ACIL ALLEN CONSULTING

REPORT TO
AUSTRALIAN ENERGY MARKET OPERATOR
12 JUNE 2019

PEAK DEMAND AND ENERGY FORECASTS

FOR THE SOUTH WEST INTERCONNECTED SYSTEM-WESTERN AUSTRALIA

FIGURES

TABLES

1 INTRODUCTION

ACIL Allen Consulting (ACIL Allen) has been commissioned by the Australian Energy Market Operator (AEMO) to develop a set of independent forecasts of energy consumption and peak demand for the South West interconnected system (SWIS).

1.1 Background

The Wholesale Electricity Market (WEM) for the SWIS commenced operation on 21 September 2006. The design of the WEM comprises two key components - wholesale electricity trading and a Reserve Capacity Mechanism (RCM).

One of AEMO's major objectives is to ensure that there is sufficient generation in place to meet the demand for electricity over time. This is achieved through the Reserve Capacity Mechanism (RCM) which sets a Reserve Capacity Requirement (RCR)[1] for two years ahead.

Annual Reserve Capacity Targets (RCTs) are published in an Electricity Statement of Opportunities (ESOO) report that considers the capacity requirements of the SWIS for the next 10 years.

The ESOO particularly supports WA's RCM by forecasting the installed generation and Demand Side Management capacity required to meet 10% (1 in 10 year) probability of exceedance (POE) and 50% (median) POE peak demand forecasts for low, expected and high demand growth (annual energy) scenarios.

1.2 Scope of work

1.2.1 Monthly and annual energy forecasts

As part of this project we have developed a set of monthly and annual sent out energy forecasts under low, expected and high economic growth scenarios.

The forecasts cover the outlook period from 2018-19 to 2028-29 and are provided on a financial year (July 1 to June 30) and Capacity Year (October 1 to September 30) basis.

The forecasts are disaggregated by customer class into residential and non-residential sectors.

1.2.2 Peak demand forecasts

Forecasts of summer and winter electricity peak demand, measured in MW, have been developed for the SWIS. In the case of winter peak demand the forecasts cover the 10 year period from 2019 to 2028, while for summer they cover the time horizon from 2019-20 to 2028-29.

[1] The RCR for a Reserve Capacity Cycle is the Reserve Capacity Target for the Capacity Year commencing on 1 October of Year 3 of the Reserve Capacity Cycle.

10%, 50% and 90% POE forecasts have been developed for each of the low, expected and high annual economic growth scenarios. While the annual energy forecasts are disaggregated by customer class, the peak demand forecasts have not been disaggregated.

1.3 Structure of this report

The subsequent sections address the inputs, methodology and forecasts in that order. Specifically:

- section 2 provides an overview of the history of the variables to be forecast, namely consumption and peak demand
- section 3 provides an overview of the history and forecasts of the drivers of energy consumption and peak demand
- section 4 describes the methodology by which the energy consumption forecasts were produced, the regression models that were used to produce the baseline and the post model adjustments that were applied to the baseline
- section 5 describes the methodology by which the peak demand forecasts were produced, the regression models that were used to produce the baseline and any post model adjustments that were applied
- section 6 presents the operational energy consumption forecasts
- section 7 presents the summer and winter peak demand forecasts

