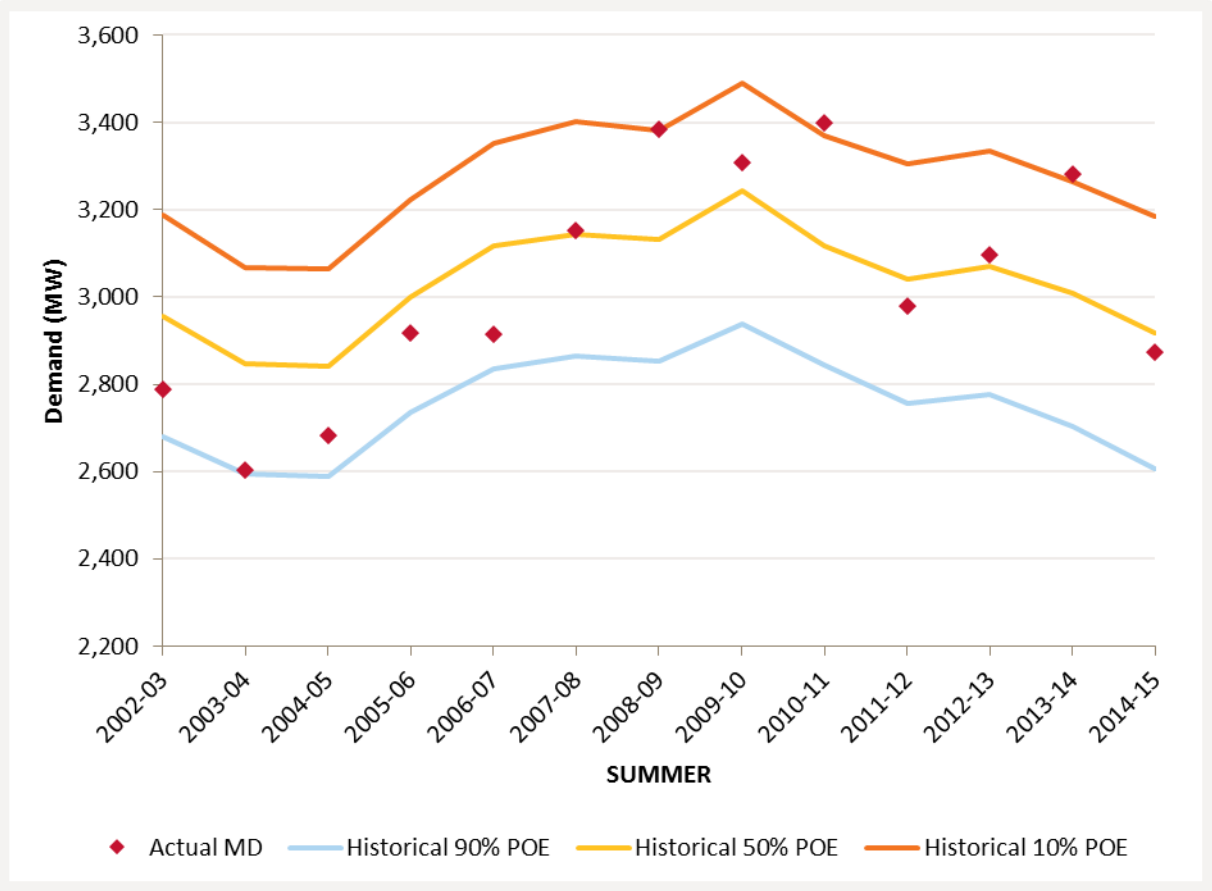


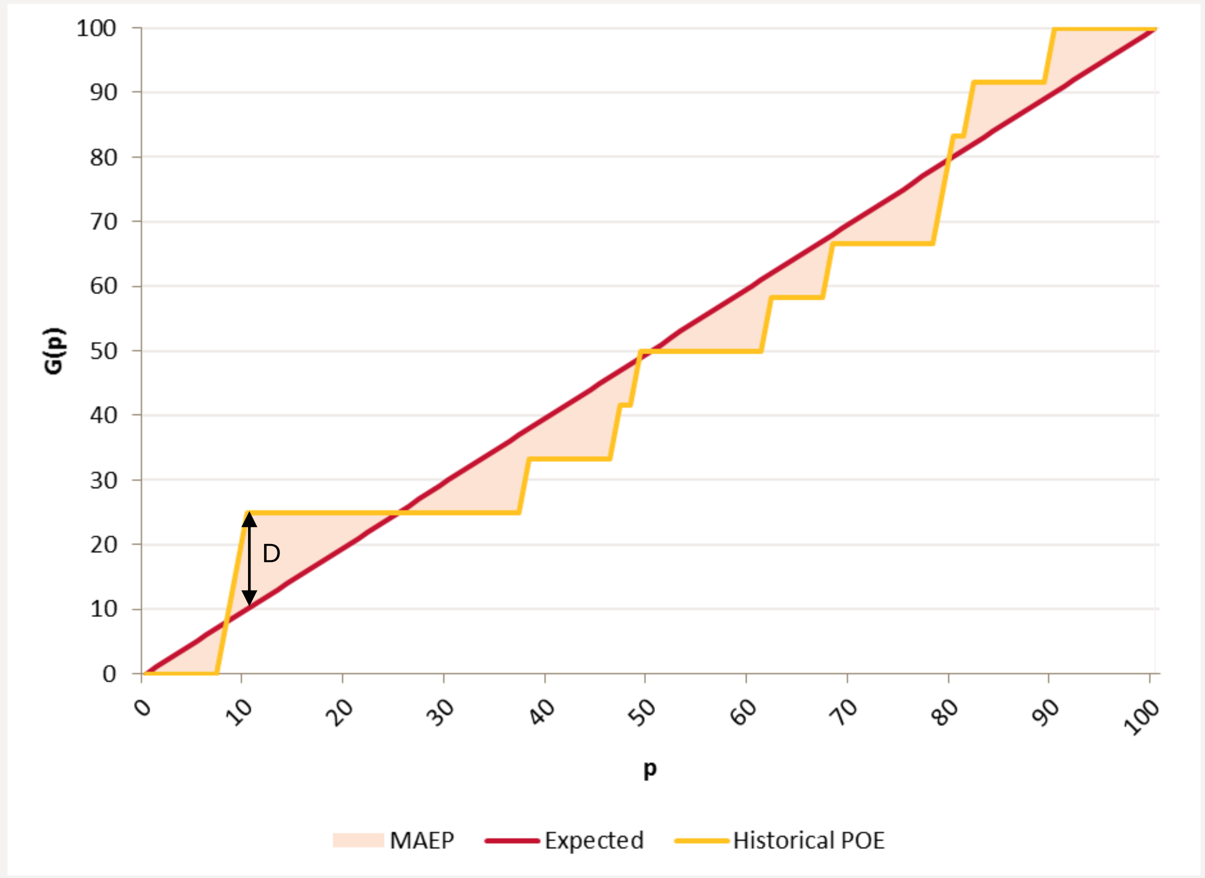
Table 27 Proportion of actual MDs exceeding 2015 NEFR SA historical POEs for operational demand

	Historical points	Percentage of actual MD above POE level
Above 10% POE	2	15%
Above 50% POE	6	46%
Above 90% POE	12	92%

Table 28 Statistical measures of summer maximum demand performance for 2015 NEFR, SA

	Value
Quantile Score	51.2
MAEP	6.2%
K-S statistic	16.2%

Figure 17 2015 NEFR illustration of K-S statistic, *D*, and MAEP for operational MD, SA



5.2.3 2015 NEFR and 2014 NEFR MD model comparison

AEMO compared the 10% POE MD from the 2014 NEFR MD model using actual economic data, against the 10% POE forecast from the 2015 NEFR for the 2014-15 summer. This provides a measure of forecast accuracy for operational demand and native demand. This is shown in Table 29.

