Attachment 04.4P

POWER AND WATER CORPORATION MAXIMUM DEMAND, ENERGY CONSUMPTION, AND CONNECTIONS FORECASTS

2017 IMPLEMENTATION OF FORECASTING PROCEDURE

September 2017

AEMO

AUSTRALIAN ENERGY MARKET OPERATOR

IMPORTANT NOTICE

Purpose

AEMO has prepared this document for the Power & Water Corporation (Northern Territory) (PWC). The purpose of the document is to state the key modelling outcomes and underlying assumptions adopted by AEMO in its implementation of the *2017 PWC Maximum Demand and Customer Connections Forecasting Procedure*. AEMO implemented the Procedure when developing demand forecasts for the forthcoming distribution determination for the 2019 to 2024 regulatory period.

This document is generally based on information provided to AEMO by PWC as at 18 August, 2017.

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CONTENTS

1. INTRODUCTION

AEMO prepared four types of forecasts for Power and Water Corporation (PWC) to support the forthcoming distribution determination. The forecasts are categorised as:

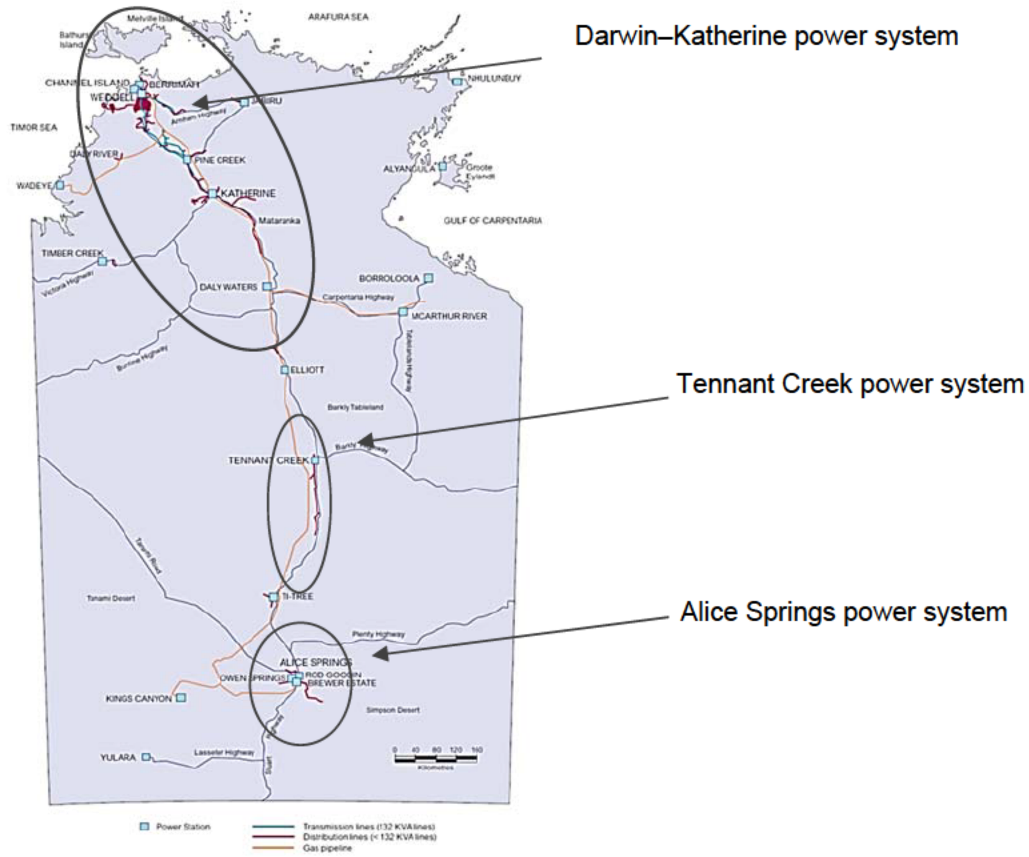
- Regional maximum demand (MD).
- Zone substation MD.
- Energy consumption.
- Customer connections.

Each forecast type has been prepared for each of the three major power systems operated by PWC in the Northern Territory (NT), pictured in Figure 1:

- Darwin–Katherine power system.
- Alice Springs power system.
- Tennant Creek power system.

The forecasts were prepared for a 10-year outlook, from 2017–18 to 2026–27.

Figure 1 Overview of PWC-operated Northern Territory power systems



2. DARWIN–KATHERINE

2.1 Customer connections

Key findings

During the 10-year outlook period, Darwin–Katherine residential connections are forecast to increase at a rate of 0.5% per annum, while the commercial categories increase by 1.5% per annum (see Table 1 and Figure 2). This is due to the combination of increasing population and Gross State Product (GSP). The forecasts for Darwin–Katherine demonstrate good alignment with historical trends.

AEMO used historical connection numbers for the three networks and each connection type (see Appendix A.1) to derive linear relationships for total connections and for these connection types:

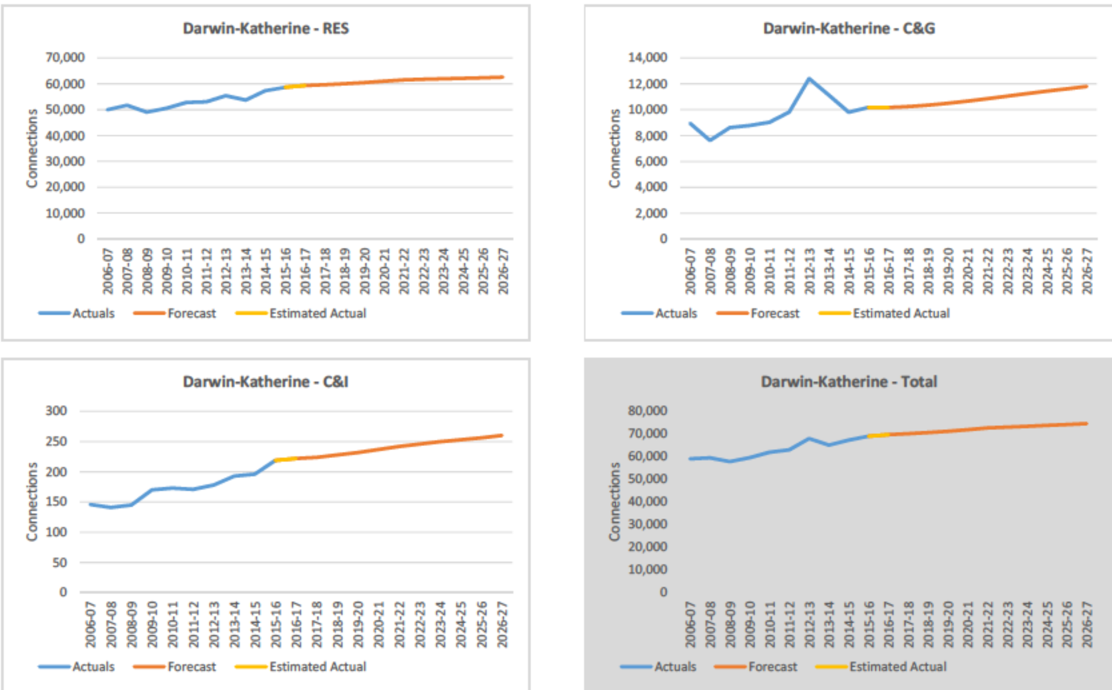
- Residential (RES).
- Commercial and government, with consumption less than 750 megawatt hours (MWh) (C&G).
- Commercial and industrial, with consumption above 750 MWh (C&I).

AEMO applied the models described in Appendix A.1 to forecast network totals for each connection type, then split the forecasts into individual regions.

Table 1 Darwin–Katherine connections forecast

	2017–18	2018–19	2019–20	2020–21	2021–22	2022–23	2023–24	2024–25	2025–26	2026–27
RES	59,678	60,028	60,485	61,016	61,556	61,756	61,957	62,154	62,351	62,547
C&G	10,233	10,343	10,502	10,684	10,870	11,052	11,235	11,421	11,611	11,800
C&I	224	228	232	237	242	246	250	253	256	260
Total	**70,135**	**70,599**	**71,219**	**71,937**	**72,668**	**73,054**	**73,442**	**73,828**	**74,218**	**74,607**

Figure 2 Darwin–Katherine connections actual and forecast



2.2 Energy consumption

Key findings

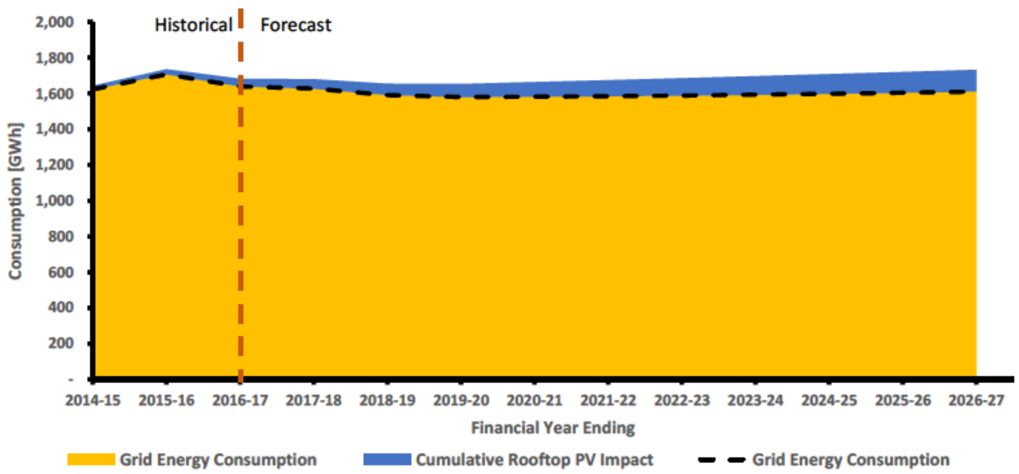
The consumption forecast for Darwin–Katherine (shown in Table 2 and 0) decreases by an average of 0.1% per annum.

The annual consumption forecast declines in 2019–20 due to the industrial load [redacted] and then increases due to the forecast population increase. The increase in consumption due to population growth is forecast to be restrained by increasing penetration of rooftop photovoltaic (PV) and the [redacted] load being removed from late 2018.

Table 2 Annual consumption forecast (GWh) for Darwin–Katherine

Type	Year	Darwin–Katherine forecast
Actual	2014–15	1,623.0
Actual	2015–16	1,707.0
Actual	2016–17	1,639.8
Forecast	2017–18	1,626.3
Forecast	2018–19	1,591.1
Forecast	2019–20	1,579.5
Forecast	2020–21	1,581.6
Forecast	2021–22	1,584.3
Forecast	2022–23	1,587.6
Forecast	2023–24	1,592.6
Forecast	2024–25	1,598.1
Forecast	2025–26	1,604.0
Forecast	2026–27	1,610.8

Figure 3 Annual consumption forecast (GWh) for Darwin–Katherine



Linear model

AEMO produced the daily 'base year' consumption model (Y_{DK}) using:

- The last three years of consumption data.
- A cooling degree day (CDD)[1] low (21 °C base temperature) (X_3).
- A three-day lagged CDD high (26 °C base temperature) (X_4).
- A workday flag variable (X_1).
- A public holiday flag variable (X_2).

Results showed a goodness-of-fit of an adjusted R^2 of 91.5%.

Equation 1 Linear model for Darwin–Katherine energy consumption

$$Y_{DK} = 2748.3 + 468.8X_1 - 506.7X_2 + 202.5X_3 + 75.8X_4$$

2.3 Regional maximum demand

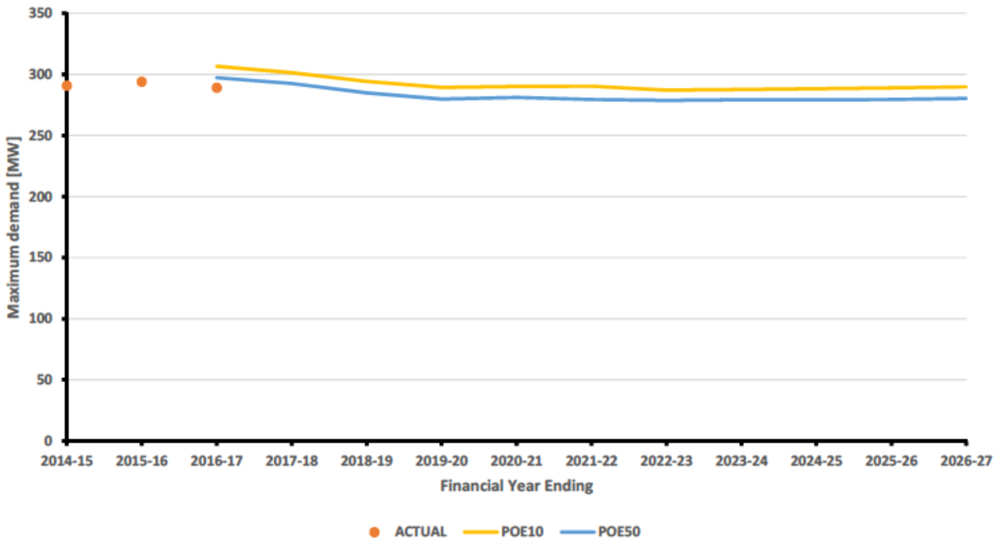
Key findings

Darwin–Katherine is a summer peaking network. Due to its climate, Darwin–Katherine does not have heating load. Installed residential and commercial PV capacity is forecast to grow from 10% of maximum underlying demand in 2017 to 30% of maximum underlying demand in 2027.