2

HISTORICAL OVERVIEW- ENERGY CONSUMPTION AND PEAK DEMAND

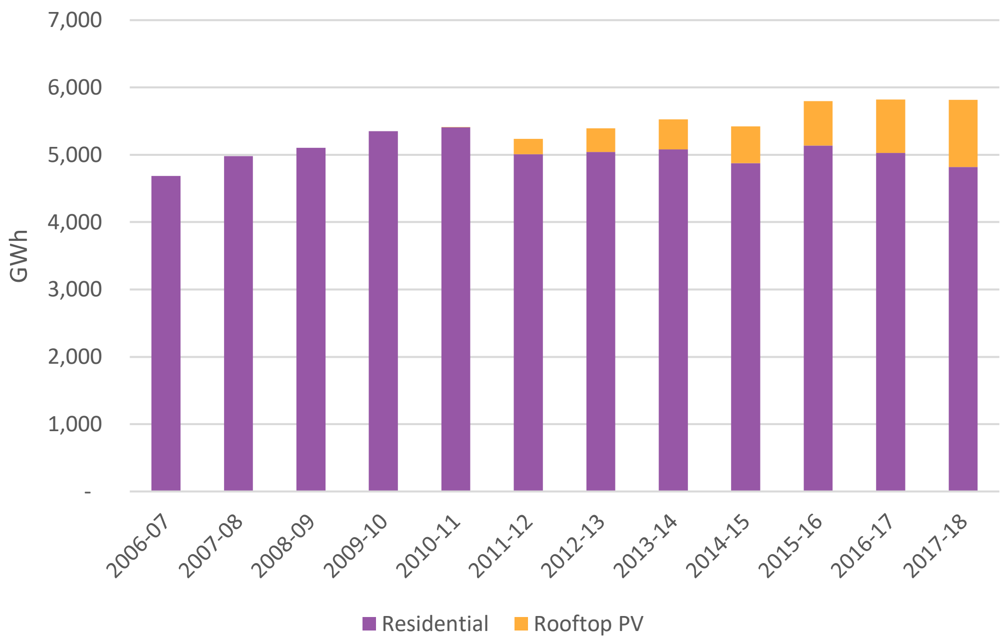
In this section we provide an overview of the historical behaviour of operational energy consumption and peak demand within the SWIS. The data series presented in this section were the basis of the dependent variables in the regression models described in section 4 and 5.

2.1 Operational energy consumption

2.1.1 Residential energy consumption

Figure 2.1 shows the historical residential consumption in the SWIS from 2006-07 to 2017-18.

FIGURE 2.1 RESIDENTIAL ENERGY CONSUMPTION, 2006-07 TO 2017-18



SOURCE: SYNERGY AND AEMO

It shows that annual residential consumption increased steadily from 4,688 GWh in 2006-07 to a peak of 5,406 GWh in 2010-11. It then declined to 5,008 GWh in 2011-12 before remaining relatively stable to the end of 2016-17. In 2017-18, residential consumption was 4,821 GWh, a decline of 4.1% on the previous year.

The slowdown in growth after 2010-11 is likely to be due to several factors:

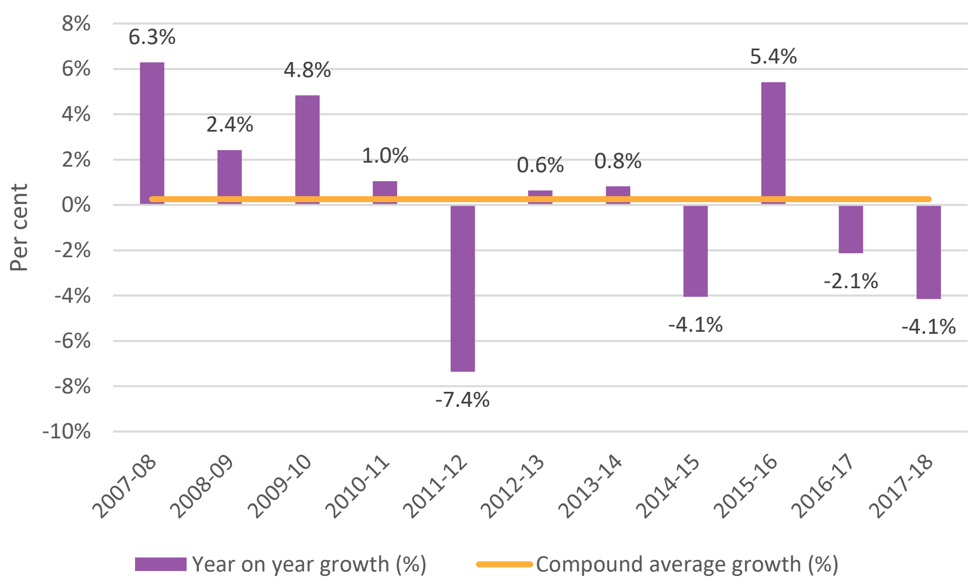
— slower economic growth
— increased rooftop PV uptake (partly driven by rising electricity prices).