Table 29 Comparison of 2014-15 summer 10% POE from 2014 NEFR and 2015 NEFR, SA

	Operational demand (2014-15 summer)	Native demand (2014-15 summer)
2014 NEFR model 10% POE forecast (MW)	3,277	3,301
2015 NEFR model 10% POE (MW)	3,185	3,204
Variance (MW)	92	97
Variance (%)	2.9%	3.0%

Lower than expected large industrial demand has contributed to the operational and native demand variance. Changes made to the 2015 NEFR MD modelling methodology are also likely to have contributed to the variance. For further information about changes in the methodology refer to the 2015 Forecasting Methodology Information Paper[24].

[24] Refer to: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/NEFR-Supplementary-Information.

CHAPTER 6. VICTORIA

6.1 Annual consumption

There is little variance between the 2014-15 annual consumption forecasts and actuals in Victoria, with Lower than expected residential and commercial consumption being the key variance.

6.1.1 Back assessment

There was 0.03% variance between the 2014 NEFR forecast and actual 2014-15 operational consumption; native consumption was 0.1% above actual.

Whilst there was very little variance between the overall consumption forecasts and actuals, variation exists between the components:

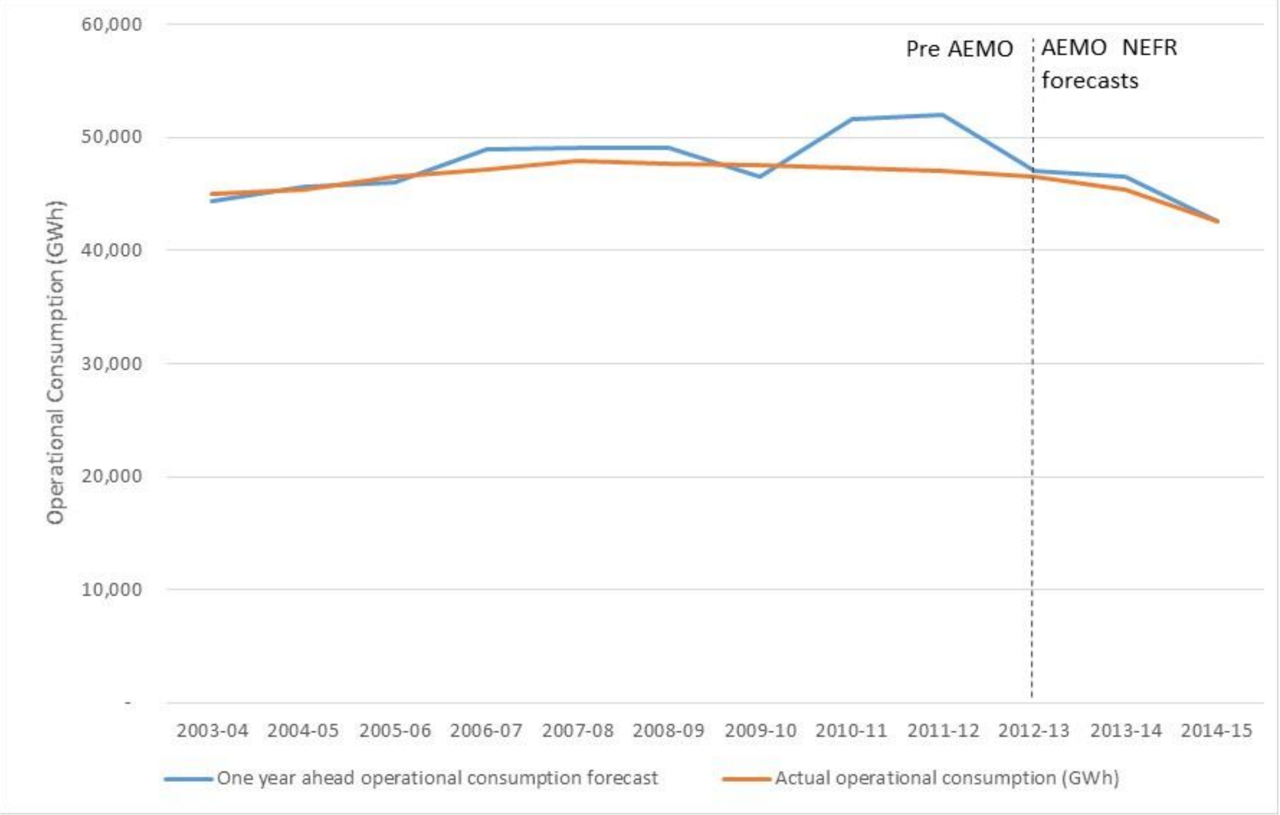
- Lower than expected residential and commercial consumption.
- Higher than expected large industrial consumption.
- Higher than expected transmission losses.

Table 30 2014 NEFR forecast of annual consumption for 2014-15, Vic

	Operational consumption	Native consumption
Forecast (GWh)	42,586	43,157
Actual (GWh)	42,574	43,133
Variance (GWh)	12	44
Variance (%)	0.03%	0.1%
Variance components	**Operational consumption**	**Native consumption**
Residential and commercial (excluding PV impact) (GWh)	335	368
PV production (GWh)	-8	-8
Large industrial (GWh)	-173	-173
Transmission losses (GWh)	-142	-142

Figure 18 shows the variances of previous one-year-ahead forecasts for operational consumption only, demonstrating a tendency to over-forecast.

Figure 18 One-year-ahead annual energy forecast variance, Vic



6.1.2 Backcast

Table 31 presents the dynamic in-sample forecast results from the 2014 and 2015 NEFR models.

The actual residential and commercial data used in the 2015 NEFR differs from the actual data from the 2014 NEFR due to the reallocation of large customers from the residential and commercial sector to the industrial sector.[25]

Both the 2014 and 2015 models fit the data well, with the resulting in-sample forecasts exhibiting neither a tendency to under- nor over-forecast. Forecasts generated from both models track the actual annual energy estimates closely.

[25] Refer to the Forecasting Methodology Information Paper for further detail: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Electricity/Planning/Reports/NEFR/2015/2015%20NEFR%20forecasting%20methodology%20information%20paper.ashx. Viewed 31 August 2015.

Table 31 2014 and 2015 NEFR dynamic in-sample residential and commercial annual energy forecasts, Vic

Financial year end	2014 NEFR residential and commercial consumption			2015 NEFR residential and commercial consumption		
	Actual (GWh)	In-sample forecast (GWh)	Variance (%)	Actual (GWh)	In-sample forecast (GWh)	Variance (%)
2003-04	34,179	34,320	0.4%	32,881	32,781	-0.3%
2004-05	34,833	34,822	0.0%	33,433	33,349	-0.3%
2005-06	36,092	35,887	-0.6%	34,720	34,463	-0.7%
2006-07	36,598	36,543	-0.1%	35,195	35,216	0.1%
2007-08	37,653	37,520	-0.4%	36,253	36,084	-0.5%
2008-09	37,450	37,463	0.0%	36,147	36,349	0.6%
2009-10	37,843	37,751	-0.2%	36,676	36,665	0.0%
2010-11	37,596	37,503	-0.2%	36,377	36,371	0.0%
2011-12	37,530	37,478	-0.1%	36,385	36,426	0.1%
2012-13	37,627	37,610	0.0%	36,312	36,575	0.7%
2013-14				35,605	35,465	-0.4%

Table 32 presents the forecast results from the 2014 and 2015 NEFR models using actual driver data.

The variance between the 2014-15 actual and 2014 NEFR forecast residential and commercial annual consumption is 0.9%. When actual driver data is used, the variance falls to 0.5% in the 2014 NEFR model and 0.6% in the 2015 NEFR model. This indicates that when driver projection error is accounted for, the variance between forecast and actual consumption is even further reduced.