Maximum operational demand currently occurs in the heat of the day between 3.00 pm and 4.00 pm in summer. Installed PV capacity is projected to push maximum operational demand later in the day during the 10-year forecast period, to around 6.00 pm.

As Figure 4 shows, maximum operational demand is forecast to decline to 2020, as a large industrial load moves from grid demand to self-supply. After 2020, maximum operational demand is forecast to decline marginally, as rooftop PV penetration continues to grow. The actual for summer 2016–17 sits 3% lower than the 50% probability of exceedance (POE)[2] forecast, due to weather conditions in 2015–16. This difference is within the typical historical range of year-to-year variability.

Figure 4 Darwin–Katherine summer MD actual and forecast



[1] CDD is explained in more detail in Appendix A.2.
[2] POE means the probability, as a percentage, that a maximum demand forecast will be met or exceeded (for example, due to weather conditions). A 10% POE forecast is expected to be met or exceeded, on average, only one year in 10, so considers more extreme weather than a 50% POE forecast, which is expected to be met or exceeded, on average, one year in two.

Data preparation

AEMO used the process described in Appendix A.3 to identify a number of outliers from 1 December 2014 to 30 June 2017. AEMO then compared these outliers against the list of network outages from 2000 to 2017 provided by PWC. Table 3 details the outliers removed from the analysis.

Table 3 List of outliers removed from sample data

REMOVE_FROM	REMOVE_TO	Reason	Outage_ID
03/12/2014 00:00	03/12/2014 03:00	Network outage	2148425
25/12/2015 16:00	25/12/2015 20:00	Network outage	2254009

Linear demand model

The linear model in Equation 2 represents the relationship between underlying demand and the drivers of demand in Darwin–Katherine. Table 4 outlines the coefficients of the hourly models for the hours relevant to MD in Equation 2.

Every degree increase in the average temperature of the previous three hours in Darwin–Katherine at 4.00 pm is expected to increase underlying demand by 7.57 megawatts (MW). Public holidays and weekends tend to have lower demand than weekdays, by around 25–27 MW. Demand between Christmas Eve and the first week of January tends be around 19.78 MW lower than other regular days in the season.

Equation 2 Linear model for Darwin–Katherine maximum demand

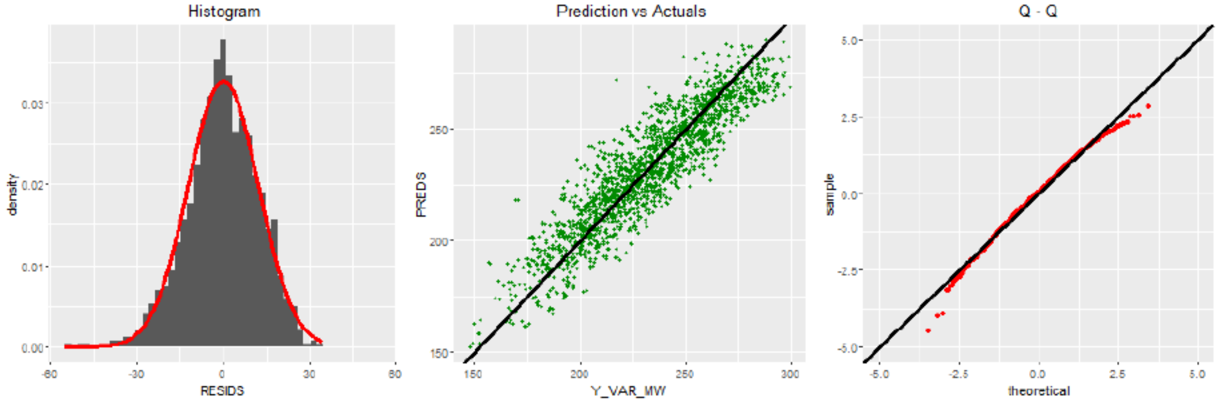
$$
\begin{aligned}
MW_{hh} = {} & \mathrm{INTERCEPT}_{hh} + \mathrm{PUBLIC\_HOLIDAY}_{hh} + \mathrm{SAT\_DUMMY}_{hh} + \mathrm{SUN\_DUMMY}_{hh} \\
& + \mathrm{SUMMER\_SHUTDOWN}_{hh} + \mathrm{COS\_HD}_{hh} + \mathrm{DRYTEMP\_C\_3HRLAG\_CD\_BASE}_{hh} \\
& + \mathrm{HEAT\_INDEX\_3DAYLAG\_CD\_EXTR}_{hh}
\end{aligned}
$$

Table 4 Linear model coefficients

Term	Hour			
	14:00	15:00	16:00	17:00
INTERCEPT	205.89	204.80	197.98	190.06
PUBLIC_HOLIDAY	-36.63	-34.47	-26.95	-19.04
SAT_DUMMY	-35.59	-33.16	-25.00	-15.48
SUN_DUMMY	-36.44	-35.36	-26.66	-14.15
SUMMER_SHUTDOWN	-22.77	-22.88	-19.78	-18.31
COS_HD	-10.78	-10.85	-9.55	-8.77
DRYTEMP_C_3HRLAG_CD_BASE	8.04	7.79	7.57	6.82
HEAT_INDEX_3DAYLAG_CD_EXTR	7.09	7.43	7.43	7.27
MODEL_SIGMA	11.32	11.90	12.23	11.67
MODEL_ID	394	394	394	394

Figure 5 shows the histogram of the residuals (RESIDS), the predicted vs actuals (PREDS vs Y_VAR_MW), and the quantile-quantile (Q-Q) plot for the 4.00 pm linear demand model, selected because MD in Darwin–Katherine occurs around 4.00 pm. The plots show that the model performs well in using the conditions in Darwin–Katherine to predict demand. The residuals follow a normal distribution around the predicted value of demand. Further information on the data preparation methodology is in Appendix A.3.

Figure 5 4.00 pm linear model histogram of residuals, predicted vs actuals, and the Q-Q plot



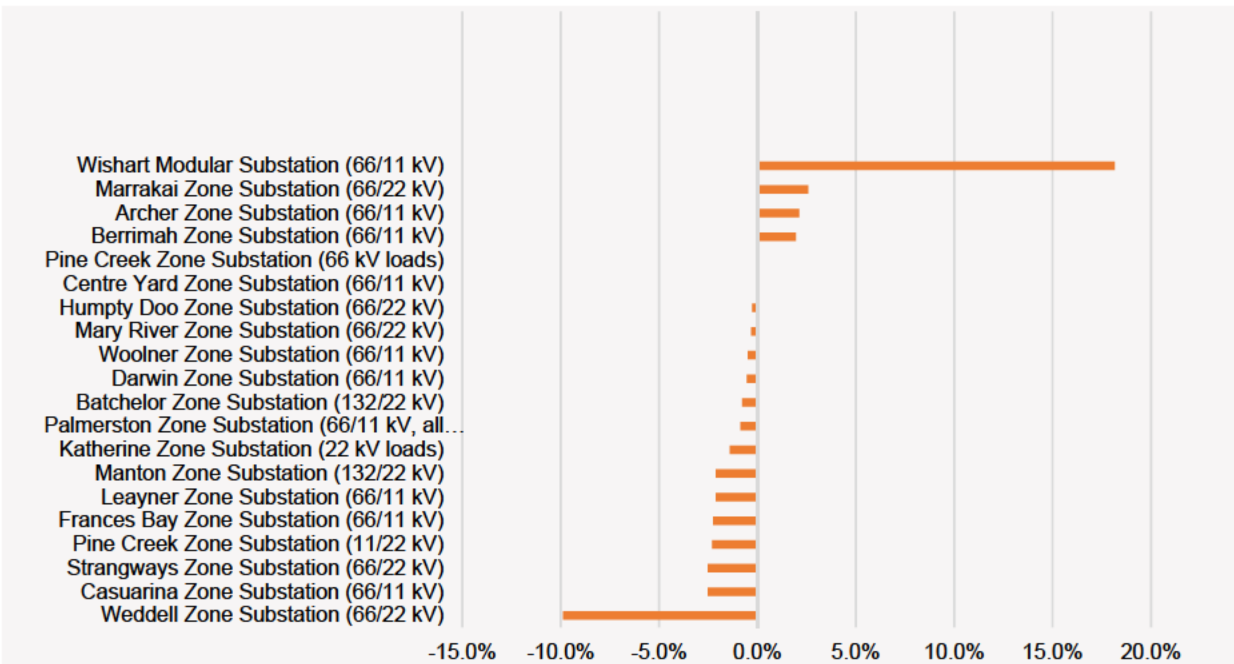
2.4 Zone substation maximum demand

Key findings

The growth rates of the non-coincident summer forecasts for the zone substations in the Darwin–Katherine system are displayed in Figure 6. High growth rates are driven by increasing load related to new industrial and residential developments in and around Darwin. Reducing demand is driven by rooftop PV and, in the case of Weddell, industrial demand.

Charts of the 10% and 50% POE forecasts are included in Appendix H.

Figure 6 Zone substation growth rates (Summer, 10% POE, 2017–18 to 2026–27)



Data preparation

In preparing the forecasts for the Darwin–Katherine Zone substations, AEMO modelled the following industrial or large loads separately:

- [redacted]
- [redacted]
- [redacted]
- [redacted]
- [redacted]

Linear demand models

The linear demand models (terms and coefficients) used for the recent season are listed in Appendix E.

3. ALICE SPRINGS

3.1 Customer connections

Key findings

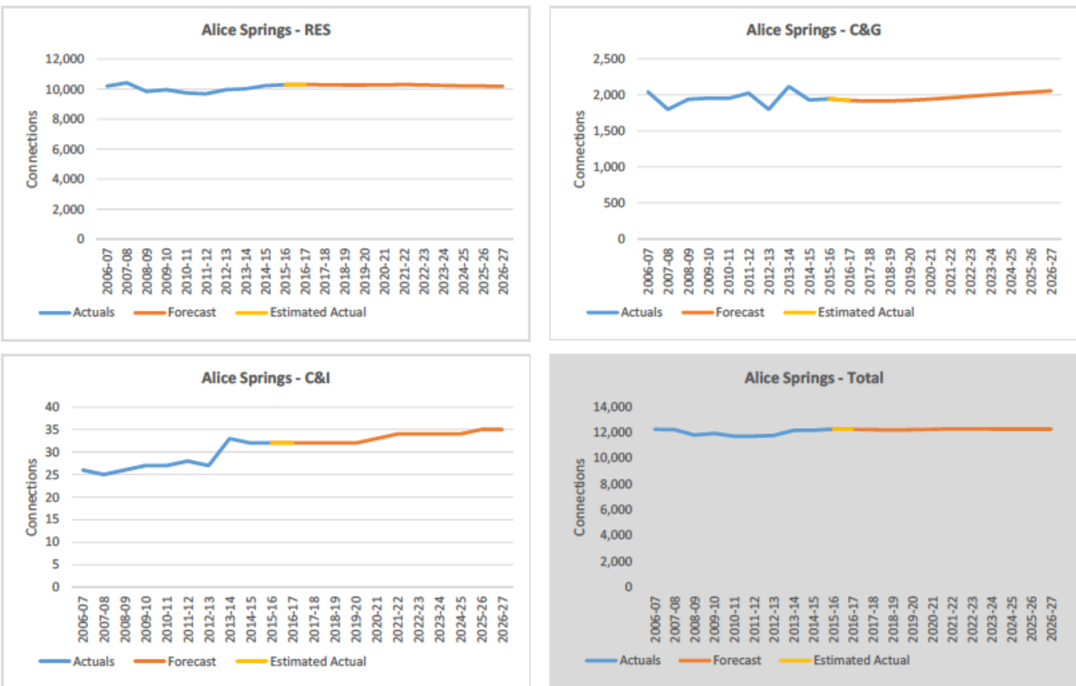
During the 10-year outlook period, residential connections are forecast to decrease at a rate of 0.1% per annum, while the commercial categories increase by 0.7% per annum (see Table 5 and Figure 7). This is due to the combination of decreasing population (affecting the residential category more than commercial) and GSP (which has a stronger effect on the commercial sector). The forecasts for Alice Springs demonstrate good alignment with historical trends.