The rooftop PV impact in **Figure 2.1** is calculated using a load trace from a sample of households with rooftop PV systems in combination with separate rooftop PV capacity projections for residential customers. Residential rooftop PV systems generated an estimated 994 GWh of energy in 2017-18, having increased from just 231 GWh in 2011-12 (see also **Figure 2.7**).

For modelling purposes residential consumption was altered to 'add back' the estimated quantity of consumption avoided through the use of rooftop PV systems. This energy was consumed, but is not seen by the meters from which the historical data were collected. It was added back to the consumption figures observed from the meters to reveal latent consumption, which was fed through to the econometric models.

The annual rate of growth in residential energy consumption in the SWIS is shown in **Figure 2.2**.

FIGURE 2.2 ANNUAL GROWTH IN RESIDENTIAL ENERGY CONSUMPTION, 2007-08 TO 2017-18



SOURCE: ACIL ALLEN

The compound average annual rate of growth in residential energy consumption between 2006-07 and 2017-18 was just 0.3%.

2.1.2 Non-residential energy consumption[2]

Non-residential energy consumption includes all customer classes other than residential. These include:

— commercial
— industrial (including large customers)
— street-lighting
— unmetered supply.

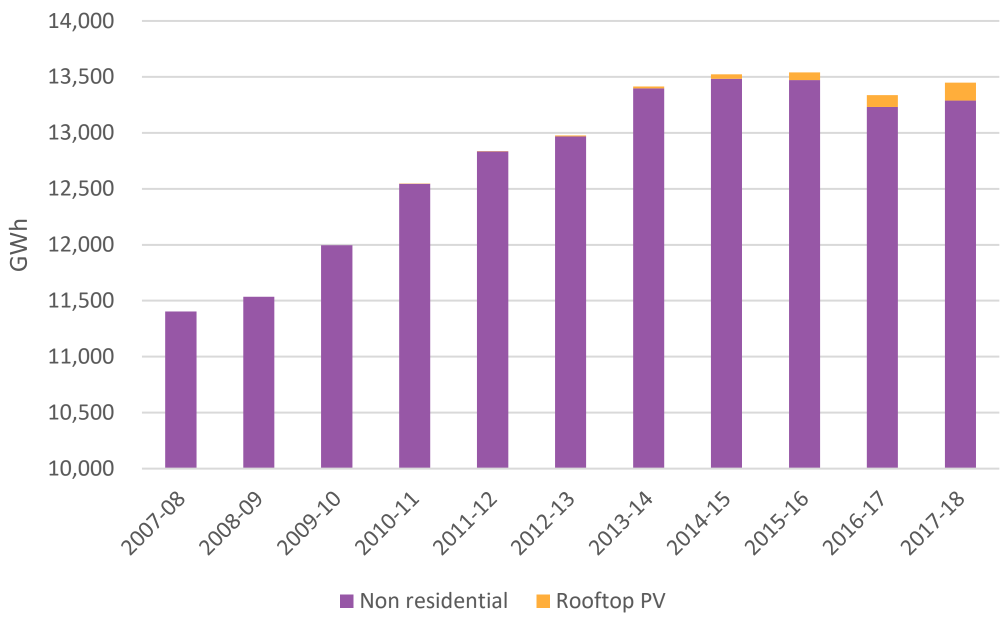
[2] Energy consumption data were obtained from Synergy which does not include all commercial customers. Non-residential energy consumption was derived by subtracting residential consumption obtained from Synergy from the total energy consumption implied by the market sent out 30 minute interval data.

Figure 2.3 shows the historical non-residential consumption in the SWIS from 2007-08 to 2017-18.

Annual non-residential consumption increased steadily from 11,405 GWh in 2007-08 to 13,473 GWh in 2015-16, before declining to 13,232 GWh in 2016-17. In 2017-18, non-residential energy consumption rose by 0.4% to 13,288 GWh.