Table 32 2014 and 2015 NEFR residential and commercial forecasts using actual driver data, Vic

	Residential & commercial consumption (GWh)	Variance (GWh)	Variance
2014-15 Actual	35,917		
2014 NEFR forecast for 2014-15	36,236	319	0.9%
2014 NEFR model using actual driver data for 2014-15	36,098	182	0.5%
2015 NEFR model using actual driver data for 2014-15	36,139	223	0.6%

6.2 Maximum demand

6.2.1 2014 model assessment

Figure 19 shows the historical distribution produced by the 2014 MD model for non-industrial demand. It shows that the historical seasonal MD values tend to fall within the 90% to 10% POE values. Approximately half of the actuals lie below the 50% POE and half lie above (refer to Table 33). With annual maximum demand, there are too few data points to reject or accept the model based on where actuals have fallen, but this allows for an intuitive, high-level check of the POE backcasts.

The statistical measures shown in Table 34 are a better means by which to assess probability forecasts. Different models can be compared against AEMO's by calculating the same scores. A lower score for each of these measures indicates better performance.

Figure 19 2014 NEFR historical POEs for non-industrial component of MD, Vic

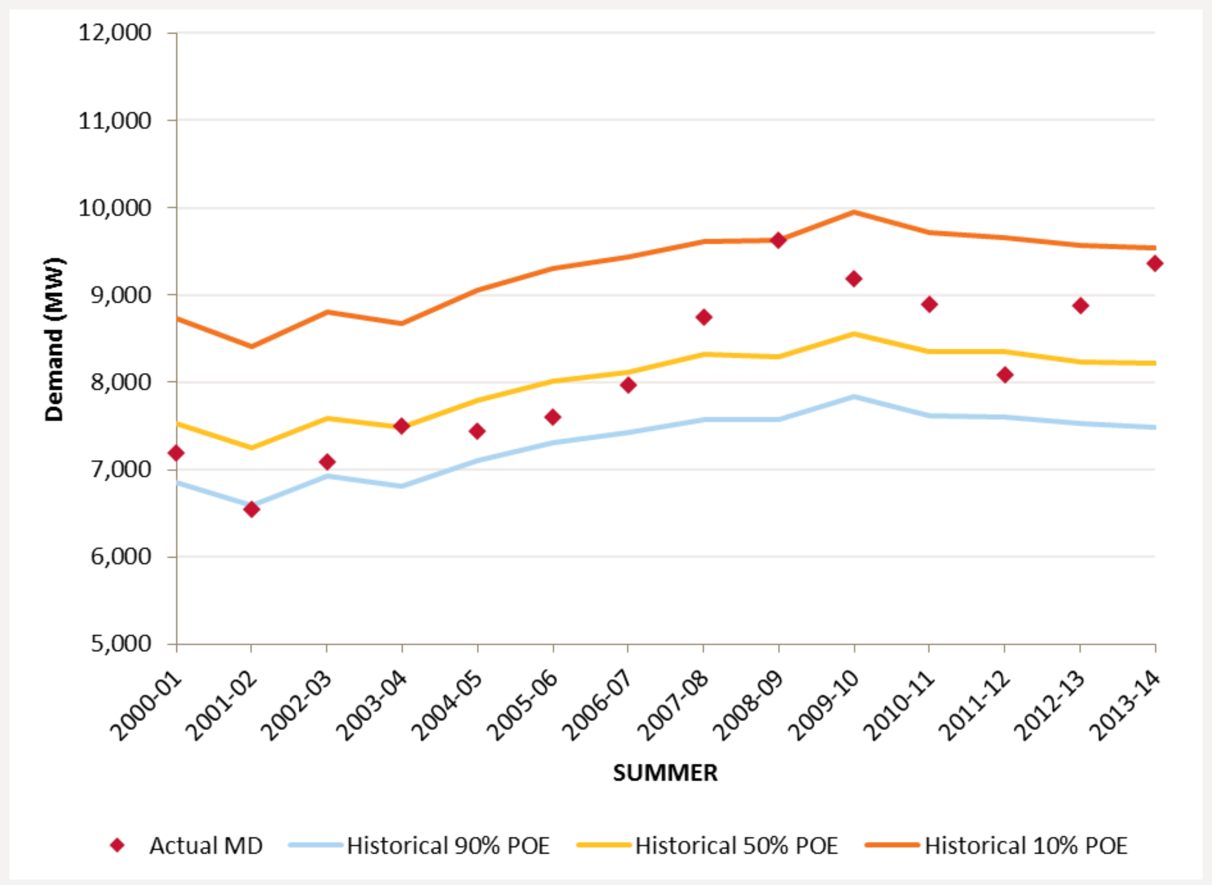


Table 33 Proportion of actual MDs exceeding 2014 NEFR Vic historical POEs for non-industrial demand

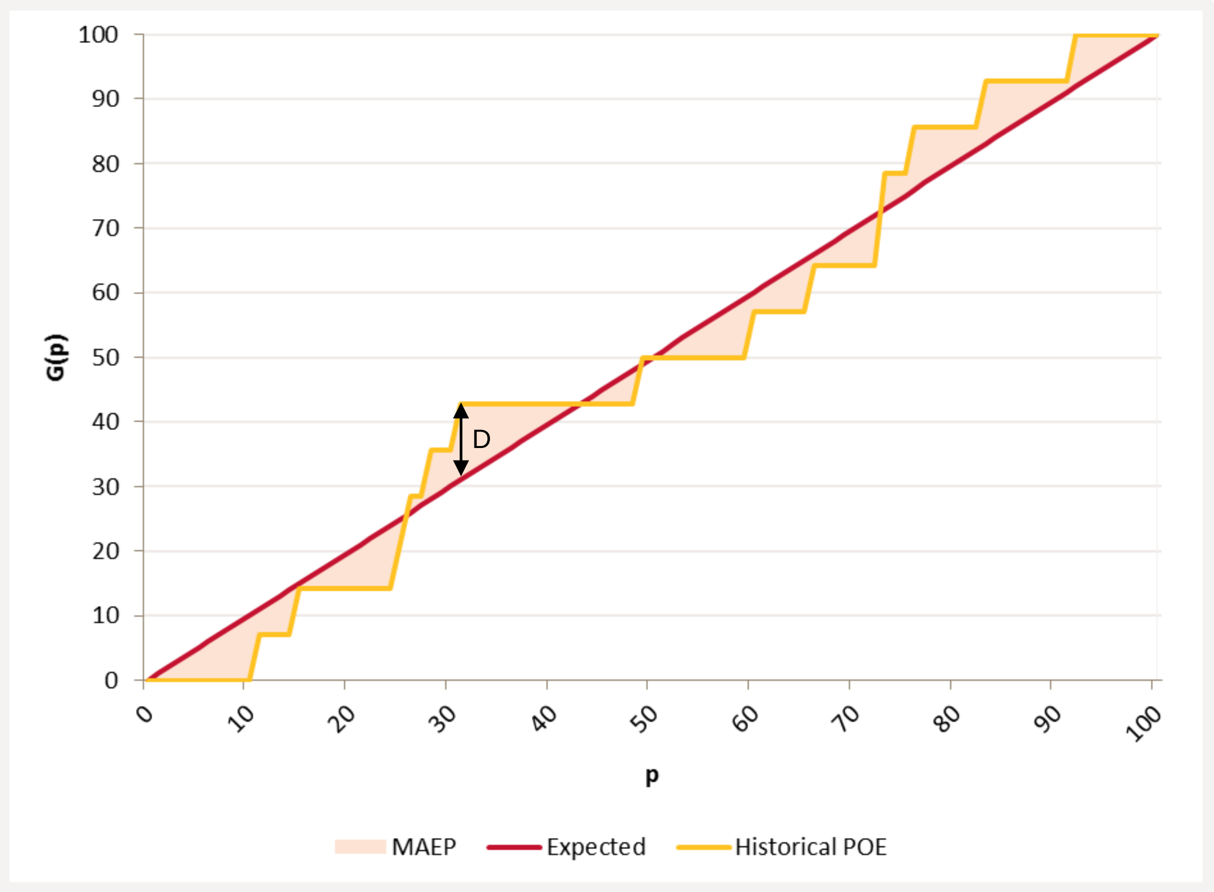
	Historical points	Percentage of actual MD above POE level
Above 10% POE	0	0%
Above 50% POE	7	50%
Above 90% POE	13	93%

Table 34 Statistical measures of summer maximum demand performance for 2015 NEFR, Vic

	Value
Quantile Score	177.7
MAEP	5.1%
K-S statistic	11.9%

Figure 20 illustrates the calculation of the K-S statistic and the MAEP. The K-S statistic is the maximum distance between the two lines and the MAEP is the area between them.