The connection forecast for Alice Springs was derived by splitting the forecasts for the total NT regulated networks. Further detail on the models is in Appendix A.1.

Table 5 Alice Springs connections forecast

	2017–18	2018–19	2019–20	2020–21	2021–22	2022–23	2023–24	2024–25	2025–26	2026–27
RES	10,277	10,256	10,258	10,276	10,300	10,269	10,242	10,217	10,195	10,175
C&G	1,913	1,915	1,927	1,944	1,962	1,979	1,998	2,017	2,037	2,057
C&I	32	32	32	33	34	34	34	34	35	35
Total	**12,222**	**12,203**	**12,217**	**12,253**	**12,296**	**12,282**	**12,274**	**12,268**	**12,267**	**12,267**

Figure 7 Alice Springs connections actual and forecast



3.2 Energy consumption

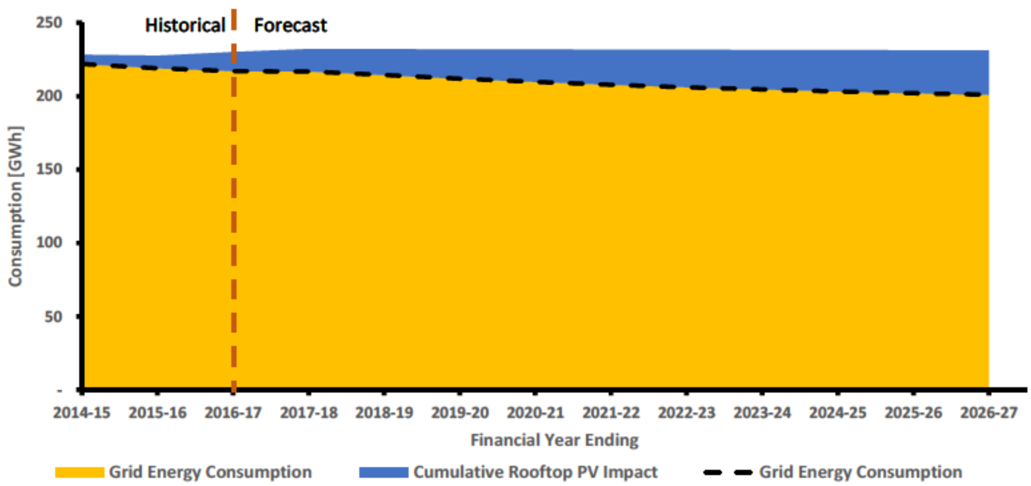
Key findings

The annual consumption forecast for Alice Springs, as shown in Table 6 and Figure 8, decreases by an average of 0.8% per annum, due to the combined effect of population decline and increasing penetration of rooftop PV.

Table 6 Annual consumption forecast (GWh) for Alice Springs

Type	Year	Alice Springs forecast
Actual	2014–15	221.2
Actual	2015–16	219.0
Actual	2016–17	217.0
Forecast	2017–18	216.8
Forecast	2018–19	214.3
Forecast	2019–20	211.9
Forecast	2020–21	209.7
Forecast	2021–22	207.8
Forecast	2022–23	206.0
Forecast	2023–24	204.6
Forecast	2024–25	203.2
Forecast	2025–26	202.0
Forecast	2026–27	200.9

Figure 8 Annual consumption forecast (GWh) for Alice Springs



Linear model

AEMO produced the daily 'base year' consumption model (Y_{AS}) using:

- The last three years of consumption data.
- A CDD (18 ºC base temperature) (X_5).

- A three-day lagged CDD (18 ºC base temperature) (X_6).
- A heating degree day (HDD)[3] (18 ºC base temperature) (X_7).
- A three-day lagged HDD (X_8).
- A workday flag variable (X_1).
- A public holiday flag variable (X_2).

Results showed a goodness-of-fit of an adjusted R^2 of 85.7%.

Equation 3 Linear model for Alice Springs energy consumption

$$Y_{AS} = 366.7 + 63.4X_1 - 68.9X_2 + 22.3X_5 + 17.4X_7 + 7.2X_8 + 5.7X_6$$

3.3 Regional maximum demand

Key findings

As shown in Figure 9, maximum operational demand is forecast to decline steadily over the next 10 years, driven by growth in PV capacity.

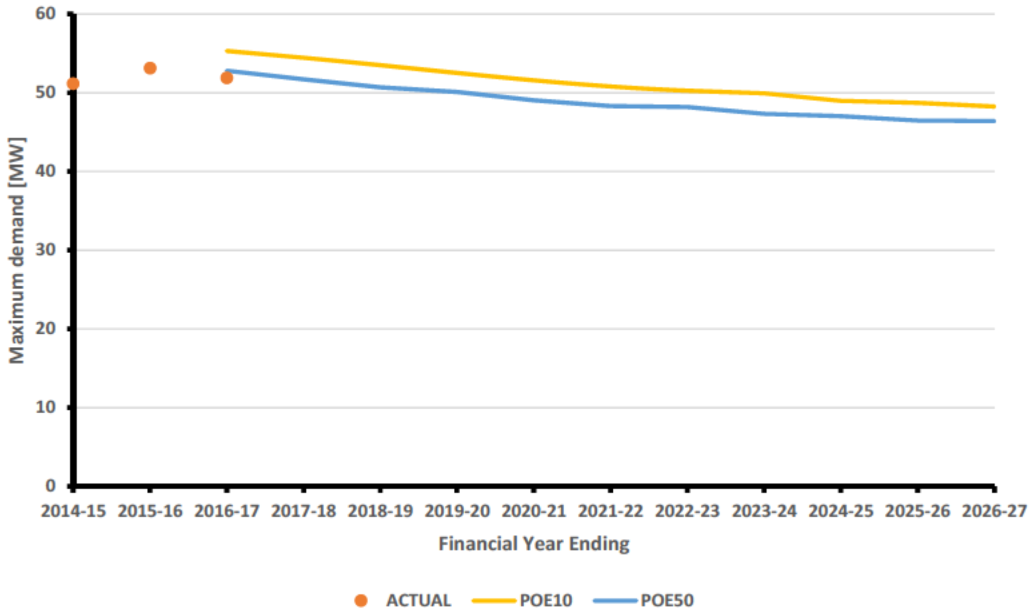
Alice Springs is a summer peaking network. Alice Springs has both cooling load and heating load, though its winter peak is roughly 10 MW (25%) lower than its summer peak.

Installed residential and commercial PV capacity is expected to grow from around 20% of maximum underlying demand in 2017 to 40% of maximum underlying demand in 2027.

Maximum operational demand currently occurs in the heat of the day, between 3.00 pm and 4.00 pm in summer. Installed PV capacity is expected to push maximum operational demand later in the day by an hour during the 10-year forecast period, to between 4.00 pm and 5.00 pm.

The actual for summer 2016–17 sits 2% lower than the 50% POE, due to weather conditions in 2015–16. This difference is within the typical historical range of year-to-year variability.

Figure 9 Alice Springs summer MD, actual and forecast



[3] HDD is explained in more detail in Appendix A.2.

Data preparation

AEMO used the process described in Appendix A.3 to identify a number of outliers from 1 December 2014 to 30 June 2017. AEMO compared these outliers against the list of network outages from 2000 to 2017 provided by PWC. Table 7 details the outliers removed from the analysis.

Table 7 List of outliers removed from sample data

REGIONID	REMOVE_FROM	REMOVE_TO	Reason	Outage_ID
AS	10/01/2015 00:00	10/01/2015 18:30	Network outage	2157487
AS	09/01/2016 17:00	09/01/2016 18:00	Network outage	2257859
AS	30/01/2016 14:00	31/01/2016 00:00	Network outage	2263507
AS	31/08/2016 00:00	02/09/2016 00:00	Too Low	
AS	08/09/2016 00:00	14/09/2016 00:00	Too Low	
AS	10/05/2017 03:00	10/05/2017 07:00	Network outage	2395257

Linear demand model

The linear model in Equation represents the relationship between underlying demand and the drivers of demand in Alice Springs. Table 8 outlines the coefficients of the hourly models for the hours relevant to MD in Equation .

Every degree increase above the CDD critical temperature in Alice Springs at 3.00 pm is expected to increase underlying demand by 1.21 MW. A degree decrease below the HDD critical temperature is expected to increase demand by 0.77 MW. Public holidays and weekends tend to have lower demand than weekdays, by around 5 MW. Demand between Christmas Eve and the first week of January tends be around 3.49 MW lower than other regular days in the season.

Equation 4 Linear model for Alice Springs maximum demand

$$
\begin{aligned}
MW_{hh} = {} & \beta_0 \text{INTERCEPT}_{hh} + \beta_2 \text{PUBLIC\_HOLIDAY}_{hh} + \beta_3 \text{SAT\_DUMMY}_{hh} + \beta_4 \text{SUN\_DUMMY}_{hh} \\
& + \beta_5 \text{SUMMER\_SHUTDOWN}_{hh} + \beta_6 \text{COS\_CD}_{hh} + \beta_7 \text{COS\_HD}_{hh} \\
& + \beta_8 \text{DRYTEMP\_C\_3DAYLAG\_CD\_EXTR}_{\text{hh}} + \beta_9 \text{DRYTEMP\_C\_DAYLAG\_CD\_EXTR}_{\text{hh}} \\
& + \beta_{10} \text{DRYTEMP\_C\_3HRLAG\_CD\_BASE}_{\text{hh}} + \beta_{11} \text{DRYTEMP\_C\_CD\_BASE}_{\text{hh}} \\
& + \beta_{12} \text{DRYTEMP\_C\_3HRLAG\_HD\_BASE}_{\text{hh}} + \beta_{13} \text{DRYTEMP\_C\_HD\_BASE}_{\text{hh}}
\end{aligned}
$$

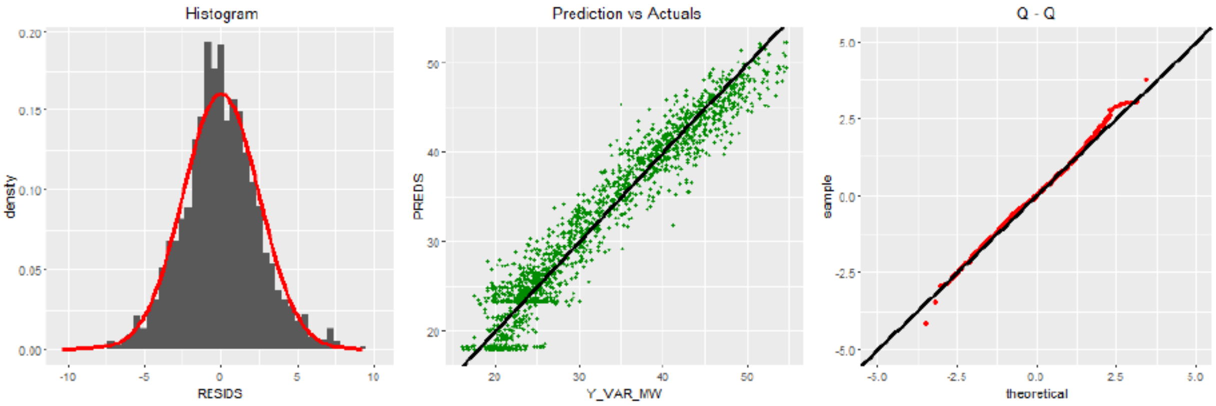
Table 8 Linear model coefficients

Term	Hour			
	14:00	15:00	16:00	17:00
INTERCEPT	23.20	23.26	23.34	21.98
PUBLIC_HOLIDAY	-5.55	-5.13	-3.90	-2.05
SAT_DUMMY	-5.00	-5.03	-3.95	-2.43
SUN_DUMMY	-5.60	-5.28	-3.94	-2.20
SUMMER_SHUTDOWN	-3.37	-3.49	-3.29	-0.99
COS_CD	1.12	1.16	1.45	0.00
COS_HD	0.00	0.00	0.00	1.50
DRYTEMP_C_3DAYLAG_CD_EXTR	0.53	0.57	0.00	0.64
DRYTEMP_C_DAYLAG_CD_EXTR	0.00	0.00	0.52	0.00

Term	Hour			
	14:00	15:00	16:00	17:00
DRYTEMP_C_3HRLAG_CD_BASE	0.00	0.00	0.00	1.20
DRYTEMP_C_CD_BASE	1.17	1.21	1.16	0.00
DRYTEMP_C_3HRLAG_HD_BASE	0.00	0.00	0.00	1.06
DRYTEMP_C_HD_BASE	1.81	0.77	1.03	0.00
MODEL_SIGMA	2.56	2.49	2.32	2.22
MODEL_ID	350	350	341	484

Figure 10 shows the histogram of the residuals, the predicted vs actuals, and the Q-Q plot for the 3.00 pm linear demand model, because MD in Alice Springs is around 3.00 pm. The plots demonstrate that the model performs well when used to predict Alice Springs' demand. The residuals (histogram in Figure 10) follow a normal distribution (overlaid in red).