This is equivalent to a compound average rate of growth in non-residential energy consumption between 2007-08 and 2017-18 of 1.5%.

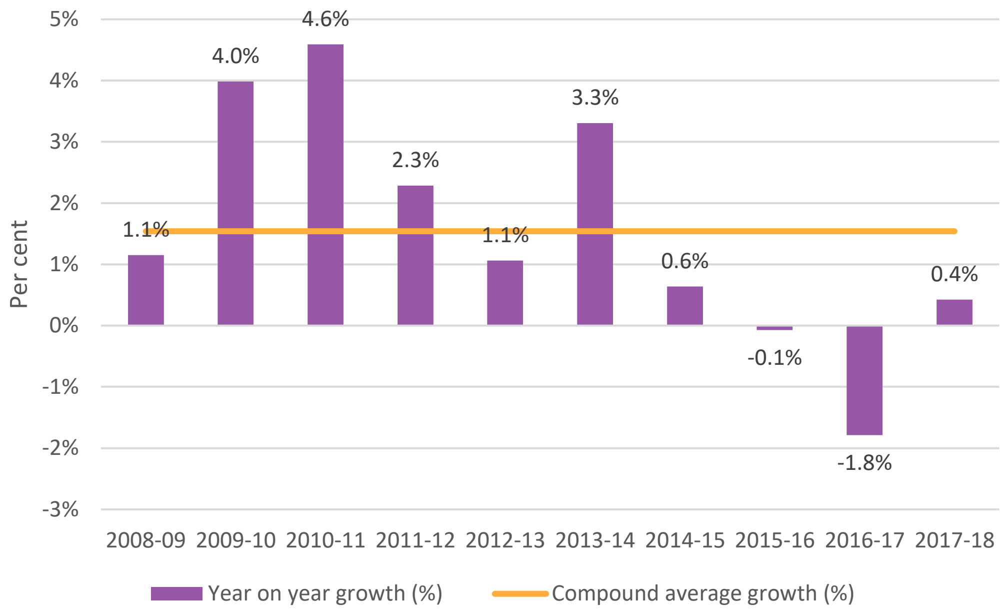
FIGURE 2.3 NON-RESIDENTIAL ENERGY CONSUMPTION, 2007-08 TO 2017-18



SOURCE: SYNERGY AND AEMO

Figure 2.4 shows the year on year growth in non-residential energy consumption. Robust growth in 2009-10 and 2010-11 of over 4% was followed by a period of slower growth, particularly in the last four years when growth in non-residential energy consumption has been well below the long-term compound annual growth rate of 1.5%. These years reflect slower economic conditions arising from the end of the mining boom and the associated loss of income and employment in the SWIS. Furthermore, in the last few years the impact of rooftop PV has increased significantly in the non-residential sector, placing further downward pressure on energy consumption.