Figure 20 2014 NEFR illustration of K-S statistic, D, and MAEP for non-industrial component of MD, Vic



6.2.2 2015 model assessment

Figure 21 shows the historical distribution produced by the 2015 MD model for operational demand. It shows that the historical seasonal MD values tend to fall within the 90% to 10% POE values. Approximately one-third of the actuals lie below the 50% POE and approximately two-thirds lie above (refer to Table 35). With annual maximum demand, there are too few data points to reject or accept the model based on where actuals have fallen, but this allows for an intuitive, high-level check of the POE backcasts.

The statistical measures shown in Table 36 are a better means by which to assess probability forecasts. Different models can be compared against AEMO's by calculating the same scores. A lower score for each of these measures indicates better performance.

Figure 22 illustrates the calculation of the K-S statistic and the MAEP. The K-S statistic is the maximum distance between the two lines and the MAEP is the area between them.

Figure 21 2015 NEFR historical POEs for operational MD, Vic

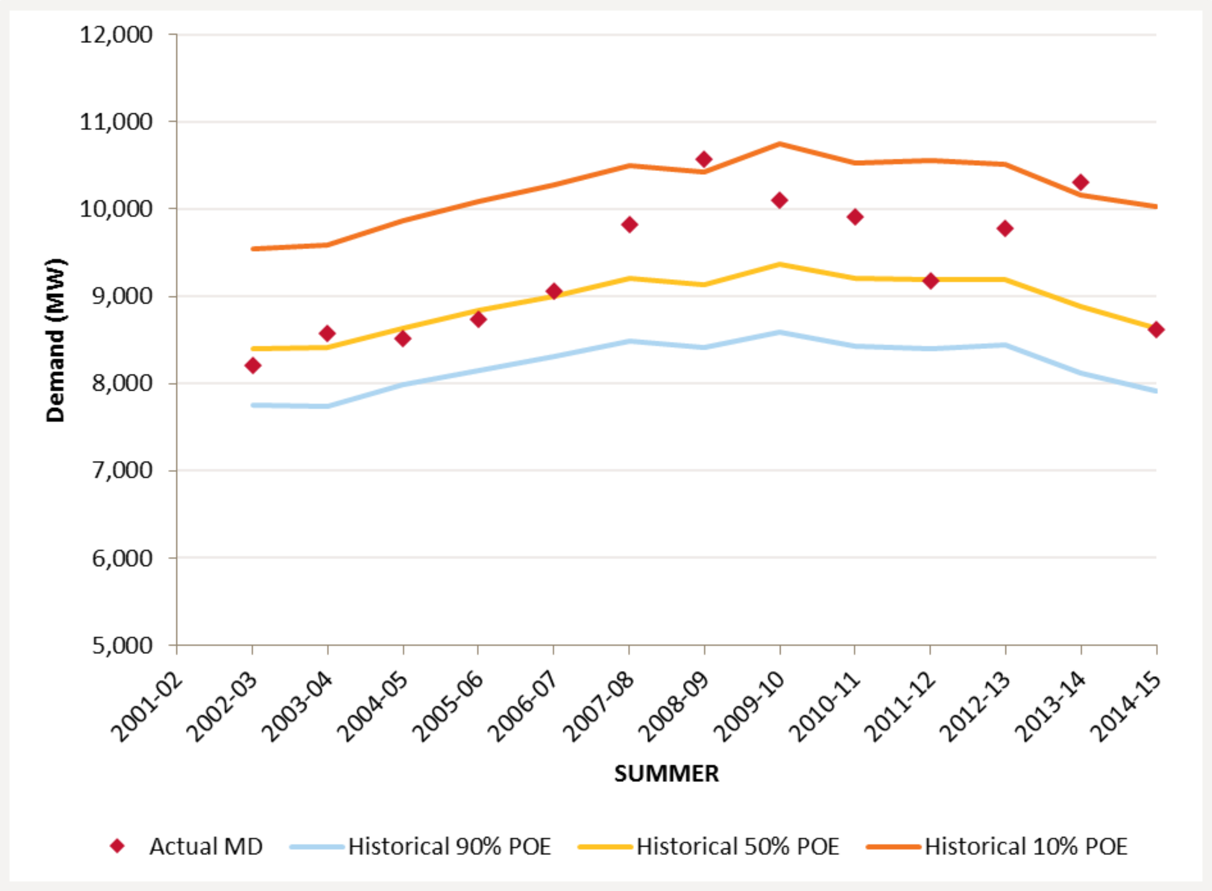


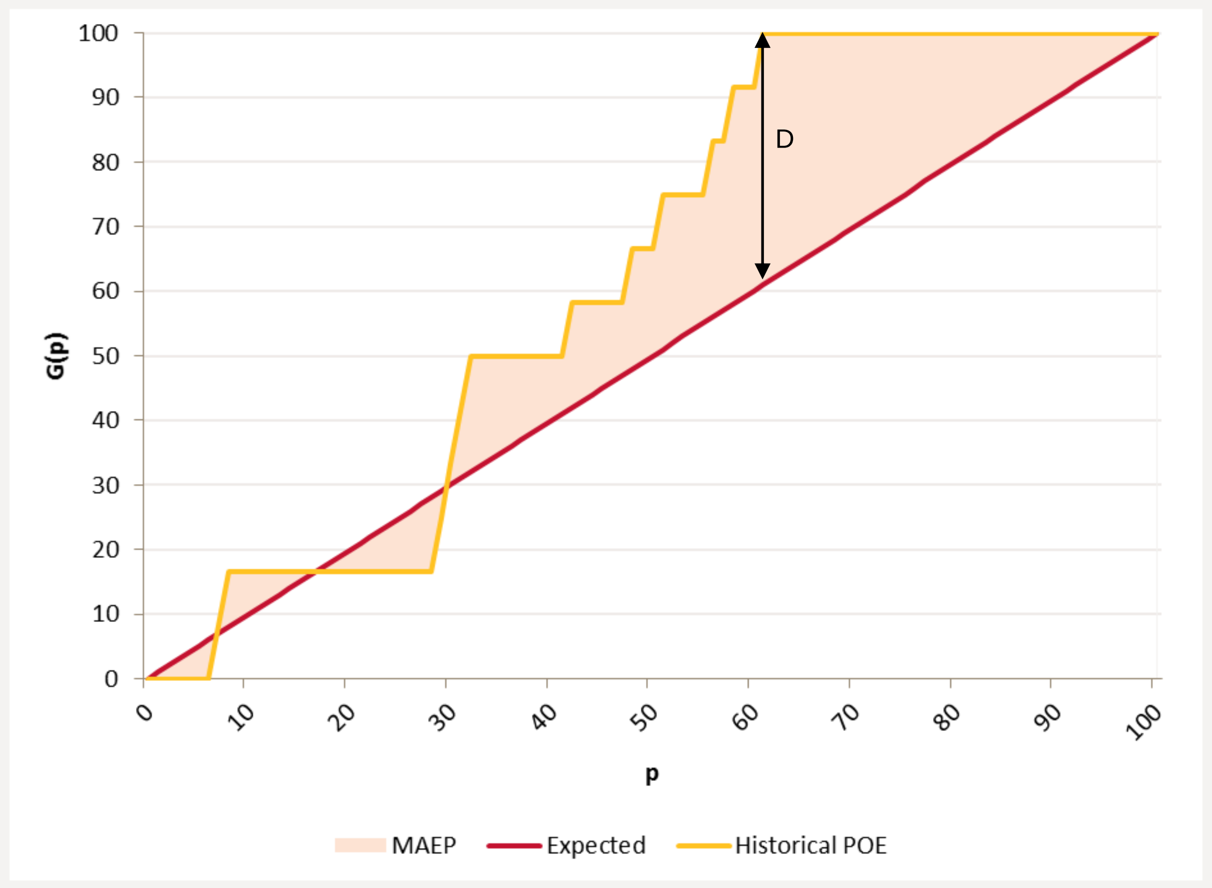
Table 35 Proportion of actual MDs exceeding 2015 NEFR Vic historical POEs for operational demand