Figure 10 3.00 pm linear model histogram of residuals, predicted vs actuals, and the Q-Q plot



3.4 Zone substation maximum demand

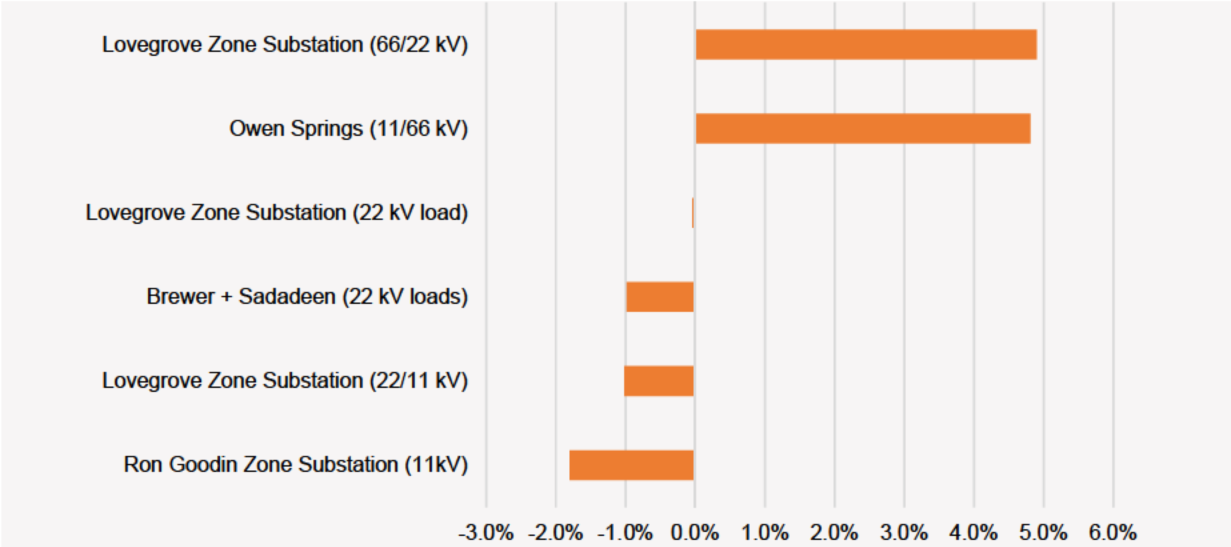
Key findings

The non-coincident summer forecasts for the zone substations in the Alice Springs system are summarised by average annual growth rate in Figure 11. Declining demand is driven by regional population growth and increasing forecast penetration of rooftop PV.

Increasing demand at Owen Springs (11/66 kV) and Lovegrove (66/22 kV) is due to the scheduled late 2018 retirement of the Ron Goodin Power Station. This retirement will increase loads on these two substations, which connect the Owen Springs Power Station with the Alice Springs 22 kV network. The majority of demand by 2019 is expected to be met by Owen Springs Power Station, with Uterne Solar Farm forecast to contribute 3.5 MW to the summer demand peak. Consequently, demand met by Owen Springs Power Station is seen at Owen Springs (11/66 kV) and Lovegrove (66/22 kV) substations.

Charts of the 10% and 50% POE forecasts are included in Appendix H.

Figure 11 Zone Substation Growth Rates (Summer, 10% POE, 2017-18 to 2026-27)



Data preparation

No industrial or large loads were modelled separately when preparing the forecasts for the Alice Springs zone substations.

Linear demand models

The linear demand models (terms and coefficients) used for the recent season are listed in Appendix E.

4. TENNANT CREEK

4.1 Customer connections

Key findings

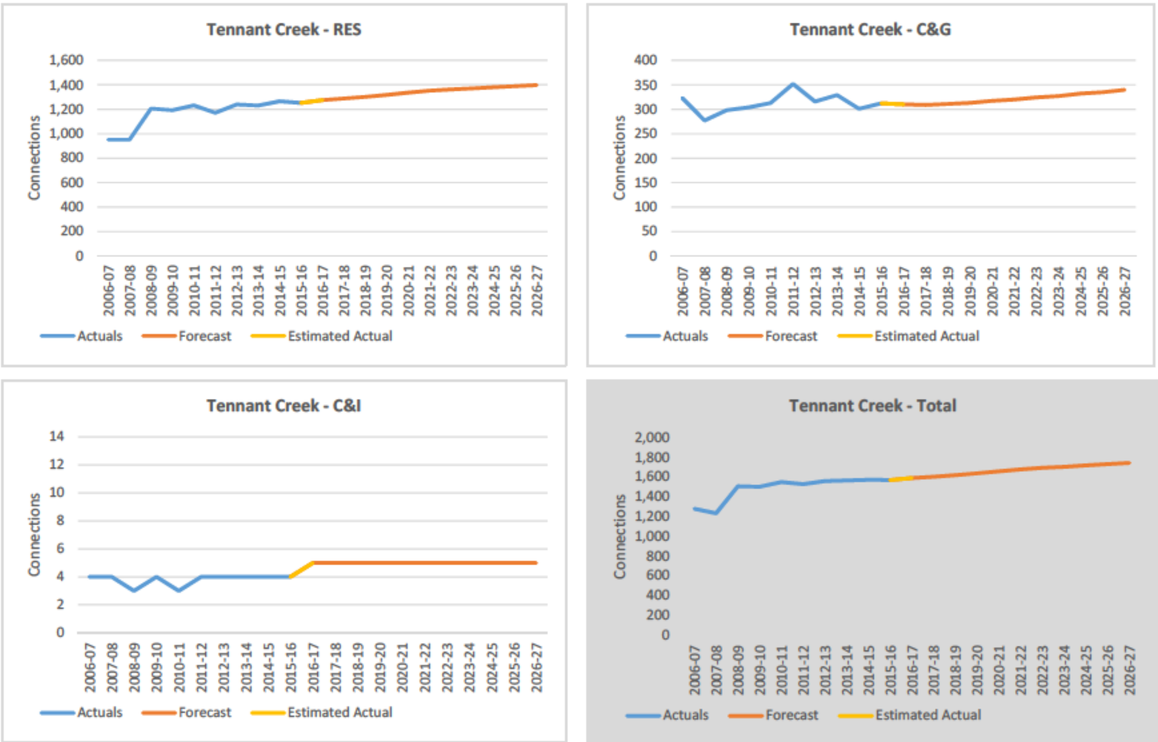
During the 10-year outlook period, both residential and commercial connections are forecast to increase at a rate of 0.9% per annum (see Table 9 and Figure 12), due to the combination of increasing population and GSP. The forecasts for Tennant Creek demonstrate good alignment with historical trends.

The connection forecasts for Alice Springs were derived by splitting the forecasts for the total NT regulated networks. Further detail on the models is in Appendix A.1.

Table 9 Tennant Creek connections forecast

	2017–18	2018–19	2019–20	2020–21	2021–22	2022–23	2023–24	2024–25	2025–26	2026–27
RES	1,288	1,302	1,318	1,336	1,352	1,363	1,371	1,381	1,389	1,397
C&G	309	311	313	317	320	324	327	332	335	340
C&I	5	5	5	5	5	5	5	5	5	5
Total	**1,602**	**1,618**	**1,636**	**1,658**	**1,677**	**1,692**	**1,703**	**1,718**	**1,729**	**1,742**

Figure 12 Tennant Creek connections, actual and forecast



4.2 Energy consumption

Key findings

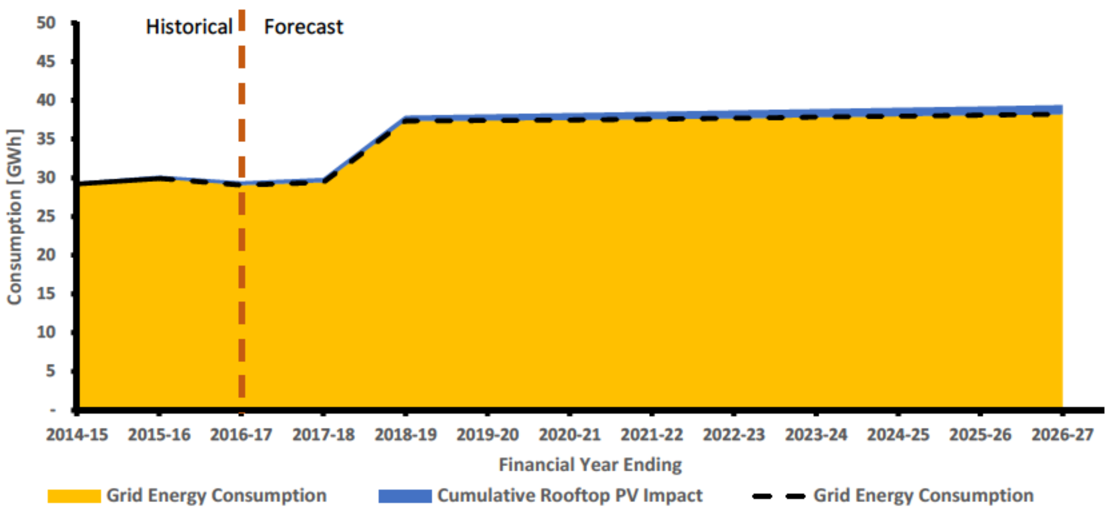
The annual consumption forecast for Tennant Creek, as shown in Table 10 and Figure 13, increases due to block loads for residential and industrial developments and loads supporting the Northern Gas Pipeline project. These block loads produce the step change in the annual consumption forecast for Tennant Creek shown in Figure 13, which results in an average increase of 3.0% per annum.

The impact of population growth is forecast to be largely cancelled out by increasing rooftop PV penetration.

Table 10 Annual consumption forecast (GWh) for Tennant Creek

Type	Year	Tennant Creek forecast
Actual	2014–15	29.2
Actual	2015–16	29.9
Actual	2016–17	29.1
Forecast	2017–18	29.4
Forecast	2018–19	37.3
Forecast	2019–20	37.4
Forecast	2020–21	37.5
Forecast	2021–22	37.6
Forecast	2022–23	37.7
Forecast	2023–24	37.8
Forecast	2024–25	37.9
Forecast	2025–26	38.1
Forecast	2026–27	38.2

Figure 13 Annual consumption forecast (GWh) for Tennant Creek



Linear model

The daily 'base year' consumption model (Y_{TC}) was produced using:

- The last three years of consumption data.
- A CDD (21 ºC base temperature) (X_9).
- A three-day lagged CDD high (26 ºC base temperature) (X_{10}).
- A HDD (18 ºC base temperature) (X_{11}).
- A workday flag variable (X_1).
- A public holiday flag variable (X_2).

Results showed a goodness-of-fit of an adjusted R^2 of 88.7%.

Equation 5 Linear model for Tennant Creek maximum demand

$$Y_{TC} = 52.4 + 7.6X_1 - 6.1X_2 + 3.5X_9 + 1.5X_{10} + 2.0X_{11}$$

4.3 Regional maximum demand

Key findings

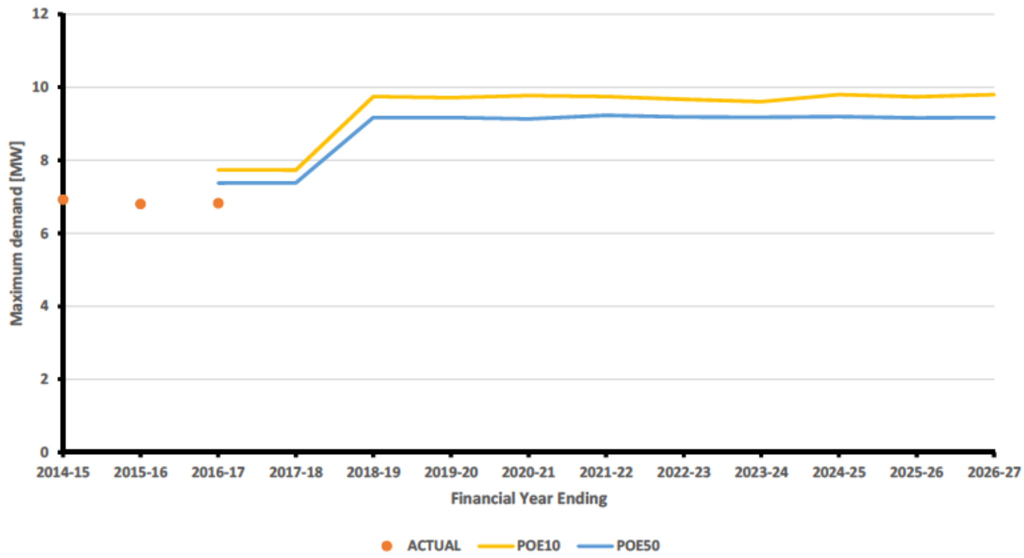
Like the other PWC regions, Tennant Creek is a summer peaking network. Tennant Creek has both cooling load and heating load, although its winter peak is roughly 2.5 MW (30%) lower than its summer peak.