	Historical points	Percentage of actual MD above POE level
Above 10% POE	2	15%
Above 50% POE	8	62%
Above 90% POE	13	100%

Table 36 Statistical measures of summer maximum demand performance for 2015 NEFR, Vic

	Value
Quantile Score	179
MAEP	14.0%
K-S statistic	39.0%

Figure 22 2015 NEFR illustration of K-S statistic, D, and MAEP for operational MD, Vic



6.2.3 2015 NEFR and 2014 NEFR MD model comparison

AEMO compared the 10% POE MD from the 2014 NEFR MD model using actual economic data, against the 10% POE forecast from the 2015 NEFR for the 2014-15 summer. This provides a measure of forecast accuracy for operational demand and native demand. This is shown in Table 37.

Table 37 Comparison of 2014-15 summer 10% POE from 2014 NEFR and 2015 NEFR, Vic

	Operational demand (2014-15 summer)	Native demand (2014-15 summer)
2014 NEFR model 10% POE forecast (MW)	10,114	10,175
2015 NEFR model 10% POE (MW)	10,034	10,098
Variance (MW)	80	77
Variance (%)	0.8%	0.8%

The forecast and estimated 10% POE values for Victoria for both operational and native demand are in good agreement between the 2015 and 2014 NEFR models.

CHAPTER 7. TASMANIA

7.1 Annual consumption

The 2014-15 annual consumption forecast for Tasmania shows under-forecasting, with most of variance caused by higher than expected industrial consumption and PV output.

7.1.1 Back assessment

The 2014 NEFR forecasts for 2014-15 operational and native consumption were lower than actual (refer to Table 38).

Both operational demand and native consumption forecasts are 0.6% below actual.

Key reasons for this variance are:

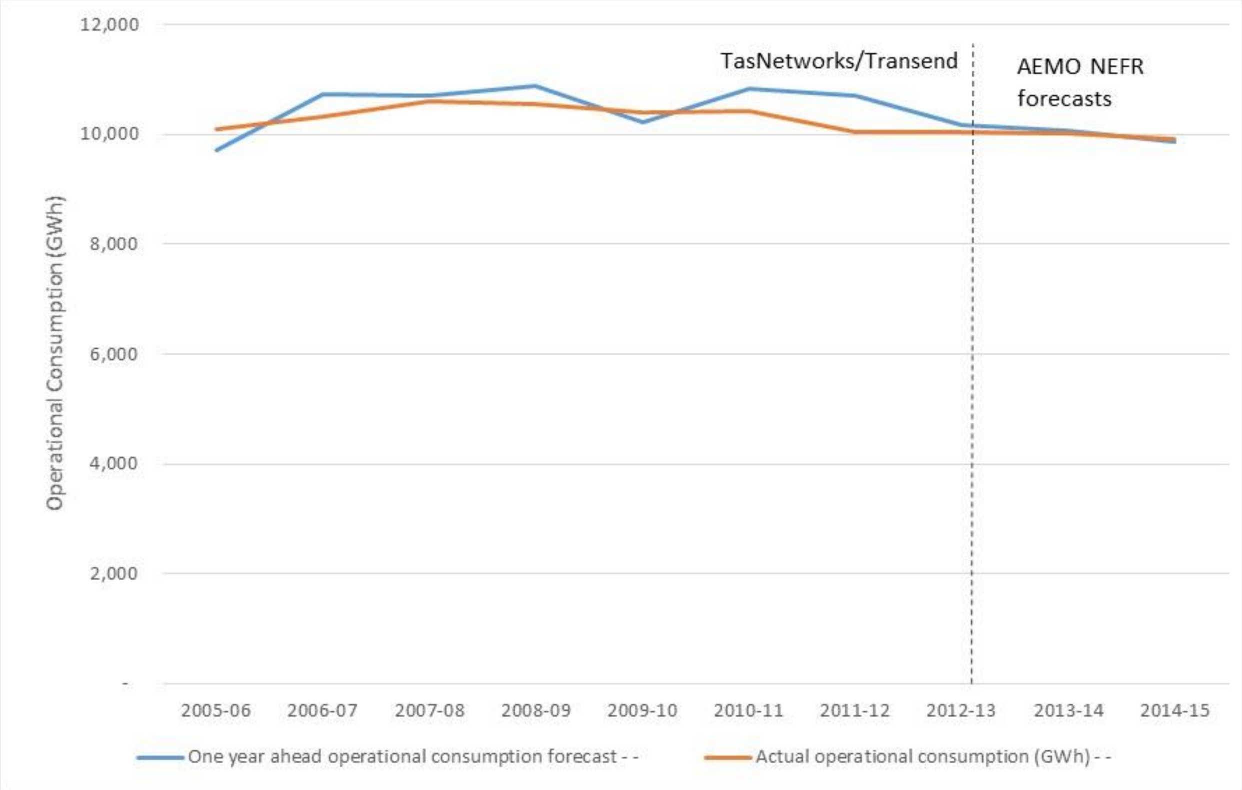
- Higher than expected rooftop PV output, reducing residential and commercial consumption from the grid.
- Higher than expected industrial consumption.

Table 38 2013 NEFR forecast of annual consumption for 2014-15, Tas

	Operational consumption	Native consumption
Forecast (GWh)	9,862	10,352
Actual (GWh)	9,924	10,411
Variance (GWh)	-62	-59
Variance (%)	-0.6%	-0.6%
Variance components	**Operational consumption**	**Native consumption**
Residential and commercial (excluding PV impact) (GWh)	24	27
PV production (GWh)	-14	-14
Large industrial (GWh)	-80	-80
Transmission losses (GWh)	8	8

Figure 23 shows the variances of previous one-year-ahead forecasts for operational consumption only, demonstrating that until recently, there has been a tendency to over-forecast operational consumption.

Figure 23 One-year-ahead annual energy forecast variance, Tas



7.1.2 Backcast

Table 39 presents the dynamic in-sample forecast results from the 2014 and 2015 NEFR models.

The actual residential and commercial data used in the 2015 NEFR differs from the actual data from the 2014 NEFR due to the reallocation of large customers from the residential and commercial sector to the industrial sector.[26]

The residential and commercial forecasts from both the 2014 and 2015 NEFR models track reasonably well against actual residential and commercial values, although not as well as other states. Neither shows a tendency to over- or under-forecast.

The forecasts generated by the 2015 NEFR model exhibits a greater degree of variance than that observed with the NEFR 2014 forecasts, particularly in the earlier years. Tasmania shows a greater variance compared to other regions because there is less historical data.