Installed residential and commercial PV capacity is forecast to grow from around 3% of maximum underlying demand in 2017 to 7% of maximum underlying demand in 2027.

Maximum operational demand currently occurs in the heat of the day, at around 3.00 pm in summer. Unlike the other PWC regions, this pattern is expected to continue to occur in the Tennant Creek region, due to its low PV capacity uptake.

As Figure 14 shows, maximum operational demand is forecast to remain flat until 2018, and then, with the introduction of a large load, to grow by about 2 MW between 2018 and 2019. From 2019, maximum operational demand is forecast to remain relatively flat.

Figure 14 Tennant Creek summer MD actual and forecast



Data preparation

The process described in Appendix A.3 was used to identify a number of outliers from 1 December 2014 to 30 June 2017. AEMO compared these outliers against the list of network outages from 2000 to 2017 provided by PWC.

As Tennant Creek is a small system, there were more network outages than in the other two systems. This characteristic made modelling Tennant Creek more difficult than the other systems. It was important to remove the outliers, because outliers can have a big impact on model fit and forecast accuracy particularly when trying to model extreme values such as maximum/minimum demand.

Table 11 details the outliers removed from the analysis.

Table 11 List of outliers removed from sample data

REGIONID	REMOVE_FROM	REMOVE_TO	Reason	Outage_ID
TC	13/02/2015 17:00	13/02/2015 18:00	Network outage	2167279
TC	10/05/2015 06:00	10/05/2015 13:00	Network outage	2190577
TC	06/11/2015 13:00	07/11/2015 09:00	Data entry error	
TC	22/11/2016 14:00	22/11/2016 16:00	Network outage	2352839
TC	09/01/2017 16:00	09/01/2017 18:00	Network outage	2366072
TC	27/02/2017 18:30	01/03/2017 11:00	Data entry error	
TC	23/03/2017 06:00	23/03/2017 08:00	Network outage	2386623
TC	26/04/2017 06:00	26/04/2017 08:00	Network outage	2392424

Linear demand model

The linear model in Equation 6 Linear model for Tennant Creek maximum demand represents the relationship between underlying demand and the drivers of demand in Tennant Creek. Table 12 outlines the coefficients of the hourly models for the hours relevant to MD in Equation 6 Linear model for Tennant Creek maximum demand

.

Every degree increase in the average temperature of the previous three hours (above the CDD critical temperature) in Tennant Creek at 3.00 pm is expected to increase underlying demand by 0.17 MW. However, a degree decrease in the average temperature of the previous three hours (below the HDD critical temperature) is expected to increase underlying demand by 0.09 MW. Generally, public holidays and weekends tend to have lower demand than weekdays, by around 0.56–0.68 MW. Demand between Christmas Eve and the first week of January tends be lower still, around 0.31 MW lower than other weekends and public holidays.

Equation 6 Linear model for Tennant Creek maximum demand

$$\begin{aligned} MW_{hh} = {} & \beta_0 \mathrm{INTERCEPT}_{hh} + \beta_2 \mathrm{PUBLIC\_HOLIDAY}_{hh} + \beta_3 \mathrm{SAT\_DUMMY}_{hh} + \beta_4 \mathrm{SUN\_DUMMY}_{hh} \\ & + \beta_5 \mathrm{SUMMER\_SHUTDOWN}_{hh} + \beta_6 \mathrm{COS\_CD}_{hh} + \beta_7 \mathrm{DRYTEMP\_C\_3DAYLAG\_CD\_EXTR}_{\mathrm{hh}} \\ & + \beta_8 \mathrm{DRYTEMP\_C\_3HRLAG\_CD\_BASE}_{\mathrm{hh}} + \beta_9 \mathrm{DRYTEMP\_C\_CD\_BASE}_{\mathrm{hh}} \\ & + \beta_{10} \mathrm{DRYTEMP\_C\_3HRLAG\_HD\_BASE}_{\mathrm{hh}} + \beta_{11} \mathrm{DRYTEMP\_C\_HD\_BASE}_{\mathrm{hh}} \end{aligned}$$

Table 12 Linear model coefficients

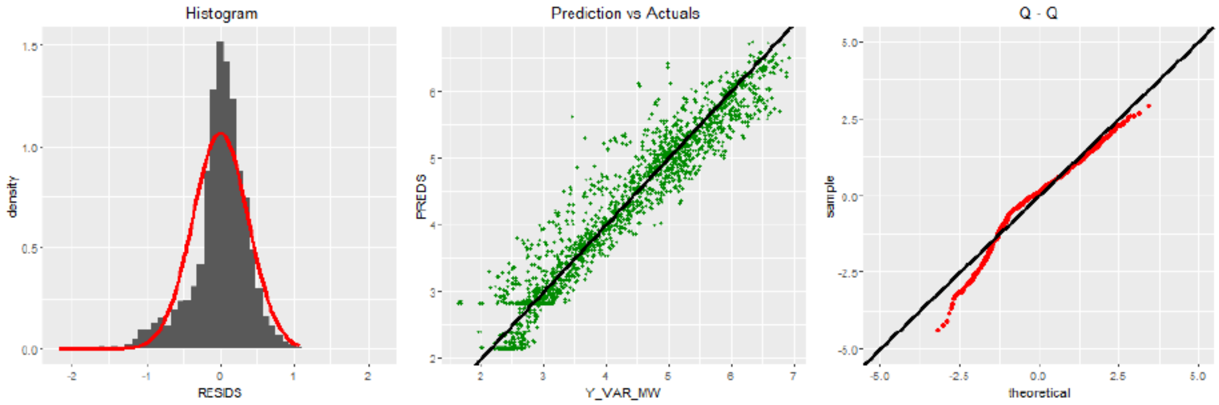
Term	Hour				
	13:00	14:00	15:00	16:00	17:00
INTERCEPT	2.84	2.82	2.82	2.78	2.71
PUBLIC_HOLIDAY	-0.64	-0.62	-0.56	-0.47	-0.34
SAT_DUMMY	-0.74	-0.73	-0.68	-0.49	-0.30
SUN_DUMMY	-0.77	-0.73	-0.65	-0.47	-0.27
SUMMER_SHUTDOWN	-0.38	-0.34	-0.31	-0.28	-0.32
COS_CD	0.30	0.29	0.27	0.26	0.27
DRYTEMP_C_3DAYLAG_CD_EXTR	0.08	0.08	0.08	0.07	0.06
DRYTEMP_C_3HRLAG_CD_BASE	0.00	0.17	0.17	0.16	0.15
DRYTEMP_C_CD_BASE	0.17	0.00	0.00	0.00	0.00
DRYTEMP_C_3HRLAG_HD_BASE	0.00	0.10	0.09	0.13	0.18
DRYTEMP_C_HD_BASE	0.09	0.00	0.00	0.00	0.00
MODEL_SIGMA	0.38	0.37	0.37	0.36	0.35
MODEL_ID	350	485	485	485	485

Figure 15 shows the histogram of the residuals, the predicted vs actuals, and the Q-Q plot for the 3.00 pm linear demand model, because MD in Tennant Creek is around 3.00 pm.

Tennant Creek was the most problematic of the three systems to model, due to the relative size of the network and instability of the system. AEMO spent a significant amount of time understanding and cleaning blackouts from the data which do not reflect the normal operation of the system. This challenge is particularly evident in the Q-Q plot, where there were more low demand events (such as blackouts) or low outliers than should be theoretical given a normal distribution. This challenge is also evident in the negative skew of the distribution of the residuals in the histogram plot.

The prediction vs actual and Q-Q charts in Figure 15 show the model performed well for MD, but there may be a problem using it to forecast minimum demand.

Figure 15 3.00 pm linear model histogram of residuals, predicted vs actuals, and the Q-Q plot



4.4 Zone substation maximum demand

Key findings

The non-coincident summer forecast for the Tennant Creek system is summarised in Table 13. The growth rate of 2.66% is driven by industrial developments at Tennant Creek.

Charts of the 10% and 50% POE forecasts are included in Appendix H.

Table 13 Zone substation growth rates (Summer, 10% POE, 2017–18 to 2026–27)

Substation name	Rate (per annum)
Tennant Creek Zone Substation (11/22 kV)	2.66%

Data preparation

No industrial or large loads were modelled separately when preparing the forecast for Tennant Creek zone substation.

Linear demand models

The linear demand models (terms and coefficients) used for the recent season are listed in Appendix E.

ABBREVIATIONS

Abbreviation	Expanded name
AS	Alice Springs
BoM	Bureau of Meteorology
C&G	Commercial & Government
C&I	Commercial & Industrial
CDD	Cooling Degree Day
DK	Darwin–Katherine
GSP	Gross State Product
GWh	Gigawatt Hour
HDD	Heating Degree Day
kV	Kilovolt
MD	Maximum Demand
MVA	Mega Volt Ampere
MW	Megawatt
NT	Northern Territory
POE	Probability of Exceedance
PV	Photovoltaic
PWC	Power and Water Corporation (Northern Territory)
RES	Residential
SCADA	Supervisory Control and Data Acquisition
TC	Tennant Creek
ZSS	Zone substation

APPENDIX A. METHODOLOGY OVERVIEW

A.1 Customer connections

Overview

PWC provided AEMO with 10 years of connection numbers for each network and each connection type. The three types of connections are:

- Residential (RES).
- Commercial and government, with consumption less than 750 megawatt hours (MWh) (C&G).
- Commercial and industrial, with consumption above 750 MWh (C&I).

Using the installation numbers, NT population (X1), and GSP (X2), AEMO developed a regression model to forecast the total, RES, and C&I connections. C&G connections were calculated as the difference to total connections.

$$Total\ connections = 46{,}541 - 3.8X_1/1000 + 155.7X_2/100$$

$$RES\ connections = 48{,}331 - 59.1X_1/1000 + 152.6X_2/100$$

$$C\&I\ connections = -57 + 0.4X_1/1000 + 0.9X_2/100$$

$$C\&G\ connections = Total\ connections - (RES\ connections + C\&I\ connections)$$

Each connection type is further split into the three individual regions (Darwin–Katherine, Alice Springs and Tennant Creek).

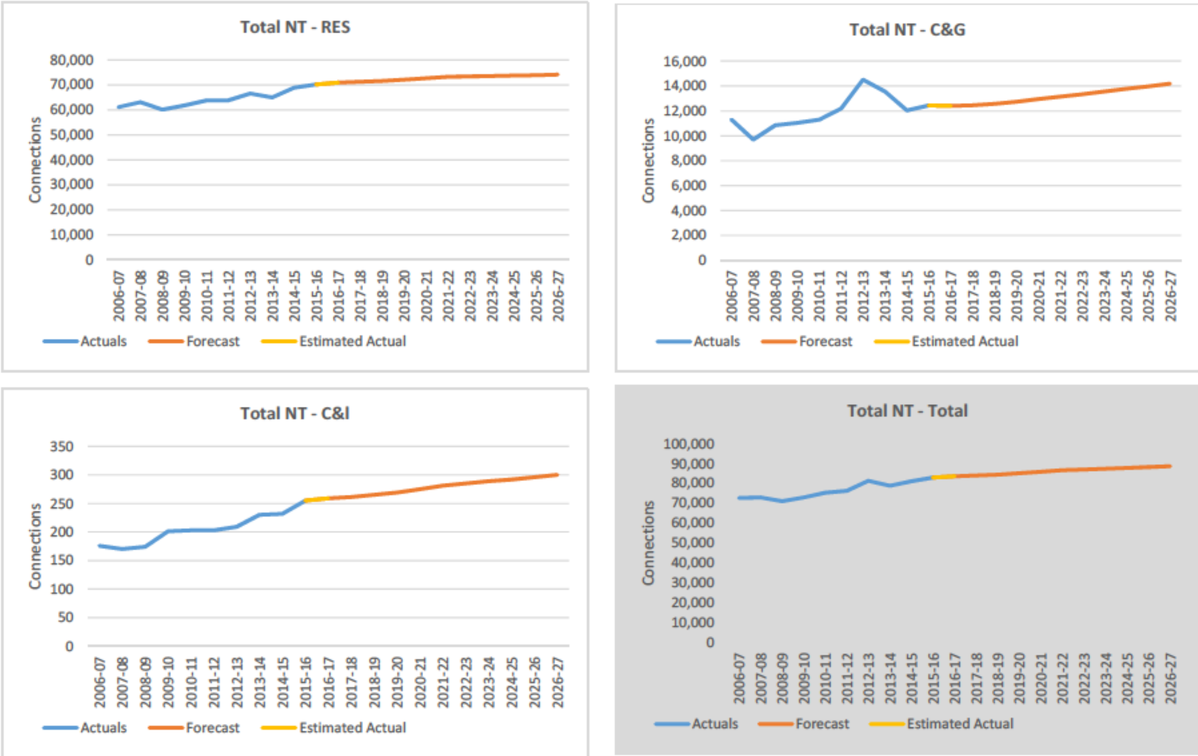
Total regulated network connections forecast

Connections forecasts were also prepared for the total of the NT regulated networks. Table 14 summarised the forecasts, and Figure 16 plots the forecasts, including historical connection numbers.