[26] Refer to the Forecasting Methodology Information Paper for further detail: http://www.aemo.com.au/Electricity/Planning/Forecasting/National-Electricity-Forecasting-Report/~/media/Files/Electricity/Planning/Reports/NEFR/2015/2015%20NEFR%20forecasting%20methodology%20information%20paper.ashx. Viewed 31 August 2015.

Table 39 2014 and 2015 NEFR dynamic in-sample residential and commercial annual energy forecasts, Tas

Financial year end	2014 NEFR residential and commercial consumption			2015 NEFR residential and commercial consumption		
	Actual (GWh)	In-sample forecast (GWh)	Variance (%)	Actual (GWh)	In-sample forecast (GWh)	Variance (%)
2003-04	4,827	4,818	-0.2%	4,231	4,590	8.5%
2004-05	4,985	4,915	-1.4%	4,397	4,221	-4.0%
2005-06	4,806	4,942	2.8%	4,220	4,349	3.1%
2006-07	4,893	4,947	1.1%	4,321	4,339	0.4%
2007-08	5,045	4,920	-2.5%	4,384	4,285	-2.3%
2008-09	5,078	4,945	-2.6%	4,402	4,330	-1.7%
2009-10	4,845	4,777	-1.4%	4,198	4,171	-0.7%
2010-11	4,542	4,765	4.9%	3,933	4,072	3.5%
2011-12	4,484	4,535	1.1%	3,826	3,798	-0.7%
2012-13	4,322	4,263	-1.4%	3,693	3,679	-0.4%
2013-14				3,664	3,686	0.6%

Table 40 presents the forecast results from the 2014 and 2015 NEFR models using actual driver data.

The variance between the 2014-15 actual and 2014 NEFR forecast residential and commercial annual consumption is 0.4%. When actual driver data is used, the 2014 NEFR model exhibits a variance of 0.8%, whereas the 2015 NEFR model exhibits a higher variance of 3.0%.

There has been a noticeable change in the consumption trend in Tasmania over the last two years. Although consumption is still declining, the trend appears to have flattened out from 2013-14 to 2014-15. A couple of reasons that have been attributed to this trend include a change in consumer behaviour and a weakening relationship between price and consumption. The 2015 NEFR tried to capture this by exploring the consumer response to price declines, however, as the results suggest, the model is now over-estimating consumption.

Table 40 2014 and 2015 NEFR residential and commercial forecasts using actual driver data, Tas

	Residential & commercial consumption (GWh)	Variance (GWh)	Variance
2014-15 Actual	3,606		
2014 NEFR forecast for 2014-15	3,622	16	0.4%
2014 NEFR model using actual driver data for 2014-15	3,634	27	0.8%
2015 NEFR model using actual driver data for 2014-15	3,714	107	3.0%

7.2 Maximum demand

7.2.1 2014 model assessment

Figure 24 shows the historical distribution produced by the 2014 MD model for non-industrial demand. It shows that the historical seasonal MD values tend to fall within the 90% to 10% POE values. Approximately two-thirds of the actuals lie below the 50% POE and approximately one-third lie above (refer to Table 41). With annual maximum demand, there are too few data points to reject or accept the model based on where actuals have fallen, but this allows for an intuitive, high-level check of the POE backcasts.

The statistical measures shown in Table 42 are a better means by which to assess probability forecasts. Different models can be compared against AEMO's by calculating the same scores. A lower score for each of these measures indicates better performance.

Figure 24 2014 NEFR historical POEs for non-industrial component of MD, Tas

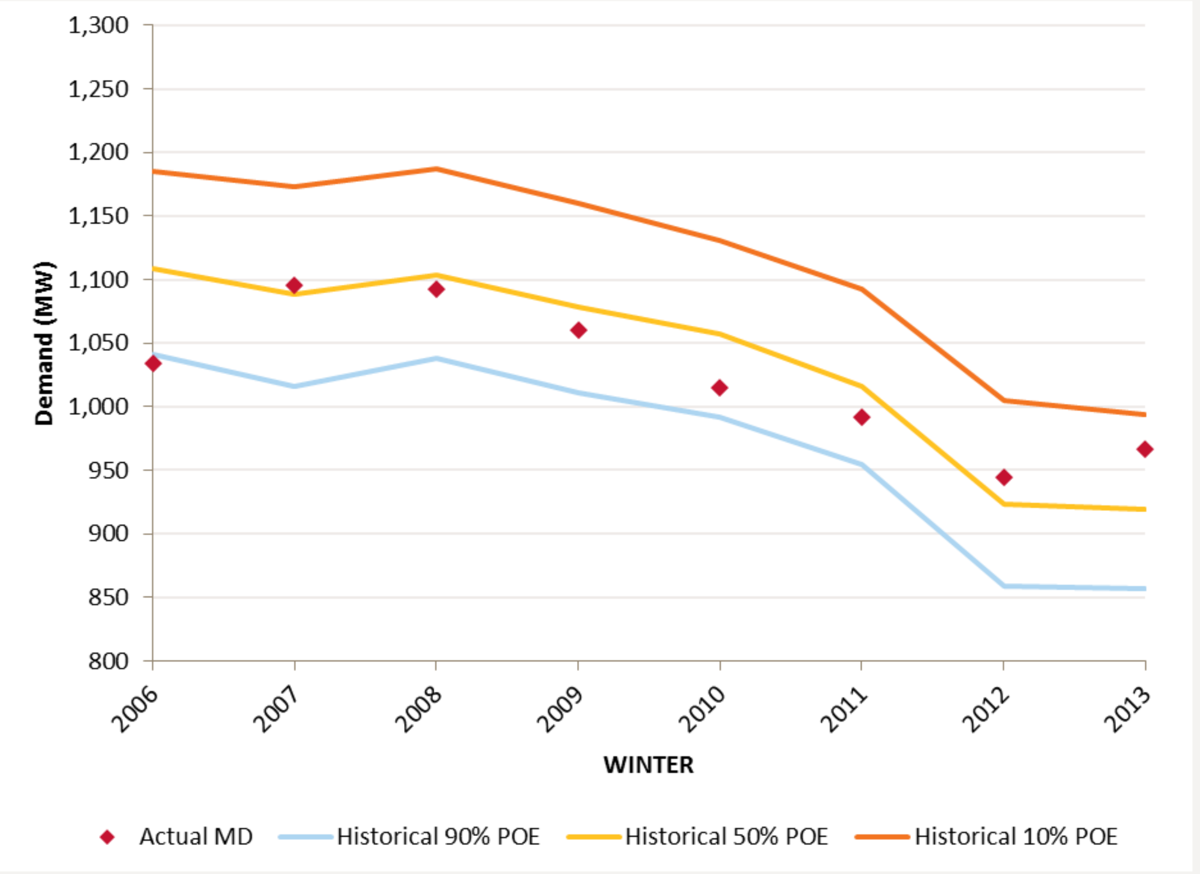


Table 41 Proportion of actual MDs exceeding 2014 NEFR Tas historical POEs for non-industrial demand