Table 14 Total NT regulated market connections forecast

	2017–18	2018–19	2019–20	2020–21	2021–22	2022–23	2023–24	2024–25	2025–26	2026–27
RES	71,243	71,586	72,061	72,628	73,208	73,388	73,570	73,752	73,935	74,119
C&G	12,455	12,569	12,742	12,945	13,152	13,355	13,560	13,770	13,983	14,197
C&I	261	265	269	275	281	285	289	292	296	300
Total	**83,959**	**84,420**	**85,072**	**85,848**	**86,641**	**87,028**	**87,419**	**87,814**	**88,214**	**88,616**

Figure 16 Total NT regulated market connections, actual and forecast



A.2 Energy consumption

Overview

The annual consumption forecasts are designed to capture the main historical drivers in electricity consumption, and expected drivers and trends over the 10-year forecast horizon. This trajectory is then used when generating the MD forecasts to capture the year-on-year variation.

The foundation of the annual consumption forecast was a weather-based regression model built from daily system consumption data, correlated against weather data from weather stations in close proximity to demand centres. This model was then used to create a 'base year' forecast. The base forecast year assumes median weather data to capture seasonal effects in electricity consumption.

The forecast was then grown on an annual basis, applying both positive (such as connections growth) and negative demand drivers (such as rooftop PV).

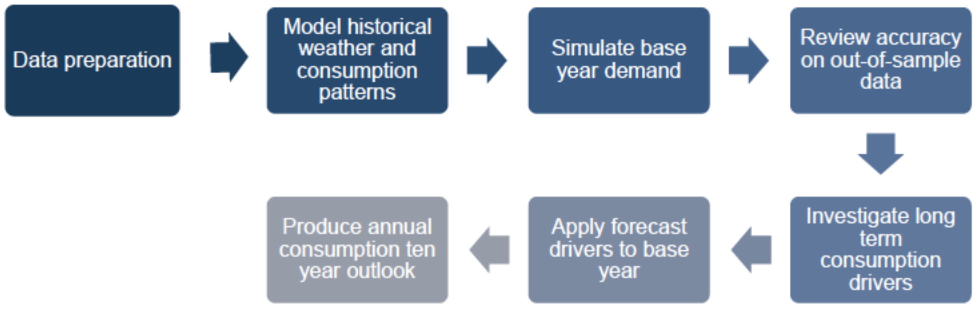
The following indicators were used to drive future changes in electricity consumption:

- Residential connection growth.
- GSP growth and large load variations.
- Rooftop PV installations.

The following sections discuss the modelling approach for accommodating weather variability and the identified drivers of consumption.

Figure 17 outlines the key steps in the annual consumption forecasting process.

Figure 17 Annual consumption forecasting process



Assumptions

Forecasts of population and GSP were sourced from the NT 2017–18 Budget Paper. The population forecasts used for each network were:

- Darwin–Katherine network – combined Greater Darwin and Katherine population.
- Alice Springs network – Alice Springs population.
- Tennant Creek network – Barkley population.

From these population forecasts, the following long-term population growth rates were adopted:

- Darwin–Katherine network – increasing by 2% per annum.
- Alice Springs network – decreasing by 0.1% per annum.
- Tennant Creek network – increasing by 0.9% per annum.

PV installations by 2016–27 were projected to reach:

- Darwin–Katherine network – 15% of households.
- Alice Springs network – 20% of households.
- Tennant Creek network – average capacity for future installations of 6.5 kilowatts (kW) per unit.

For commercial rooftop PV installations, the average capacity was assumed to be 30 kW per unit, and AEMO forecast a total of 418 units would be installed over the 10-year forecast period, with a higher uptake of about 60 units per year in the first four years of the forecast.

The installed capacity projection for each power system is in Table 15.

Table 15 Rooftop PV installed capacity projection (MW)

Year	Darwin–Katherine	Alice Springs	Tennant Creek
2017–18	44.3	12.2	0.4
2018–19	51.1	13.7	0.4
2019–20	57.9	15.2	0.5
2020–21	63.6	16.5	0.6
2021–22	69.0	17.7	0.6
2022–23	74.3	18.7	0.6
2023–24	78.5	19.5	0.7
2024–25	82.6	20.3	0.7
2025–26	86.6	21.0	0.7
2026–27	90.1	21.6	0.7

Weather variability

The relationship of daily electricity consumption with daily weather data enables an assessment of the changes in electricity consumption due to customer behavioural responses, with use of appliances such as air-conditioners and heaters resulting from hot and cold weather.

The methodology used a linear-based regression model to capture the historical relationships, by testing the correlation with different meteorological variables such as temperature, humidity, wind speed, and dew point.

Splitting the consumption behaviour into heating and cooling components supports a more granular MD forecast.

To determine cooling load levels, a cooling degree day (CDD) parameter was used as an indicator of how much energy is consumed by cooling equipment. It links each day's average temperature to a threshold base temperature. On days when the average temperature rises above the base temperature, energy for cooling is said to be required.

CDDs are calculated in accordance with Equation , where the average daily temperature is denoted as T_{avg}, and the base temperature is denoted as T_{base}.

Equation 7 Formula for CDD

$$CDD = Max(T_{avg} - T_{base}, 0)$$

Similarly, to determine heating load levels an HDD parameter was defined analogous to the CDD. When the daily average temperature is below the HDD base temperature energy is said to be required for heating.

The formula for HDD is below in Equation .

Equation 8 Formula for HDD

$$HDD = Max(T_{base} - T_{avg}, 0)$$

To obtain the best correlation of HDDs and CDDs with demand, T_{base} was chosen after examining the correlation between grid demand on a daily level against multiple values of T_{base}, because differences can occur across climate regions.

To capture latent heating and cooling effects (for example, a heatwave or a cold snap over a few days) which drive a larger increase in electricity demand, not captured by T_{avg} alone, AEMO tested lagged CDD and HDD variables against grid data in the regression model for their significance in driving electricity consumption.

Other meteorological variables, such as wind speed, wind direction, humidity, and dew point, were trialled in the regression model in a step-wise fashion, with their inclusion based on their level of significance when performing out-of-sample testing on the model.

Because electricity demand has also been shown to exhibit differences on weekends, public holidays, and across holiday periods, additional categorical parameters which reflect day types were included in the regression model to best capture expected consumption behaviours on these days.

AEMO then assessed the performance of the model and selected the most significant parameters which best describe electricity consumption in terms of heating, cooling, and base load for the base year.

Consumption forecast (excluding large loads)

AEMO calculated an average annual consumption level for customers in the NT using a combination of metered data and publicly available data.

The average consumption level was split into base, cooling, and heating loads, to enable monitoring of different growth patterns over the forecast horizon.

AEMO calculated the forecast by taking the average customer's usage, multiplied by the number of customers expected over the forecast period. The growth in consumption expected from new customers was then added to the base year consumption, as determined by the regression model.

Forecast rooftop PV output over the next 10 years was then removed from the total forecast to calculate a total expected forecast for customers excluding large loads.

Gross State Product forecasts and large loads

AEMO used GSP forecasts in conjunction with a registry of expected large loads d to derive the consumption forecast for non-residential customer sectors.

Economic activity and electrical consumption were correlated by examining the historical relationship of GSP with non-residential consumption, providing a baseline relationship for the growth forecast in Darwin–Katherine. Historical GSP and future estimates were used to calculate Darwin–Katherine growth forecasts.

The load log was also used to capture any committed projects in the pipeline which may not have been captured by examining GSP forecasts. Projects which were not committed may have been considered for inclusion if they were expected to be reasonably likely to proceed and well justified, and network augmentation lead times were longer than project commitment times. The certainty around the likelihood of these loads proceeding is generally limited to 24 months in advance.

For this forecast, PWC only considered those loads logged in this time period, unless further confirmation was obtained.

Using regression on daily demand data, AEMO developed a 'base year' consumption model for each network region reflecting current consumption patterns.

A.3 Regional Maximum Demand

Overview

AEMO developed regional MD by season using a probabilistic methodology because demand is dependent on weather conditions and random shocks in response to weather, and these vary from year to year.

Due to this variability, forecast MD is expressed as probability of exceedance (POE) values from a distribution, rather than a point forecast. For any given season or year:

- A 10% POE MD value is expected to be exceeded, on average, one year in ten.
- A 50% POE MD value is expected to be exceeded, on average, one year in two.

AEMO produced MD values for summer (defined as November to March) and winter (defined as June to August) for each regional power system. As each PWC region peaks in summer, the summer MD value represents the regional annual MD.

Data preparation

PWC provided AEMO with half-hourly regional demand data (in megawatts (MW)) for Alice Springs, Darwin–Katherine, and Tenant Creek from July 2013 to July 2017.

AEMO sourced half-hourly weather data from airport weather stations in Darwin, Tennant Creek, and Alice Springs from the Bureau of Meteorology (BoM).

PWC provided current rooftop photovoltaic (PV) installed capacity from the PWC PV database, which was mapped to the PWC network. AEMO used this to estimated historical rooftop PV generation as described in Section 3 of the *2017 PWC Maximum Demand and Customer Connections Forecasting Procedure*.

AEMO performed its modelling on underlying demand. This represents the power consumers draw from the power point, as opposed to the power sent out from generating sources. The forecasts, however, were finalised to represent power required to be sent out from the generating sources.

Exploratory data analysis

Exploratory data analysis (EDA) was used to detect outliers and identify important demand drivers for the model development stage.

Outlier detection and removal

AEMO used outlier detection procedures to find and remove outliers which were due to data errors or outages. AEMO specified a basic linear model, and examined all observations that were more than three standard deviations from the predicted value for each half hour.

AEMO then used the list of network outages from 2000 to 2017 provided by PWC to confirm whether the lower demand outliers were driven by network outages.

AEMO also removed some outliers that were due to obvious data entry errors. On a number of occasions, there were high demand outliers where the demand value at 3.00 pm or 4.00 pm (when demand is high) was carried forward to 1.00 am or 2.00 am (when demand is low).

EDA to identify important demand drivers

AEMO also used EDA to identify key variables that drive demand, by examining the summary statistics of each variable, the correlation between each explanatory variable to identify multicollinearity, and the correlation between the explanatory variables and demand. For a list of all variables considered, see Appendix D.

Broadly, the EDA process examined:

- Weather – temperature variables including cooling degree days (CDDs) and heating degree days (HDDs), outlined in Section 5.2 of the *2017 PWC Maximum Demand and Customer Connections Forecasting Procedure*.
- Calendar/seasonal variables, including weekend and public holiday Boolean (true/false) variables

During this process, AEMO explored different critical temperature cut-offs to formulate the CDD and HDD variables. AEMO selected the critical temperature cut-offs that best captured the inflection point in the relationship between temperature and demand.

Model development and selection

AEMO specified 24 models for each hour of the day for each of the three regions using the variables identified as important in the EDA step.

The models were trained on 2.5 years of historical data, from 1 December 2014 to 30 June 2017, at half-hourly frequency. The hourly demand models using half-hourly data resulted in two data points for each hourly model for each day in the sample data, comprising roughly 1,900 data points per model.

These models describe the relationship between underlying demand and explanatory variables including calendar effects such as public holidays, day of the week and month in the year and weather effects (CDD and HDD as described in Section 5.2 of the *2017 PWC Maximum Demand and Customer Connections Forecasting Procedure*).

AEMO specified an array of models for each hour using the variables available, and explored a range of model formulations and variables with different combinations of variables and measure for weather. The models were linear in the parameters.

These models helped find the most accurate description of the electricity demand. AEMO then used an algorithm which culled any models that had:

- Variance Inflation Factor[4] greater than 4.
- Nonsensical coefficients signs – all the coefficients must have reasonable signs. Cooling degree and heating degree variables should be positively correlated with demand, and weekend and public holidays should be negatively correlated with demand unless it is a tourist economy.
- Insignificant coefficients.