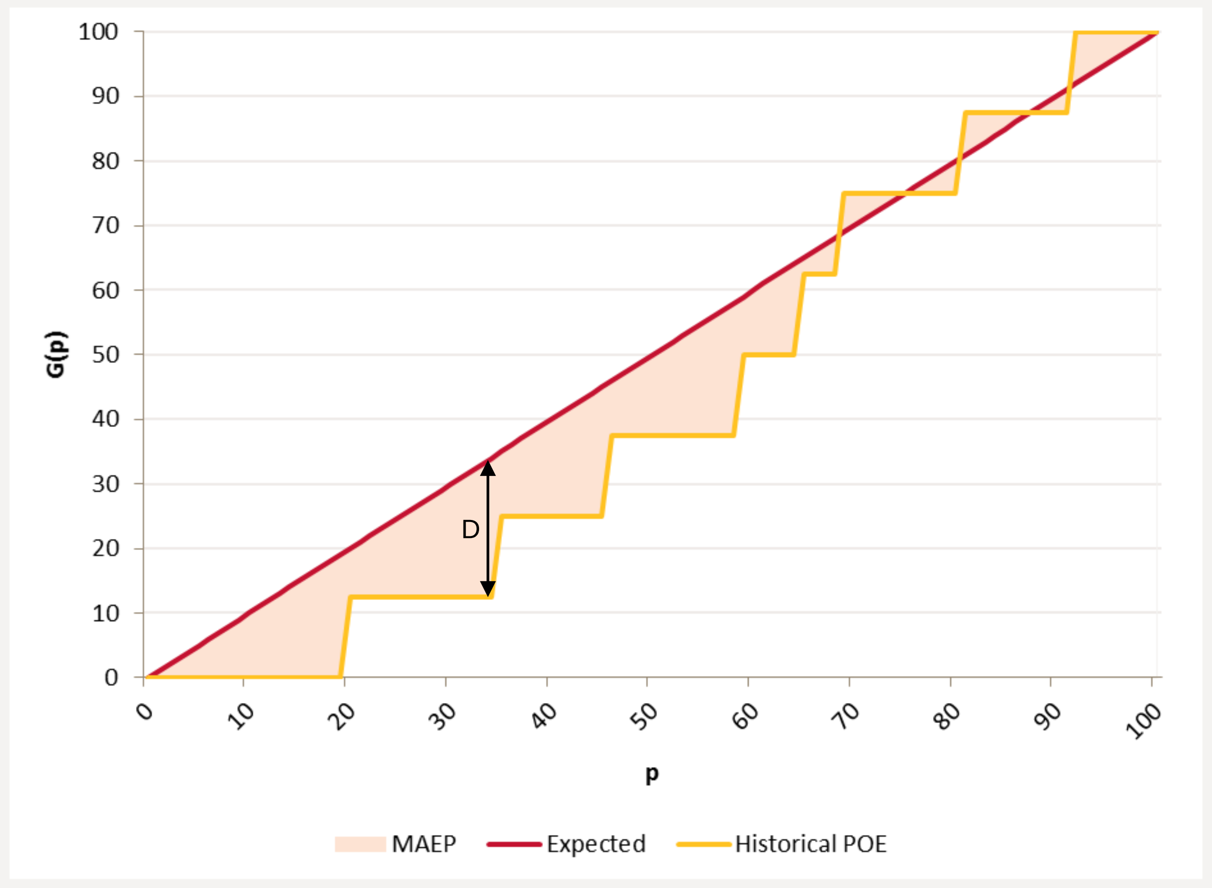
	Historical points	Percentage of actual MD above POE level
Above 10% POE	0	0%
Above 50% POE	3	38%
Above 90% POE	7	88%

Table 42 Statistical measures of winter maximum demand performance for 2015 NEFR, Tas

	Value
Quantile Score	11.3
MAEP	9.5%
K-S statistic	22.5%

Figure 25 illustrates the calculation of the K-S statistic and the MAEP. The K-S statistic is the maximum distance between the two lines and the MAEP is the area between them.

Figure 25 2014 NEFR illustration of K-S statistic, D, and MAEP for non-industrial component of MD, Tas



7.2.2 2015 model assessment

Figure 26 shows the historical distribution produced by the 2015 MD model for operational demand. It shows that the historical seasonal MD values tend to fall within the 90% to 10% POE values. Approximately two-thirds of the actuals lie below the 50% POE and approximately one-third lie above (refer to Table 43). With annual maximum demand, there are too few data points to reject or accept the model based on where actuals have fallen, but this allows for an intuitive, high-level check of the POE backcasts.

The statistical measures shown in Table 44 are a better means by which to assess probability forecasts. Different models can be compared against AEMO's by calculating the same scores. A lower score for each of these measures indicates better performance.

Figure 27 illustrates the calculation of the K-S statistic and the MAEP. The K-S statistic is the maximum distance between the two lines and the MAEP is the area between them.