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

- Goodness-of-fit – R-Squared, Akaike information criterion, and Bayesian information criterion.
- Out-of-sample goodness-of-fit – for each model, AEMO performed 10-fold cross validation[5] to calculate the out-of-sample forecast accuracy.
- Histogram of the residuals, quantile-quantile (Q-Q) plot, and residual plots.

Simulate base year (weather normalisation)

AEMO then used the linear models selected above to simulate demand for each region. AEMO simulated historical weather events to develop a weather distribution to weather normalise demand and random shocks in response to demand drivers.

Equation 9 Demand and randomised shock

$$MW_{hh} = f(x_{hh}) + \varepsilon_{hh}$$

where

- $f(x_{hh})$ is the relationship between demand and the demand drivers such as weather
- ε_{hh} represents random normally distributed[6] changes in demand not explained by the model demand drivers.

AEMO simulated weather for the base year by bootstrapping historical weather observations (x_{hh}, the first term in Equation) to create a year consisting of 17,520 half-hourly weather observations. The process built a synthetic weather year by randomly selecting 26 fortnightly weather patterns ("weather blocks"), ensuring that the weather block was assigned to the corresponding time of the year.

AEMO bootstrapped from historical weather data from 1 July 2006 to 30 June 2017. As the bootstrapping method sampled actual historical weather blocks, the process preserved the natural relationship between time-of-year, temperature, and solar irradiance. No warming trend was applied to the historical weather data to account for the presence of climate change.

AEMO performed 1,000[7] weather simulations to create 1,000 weather years of simulated weather data, each consisting of 17,520 half-hourly weather observations.

AEMO then used the linear models to estimate demand for the given conditions of the synthetic year and the relationship between demand and the conditions implied by the models.

At the same time, AEMO simulated a random shock, meaning the component of demand variability that is not explained by weather conditions and other demand drivers captured in the linear model (ε_{hh}, the second term in Equation). This shock recognises that there is some variability the model does not

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

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

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

[7] Previous tests have found that 500 Monte Carlo simulations is a sufficient number of simulations to converge to a stable result that varies by less than half a percent.

capture, but which is important to include in the weather-normalisation process. The process produces half-hourly demand traces for 1,000 synthetic years.

The simulation process recognises that there are several drivers of demand including weather, day of week, and hour of day, as well as random shocks in demand. The process also preserves the probabilistic relationship between demand and the drivers of demand.

Forecast probability of exceedance

The demand values produced by the previous process reflected the relationship between demand and weather conditions as at the reference year 2017. The forecast process grows the demand values by economic, demographic and technical conditions.

AEMO grew all the components of demand in the half-hourly demand traces produced by Equations 2, 4 and 6 and the simulation process by the growth in annual consumption (see Chapter A.2 for more detail).

The annual growth index was found by considering the forecast year-on-year change in annual consumption as described in Chapter A.2. AEMO then applied the forecast year-on-year change to each of the 17,520 half-hours for each simulation and each forecast year, to grow the demand for each half-hour in the relevant forecast year.

As the linear models were trained on underlying demand, they represent the relationship between underlying demand and conditions. To find the grid MD, AEMO translated demand from underlying to operational demand by subtracting PV generation given the solar irradiance from underlying demand for each half-hour.

AEMO then extracted the operational MD values. This is the maximum half-hourly prediction of the 17,520 half-hourly predictions in a given year, for each year in the forecast horizon, such that there were 1,000 values for each forecast year. From the 1,000 simulated maxima, AEMO then extracted the 50% and 10% POEs as well as the weather and calendar conditions at the time of MD.

Finally, AEMO calculated PV generation using the most probable weather conditions at the time of 10% and 50% POE MD, to calculate operational demand. For demand definitions, see Appendix C.

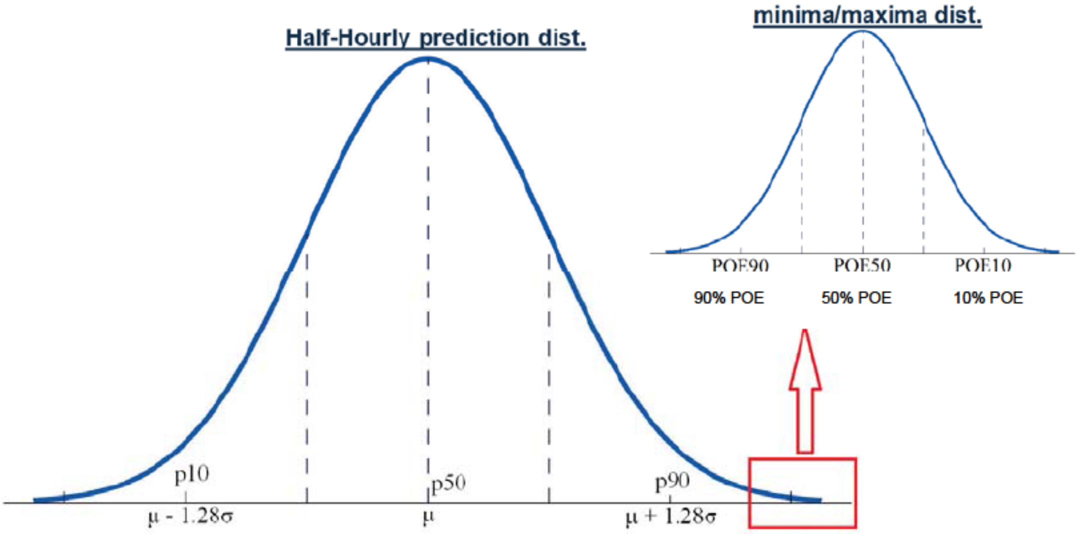
In Figure 18:

- The first bell (or normal) curve represents the distribution of the 17,520 half-hours for each simulation for each forecast year. Data for one half-hour representing the largest predicted MD, indicated by the red box and arrow, was then extracted from the 17,520 half-hours and added to the distribution of annual maxima, represented by the smaller bell curve. This extraction was repeated 1,000 times, once for each simulation.
- The second smaller bell curve represents the distribution of maxima which may or may not be normally distributed.[8]

AEMO extracted MD values by region from this maxima distribution by selecting the 50th and 90th percentile as 50% POE and 10% POE values, respectively.

[8] It is not necessary for the minima or maxima to follow a normal distribution. Regardless of whether the distribu ion is skewed, leptokurtic, mesokurtic or platykur ic, the percentiles can be found by ranking the minimum/maximum demand values and extracting the desired percentile.

Figure 18 Theoretical distribution of annual half-hourly data to derive minima/maxima distribution



A.4 Zone substation maximum demand

Overview

AEMO developed zone substation MD using a probabilistic methodology, because demand is dependent on weather conditions. Forecast MD is represented by a POE from a distribution rather than a point forecast. For any given season or year:

- A 10% POE MD value is expected to be exceeded, on average, one year in ten.
- A 50% POE MD value is expected to be exceeded, on average, one year in two.

AEMO produced MD values for summer (defined as November to March) and winter (defined as June to August) for each zone substation.

Data

Forecasts of MD at the zone substations were prepared using MW loads from the zone substation and meter data files. Generally the primary data source was SCADA, using instantaneous readings on the half-hour or hour from the transformers, and the secondary data source was revenue meter data at network assets. Data was cleaned and adjusted for load transfers, switching and data errors. Where data was available only as Mega Volt Ampere (MVA), MW loads were obtained by applying observed power factors to the cleaned MVA load.

Embedded generation and rooftop PV

AEMO removed the effect of rooftop PV from the demand history to provide an estimate of underlying customer demand. Installed PV capacities at each zone substation were estimated from installation records maintained by PWC. The relative percentages of installed capacity at each substation are in Appendix F. No embedded generators were identified for explicit treatment in the demand history across PWC's three regions.

Weather data

Relative humidity and temperature readings were obtained from BoM stations in the NT.

These measurements were used to calculate a heat index[9], a measure of how hot it feels when relative humidity is factored in with the actual air temperature. From these readings, daily maximum temperature, daily maximum heat index and daily minimum temperature were prepared for testing demand-weather relationships.

The decision to apply the heat index, maximum temperature or minimum temperature in the demand-weather relationship was based on which measurements better correlated to demand. A full list of each zone substations' weather station and demand-weather model parameters is in Appendix B and Appendix E.

Weather normalisation

30 years of weather data were used and 500 simulations per year were performed to generate a distribution of MD. The 50th and 90th percentiles were selected from the MD distribution as the 50% POE and 10% POE levels.

Block loads, transfers, and switching

AEMO applied block loads, transfers, and switching periods in the forecast, if categorised as committed. These were applied as post-model adjustments to the zone substation MD forecasts. Typically, these changes were in units of MVA, and were therefore converted to MW using a power factor obtained from historical data. The block loads, transfers, and switching included in the forecasts are summarised in Appendix G.

Reconciliation and coincidence

The non-coincident zone substation forecasts were reconciled to the relevant regional MD forecasts from Chapters 2.3, 3.3 and 4.3 for each year in the 10-year forecast period. The reconciliation process also produced coincident zone substation forecasts in MW, starting from an unreconciled estimate of coincident demand based on diversity factors representing the ratio of coincident-to-non-coincident MD at the zone substation.

Regional diversification

AEMO produced NT-wide system MD estimates for regulatory information notice template tables 3.4.3.1 to 3.4.3.4, where system demand was defined as the sum of the three PWC power systems.

The three power systems peak at different times, much as zone substations peak at different times within a single network. The individual coincident peaks of each network were diversified to produce an NT-wide system peak. The timing of the NT-wide peak was closely aligned with Darwin–Katherine's peak, due to its relative size within NT.

Generator connection point forecasts

AEMO produced MD estimates at the generator connection points for regulatory information notice template tables 3.4.3.2 and 3.4.3.4.

In networks other than NT, these network elements are typically transmission connection points.

AEMO used generator output data in MW from 2015 to 2017 to estimate each generator's non-coincident MD, and projected this forward with no growth as the forecast maximum output to 2024. NT-wide non-coincident MD at the generator connection points has been provided as the sum of all generators' non-coincident forecasts. NT-wide coincident MD at the generator connection points is equivalent to NT-wide coincident MD, as calculated in 'Regional diversification' above.

[9] The heat index is described at: http://www.wpc.ncep.noaa.gov/html/heatindex.shtml and the formulation used is described at: https://cran.r-project.org/web/packages/weathermetrics/weathermetrics.pdf.

APPENDIX B. WEATHER STATION SELECTION FOR SUBSTATIONS

Zone substations were paired with weather from Bureau of Meteorology (BoM) stations.

Table 16 Weather station selection

Substation ID	BoM station ID	BoM station Name
Archer_66_11	14015	Darwin Airport
Batchelor_132_22	14015	Darwin Airport
Berrimah_66_11	14015	Darwin Airport
Casuarina_66_11	14015	Darwin Airport
Centre_Yard_66_11	14015	Darwin Airport
Cosmo_Howley_66_66	14901	Douglas River
Darwin_66_11	14015	Darwin Airport
Frances_Bay_66_11	14015	Darwin Airport
Hudson_Creek_132_66	14015	Darwin Airport
Humpty_Doo_66_22	14015	Darwin Airport
Katherine_132_22	14932	Tindal
Leanyer_66_11	14015	Darwin Airport
Manton_132_22	14015	Darwin Airport
Marrakai_66_22	14015	Darwin Airport
Mary_River_66_22	14901	Douglas River
Strangways_66_22	14015	Darwin Airport
Palmerston_66_11	14015	Darwin Airport
Palmerston_11_22	14015	Darwin Airport
Pine_Creek_66_66	14901	Douglas River
Pine_Creek_11_22	14901	Douglas River
Pine_Creek_11_66	14901	Douglas River
Pine_Creek_132_66	14901	Douglas River
Tindal_22_11	14932	Tindal
Weddell_66_22	14015	Darwin Airport
Wishart_Modular_66_11	14015	Darwin Airport
Woolner_66_11	14015	Darwin Airport
Brewer_Sadadeen_22_22	15590	Alice Springs Airport
Brewer_Sadadeen_22_22	15590	Alice Springs Airport
Lovegrove_22_11	15590	Alice Springs Airport
Lovegrove_22_22	15590	Alice Springs Airport
Lovegrove_66_22	15590	Alice Springs Airport
Owen_Springs_11_66	15590	Alice Springs Airport
Sadadeen_11_11	15590	Alice Springs Airport
Brewer_Sadadeen_22_22	15590	Alice Springs Airport
Tennant Creek	15135	Tennant Creek Airport

APPENDIX C. DEMAND DEFINITIONS

Name	Abbreviation	Formula
Operational demand as generated	OPGEN_MW	MW reported by PWC
Operational demand sent out	OPSO_MW	= OPGEN_MW + AUX (which is assumed to be zero)
Native demand	NATSO_MW	= OPSO_MW + Non-scheduled generation (which is assumed to be zero)
Delivered demand	DEL_MW	= NATSO_MW – Losses (which are assumed to be zero)
PV Generation	PV_GEN_MW	
Underlying demand	UND_MW	= DEL_MW + PVGEN_MW

APPENDIX D. WEATHER MODEL VARIABLES

The following weather model variables were tested for the regional MD forecasts.