Figure 26 2015 NEFR historical POEs for operational MD, Tas

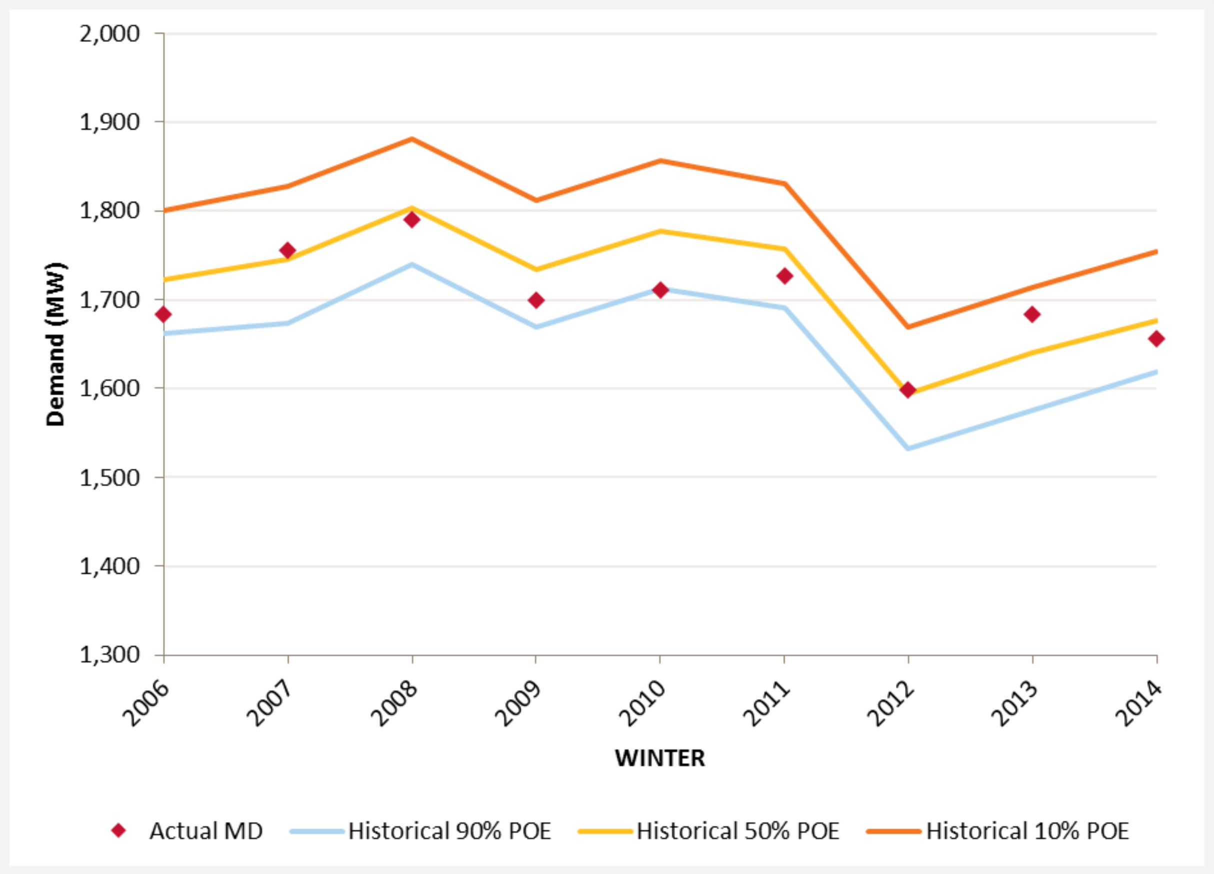


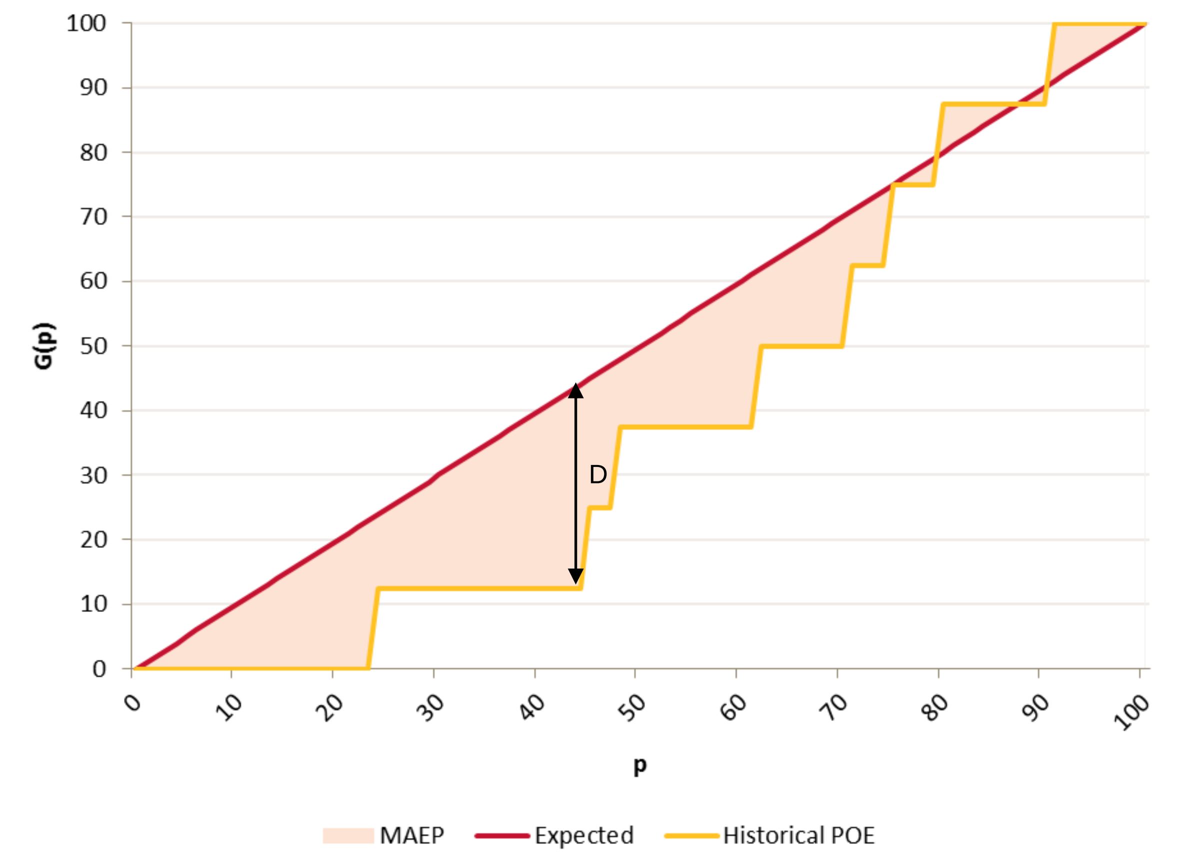
Table 43 Proportion of actual MDs exceeding 2015 NEFR Tas historical POEs for operational demand

	Historical points	Percentage of actual MD above POE level
Above 10% POE	0	0%
Above 50% POE	3	33%
Above 90% POE	8	89%

Table 44 Statistical measures of winter maximum demand performance for 2015 NEFR, Tas

	Value
Quantile Score	10.6
MAEP	13.7%
K-S statistic	33.9%

Figure 27 2015 NEFR illustration of K-S statistic, D, and MAEP for operational MD, Tas



7.2.3 2015 NEFR and 2014 NEFR MD model comparison

AEMO compared the 10% POE MD from the 2014 NEFR MD model using actual economic data, against the 10% POE forecast from the 2015 NEFR for the 2014 winter.[27] This provides a measure of forecast accuracy for operational demand and native demand. This is shown in Table 45.

Table 45 Comparison of 2014 winter 10% POE from 2014 NEFR and 2015 NEFR, Tas

	Operational demand (2014 winter)	Native demand (2014 winter)
2014 NEFR model 10% POE forecast (MW)	1,756	1,820
2015 NEFR model 10% POE[28] (MW)	1,754	1,805
Variance (MW)	2	15
Variance (%)	0.1%	0.8%

The forecast and estimated 10% POE values for operational demand and native demand are closely aligned between the 2015 and 2014 NEFR models.

27 Tasmania is the only winter-peaking region.
28 Using actual economic data.

APPENDIX A. ONE-YEAR-AHEAD ANNUAL CONSUMPTION FORECAST VARIANCE

A.1 Queensland

Table 46 One-year-ahead annual consumption forecast variance for Queensland

Financial year end	One-year-ahead operational consumption forecast (GWh)	Actual operational consumption (GWh)	Variance (%)	Source
2009-10	50,030	49,175	1.7%	Powerlink
2010-11	52,238	47,621	9.7%	Powerlink
2011-12	51,457	47,555	8.2%	Powerlink
2012-13	49,203	47,160	4.3%	AEMO
2013-14	48,733	46,412	5.0%	AEMO
2014-15	45,362	48,356	-6.2%	AEMO

A.2 New South Wales

Table 47 One-year-ahead annual consumption forecast variance for New South Wales

Financial year end	One-year-ahead operational consumption forecast (GWh)	Actual operational consumption (GWh)	Variance (%)	Source
2009-10	74,998	74,050	1.3%	TransGrid
2010-11	77,167	73,755	4.6%	TransGrid
2011-12	75,120	71,167	5.6%	TransGrid
2012-13	69,134	67,627	2.2%	AEMO
2013-14	68,528	65,920	4.0%	AEMO
2014-15	65,321	67,145	-2.7%	AEMO

A.3 South Australia

Table 48 One-year-ahead annual consumption forecast variance for South Australia

Financial year end	One-year-ahead operational consumption forecast (GWh)	Actual operational consumption (GWh)	Variance (%)	Source
2009-10	14,139	13,616	3.8%	Pre AEMO
2010-11	14,303	13,725	4.2%	Pre AEMO
2011-12	14,358	13,367	7.4%	Pre AEMO
2012-13	12,941	13,319	-2.8%	AEMO
2013-14	12,746	12,873	-1.0%	AEMO
2014-15	12,560	12,468	0.7%	AEMO

A.4 Victoria

Table 49 One-year-ahead annual consumption forecast variance for Victoria

Financial year end	One-year-ahead operational consumption forecast (GWh)	Actual operational consumption (GWh)	Variance %	Source
2009-10	46,467	47,606	-2.4%	Pre AEMO
2010-11	51,657	47,319	9.2%	Pre AEMO
2011-12	51,954	47,053	10.4%	Pre AEMO
2012-13	47,042	46,508	1.1%	AEMO
2013-14	46,520	45,436	2.4%	AEMO
2014-15	42,586	42,574	0.03%	AEMO

A.5 Tasmania

Table 50 One-year-ahead annual consumption forecast variance for Tasmania

Financial year end	One-year-ahead operational consumption forecast (GWh)	Actual operational consumption (GWh)	Variance %	Source
2009-10	10,233	10,406	-1.7%	Transend/ TasNetworks
2010-11	10,824	10,425	3.8%	Transend/ TasNetworks
2011-12	10,711	10,047	6.6%	Transend/ TasNetworks
2012-13	10,162	10,033	1.3%	AEMO
2013-14	10,077	10,028	0.5%	AEMO
2014-15	9,862	9,924	-0.6%	AEMO