X variable	Purpose	Weather variable	Temporal
DRYTEMP_C_3DAYLAG_HD_EXTR	Cold wave measure	Dry bulb temperature	3 Day rolling average
DRYTEMP_C_DAYLAG_HD_EXTR	Cold wave measure	Dry bulb temperature	1 Day rolling average
HEAT_INDEX_3DAYLAG_HD_EXTR	Cold wave measure	Heat index	3 Day rolling average
HEAT_INDEX_DAYLAG_HD_EXTR	Cold wave measure	Heat index	1 Day rolling average
DRYTEMP_C_3HRLAG_CD_BASE	Current cooling degrees	Dry bulb temperature	3 Hour rolling average
DRYTEMP_C_3HRLAG_CD_EXTR	Current cooling degrees	Dry bulb temperature	3 Hour rolling average
DRYTEMP_C_CD_BASE	Current cooling degrees	Dry bulb temperature	Instantaneous
DRYTEMP_C_CD_EXTR	Current cooling degrees	Dry bulb temperature	Instantaneous
HEAT_INDEX_3HRLAG_CD_BASE	Current cooling degrees	Heat index	3 Hour rolling average
HEAT_INDEX_3HRLAG_CD_EXTR	Current cooling degrees	Heat index	3 Hour rolling average
HEAT_INDEX_CD_BASE	Current cooling degrees	Heat index	Instantaneous
HEAT_INDEX_CD_EXTR	Current cooling degrees	Heat index	Instantaneous
DRYTEMP_C_3HRLAG_HD_BASE	Current heating degrees	Dry bulb temperature	3 Hour rolling average
DRYTEMP_C_3HRLAG_HD_EXTR	Current heating degrees	Dry bulb temperature	3 Hour rolling average
DRYTEMP_C_HD_BASE	Current heating degrees	Dry bulb temperature	Instantaneous
DRYTEMP_C_HD_EXTR	Current heating degrees	Dry bulb temperature	Instantaneous
HEAT_INDEX_3HRLAG_HD_BASE	Current heating degrees	Heat index	3 Hour rolling average
HEAT_INDEX_3HRLAG_HD_EXTR	Current heating degrees	Heat index	3 Hour rolling average
HEAT_INDEX_HD_BASE	Current heating degrees	Heat index	Instantaneous
HEAT_INDEX_HD_EXTR	Current heating degrees	Heat index	Instantaneous
DRYTEMP_C_3DAYLAG_CD_EXTR	Heat Wave measure	Dry bulb temperature	3 Day rolling average
DRYTEMP_C_DAYLAG_CD_EXTR	Heat Wave measure	Dry bulb temperature	1 Day rolling average
HEAT_INDEX_3DAYLAG_CD_EXTR	Heat Wave measure	Heat index	3 Day rolling average
HEAT_INDEX_DAYLAG_CD_EXTR	Heat Wave measure	Heat index	1 Day rolling average
MONTH	Month of year	NA	NA
PUBLIC_HOLIDAY	Public holiday Boolean	NA	NA
WEEKEND	Public holiday Boolean	NA	NA
SCHOOL_HOLIDAY	School holiday Boolean	NA	NA
SUMMER_SHUTDOWN	Summer/Christmas Boolean	NA	NA
COS_CD	Seasonality of cooling degrees	NA	NA
COS_HD	Seasonality of heating degrees	NA	NA

APPENDIX E. ZONE SUBSTATION DEMAND-WEATHER MODELS

The following table lists the coefficients that were used for creating demand-weather relationships with daily data. Only model coefficients for the most recent seasons are reported. An NA value signifies that the coefficient was not used. The R-squared value for each relationship is provided as an indicator of the strength of the demand-weather relationship. In situations where the relationship was weak, a constant model was generally adopted and in these situations only the intercept is used.

Analysis by AEMO indicated that the heat index correlated well with demand at many zone substations in the Darwin region.

Substation ID	Season	Season Year	Intercept	Max Temp	Min Temp	Heat Index	R-squared
Brewer_Sadadeen_22_22	Summer	2017	-1.7189	0.2279	NA	NA	0.6802
Brewer_Sadadeen_22_22	Winter	2016	5.7032	NA	-0.0827	NA	0.4116
Lovegrove_22_11	Summer	2017	-5.1857	0.5641	NA	NA	0.5447
Lovegrove_22_11	Winter	2016	14.5471	NA	-0.2103	NA	0.4002
Lovegrove_22_22	Summer	2017	0.5535	NA	NA	NA	NA
Lovegrove_22_22	Winter	2016	0.4638	NA	NA	NA	NA
Lovegrove_66_22	Summer	2017	0.1959	0.5068	NA	NA	0.2236
Lovegrove_66_22	Winter	2016	26.4053	-0.3475	NA	NA	0.1838
Owen_Springs_11_66	Summer	2017	1.8550	0.4189	NA	NA	0.1635
Owen_Springs_11_66	Winter	2016	24.3709	-0.3419	NA	NA	0.1743
Sadadeen_11_11	Summer	2017	-1.1471	0.5459	NA	NA	0.5563
Sadadeen_11_11	Winter	2016	9.8770	-0.0867	-0.3436	NA	0.2812
Tennant_Creek_11_22	Summer	2017	-1.5165	0.1919	NA	NA	0.5717
Tennant_Creek_11_22	Winter	2016	2.5879	NA	0.0823	NA	0.3736
Archer_66_11	Summer	2017	-27.7329	1.5384	NA	NA	0.4964
Archer_66_11	Winter	2016	-11.0056	NA	NA	0.9235	0.8081
Batchelor_132_22	Summer	2017	-1.3266	0.0843	NA	NA	0.3274
Batchelor_132_22	Winter	2016	-0.3012	NA	NA	0.0509	0.3775
Berrimah_66_11	Summer	2017	-13.5851	1.1431	NA	NA	0.6111
Berrimah_66_11	Winter	2016	-0.5125	NA	NA	0.6770	0.5829
Casuarina_66_11	Summer	2017	-2.8226	NA	NA	0.9594	0.6509
Casuarina_66_11	Winter	2016	-5.5067	NA	NA	0.9232	0.8381
Centre_Yard_66_11	Summer	2017	-0.1951	NA	NA	0.0086	0.4226
Centre_Yard_66_11	Winter	2016	0.2179	NA	NA	-0.0030	0.2150
Cosmo_Howley_66_66	Summer	2017	3.7139	NA	NA	NA	NA
Cosmo_Howley_66_66	Winter	2016	2.9957	NA	NA	NA	NA
Darwin_66_11	Summer	2017	-2.7112	NA	NA	0.6890	0.2706
Darwin_66_11	Winter	2016	-6.8835	NA	NA	0.8991	0.4978
Frances_Bay_66_11	Summer	2017	5.4743	NA	NA	0.3662	0.3341

Substation ID	Season	Season Year	Intercept	Max Temp	Min Temp	Heat Index	R-squared
Frances_Bay_66_11	Winter	2016	-0.9109	NA	NA	0.5773	0.6525
Hudson_Creek_132_66	Summer	2017	-7.8703	5.0688	NA	NA	0.3902
Hudson_Creek_132_66	Winter	2016	11.2024	NA	NA	3.5661	0.5590
Humpty_Doo_66_22	Summer	2017	-1.0453	0.0656	NA	NA	0.4813
Humpty_Doo_66_22	Winter	2016	1.1771	0.0076	NA	NA	0.0082
Katherine_132_22	Summer	2017	-12.4692	0.9372	NA	NA	0.6867
Katherine_132_22	Winter	2016	-3.8637	0.6260	NA	NA	0.5148
Leanyer_66_11	Summer	2017	-7.3337	0.5328	NA	NA	0.6568
Leanyer_66_11	Winter	2016	-4.2343	NA	NA	0.3717	0.7703
Manton_132_22	Summer	2017	-2.2259	0.1369	NA	NA	0.4726
Manton_132_22	Winter	2016	-0.1615	0.0873	NA	NA	0.3087
Marrakai_66_22	Summer	2017	-0.6742	0.0396	NA	NA	0.5805
Marrakai_66_22	Winter	2016	-0.0439	0.0235	NA	NA	0.4051
Mary_River_66_22	Summer	2017	1.7996	NA	NA	NA	NA
Mary_River_66_22	Winter	2016	1.9889	NA	NA	NA	NA
Palmerston_11_22	Summer	2017	-2.8962	0.1930	NA	NA	0.5006
Palmerston_11_22	Winter	2016	-0.2856	NA	NA	0.1136	0.7445
Palmerston_66_11	Summer	2017	-1.1604	NA	NA	0.5391	0.3716
Palmerston_66_11	Winter	2016	-2.5880	NA	NA	0.5581	0.7732
Pine_Creek_11_22	Summer	2017	-0.2231	0.0221	NA	NA	0.5993
Pine_Creek_11_22	Winter	2016	0.3022	0.0274	NA	NA	0.0886
Pine_Creek_11_66	Summer	2017	24.2309	NA	NA	NA	NA
Pine_Creek_11_66	Winter	2016	23.5804	NA	NA	NA	NA
Pine_Creek_132_66	Summer	2017	19.9378	NA	NA	NA	NA
Pine_Creek_132_66	Winter	2016	19.4541	NA	NA	NA	NA
Pine_Creek_66_66	Summer	2017	8.0406	NA	NA	NA	NA
Pine_Creek_66_66	Winter	2016	7.7178	NA	NA	NA	NA
Strangways_66_22	Summer	2017	-24.6988	1.3521	NA	NA	0.5666
Strangways_66_22	Winter	2016	4.9330	0.4560	NA	NA	0.2277
Tindal_22_11	Summer	2017	1.3106	0.0575	NA	NA	0.3699
Tindal_22_11	Winter	2016	2.0176	NA	0.0455	NA	0.2505
Weddell_66_22	Summer	2017	1.5007	0.0989	NA	NA	0.3890
Weddell_66_22	Winter	2016	0.9504	NA	NA	0.1033	0.4984
Wishart_Modular_66_11	Summer	2017	1.4039	NA	NA	0.0374	0.1123
Wishart_Modular_66_11	Winter	2016	0.6993	NA	NA	0.0604	0.2181
Woolner_66_11	Summer	2017	-7.3721	1.0912	NA	NA	0.5794
Woolner_66_11	Winter	2016	-9.8497	NA	NA	1.0075	0.7877

APPENDIX F. ZONE SUBSTATION ROOFTOP PV

The following table summarises the relative percentages used to disaggregate the regional installed capacity forecast to zone substations.

Region	Substation ID	Rooftop PV percentage
DK	Archer_66_11	13.2
DK	Batchelor_132_22	0.7
DK	Berrimah_66_11	9.8
DK	Casuarina_66_11	18
DK	Centre_Yard_66_11	1.1
DK	Cosmo_Howley_66_66	0
DK	Darwin_66_11	2.6
DK	Frances_Bay_66_11	1.1
DK	Hudson_Creek_132_66	0
DK	Humpty_Doo_66_22	0.4
DK	Katherine_132_22	8.3
DK	Leanyer_66_11	10
DK	Manton_132_22	0.8
DK	Marrakai_66_22	1.2
DK	Mary_River_66_22	0.4
DK	Palmerston_11_22	2
DK	Palmerston_66_11	8.7
DK	Pine_Creek_11_22	0.8
DK	Pine_Creek_11_66	0
DK	Pine_Creek_132_66	0
DK	Pine_Creek_66_66	0
DK	Strangways_66_22	12
[redacted]		[redacted]
DK	Weddell_66_22	0.3
DK	Wishart_Modular_66_11	1.4
DK	Woolner_66_11	9.1
AS	Brewer_Sadadeen_22_22	6.3
AS	Lovegrove_22_11	53.2
AS	Lovegrove_22_22	0.1
AS	Lovegrove_66_22	53.3
AS	Owen_Springs_11_66	0
AS	Sadadeen_11_11	40.4
TC	Tennant_Creek_11_22	100

APPENDIX G. BLOCK LOAD ADJUSTMENTS

This table summarises future block loads which were included in the zone substation forecasts. The season represents when the block load takes effect, and the year represents the associated year.

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

APPENDIX H. SUBSTATION SUMMER MD FORECASTS