FIGURE 2.4 ANNUAL GROWTH IN NON-RESIDENTIAL ENERGY CONSUMPTION, 2008-09 TO 2017-18

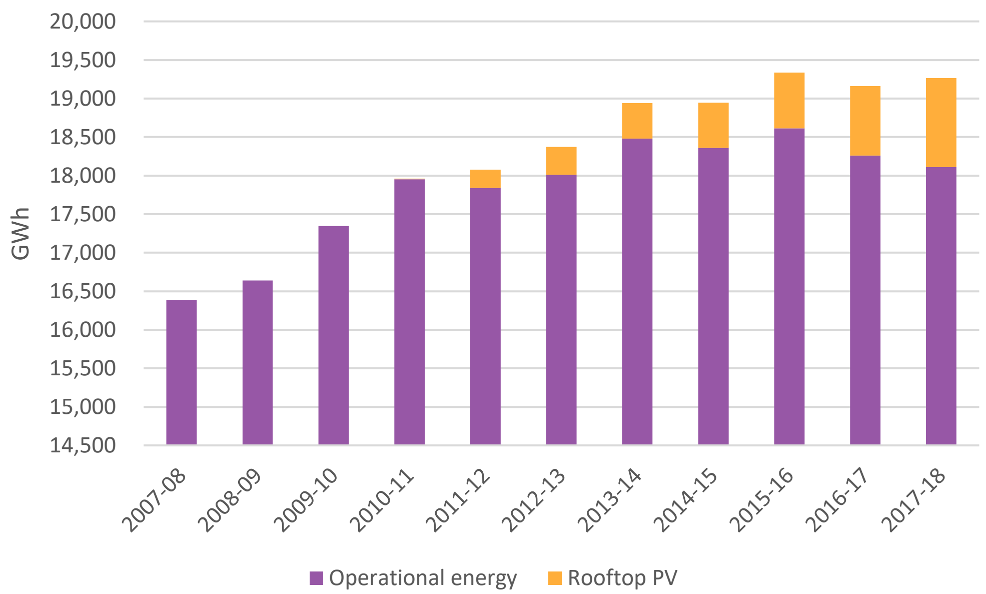


SOURCE: ACIL ALLEN

2.1.3 Total operational energy consumption

Total operational energy consumption in the SWIS is shown in **Figure 2.5**. Over the period from 2007-08 to 2017-18, estimated total operational energy consumption in the SWIS increased from 16,387 GWh to 18,109 GWh.

FIGURE 2.5 TOTAL OPERATIONAL ENERGY CONSUMPTION, 2007-08 TO 2017-18

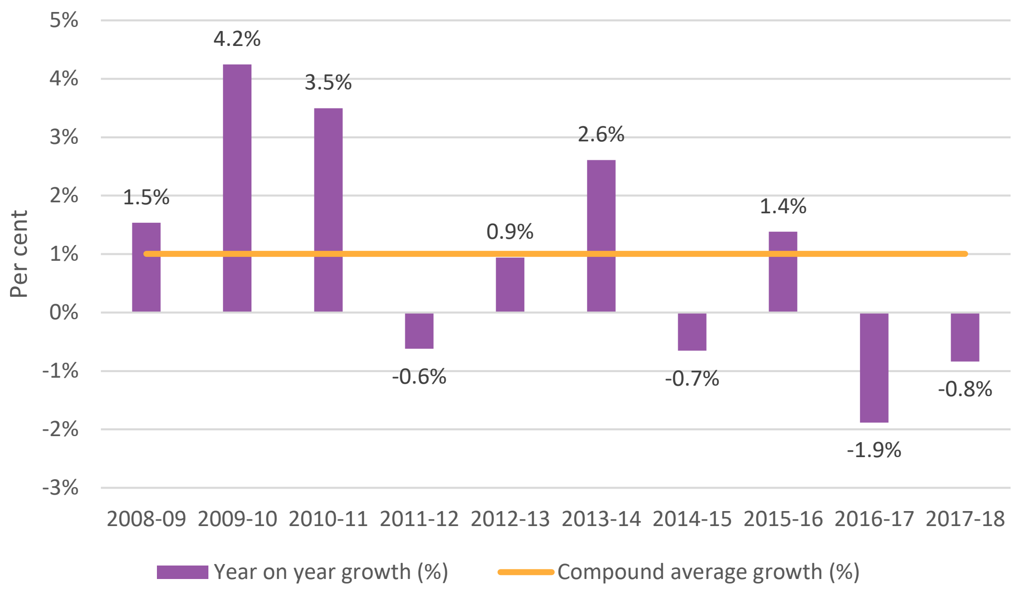


SOURCE: SYNERGY AND AEMO

Over the last 10 years, total operational energy consumption increased at a compound average growth rate of 1.0%. From 2008-09 to 2010-11, average annual growth in operational energy consumption was well in excess of the long-term average. From 2011-12 onwards, total operational energy consumption was below average in five out of seven years (see **Figure 2.6**).

In 2016-17, operational energy declined by 1.9%, the largest decline since 2008-09. This was followed by a further decline of 0.8% in 2017-18.

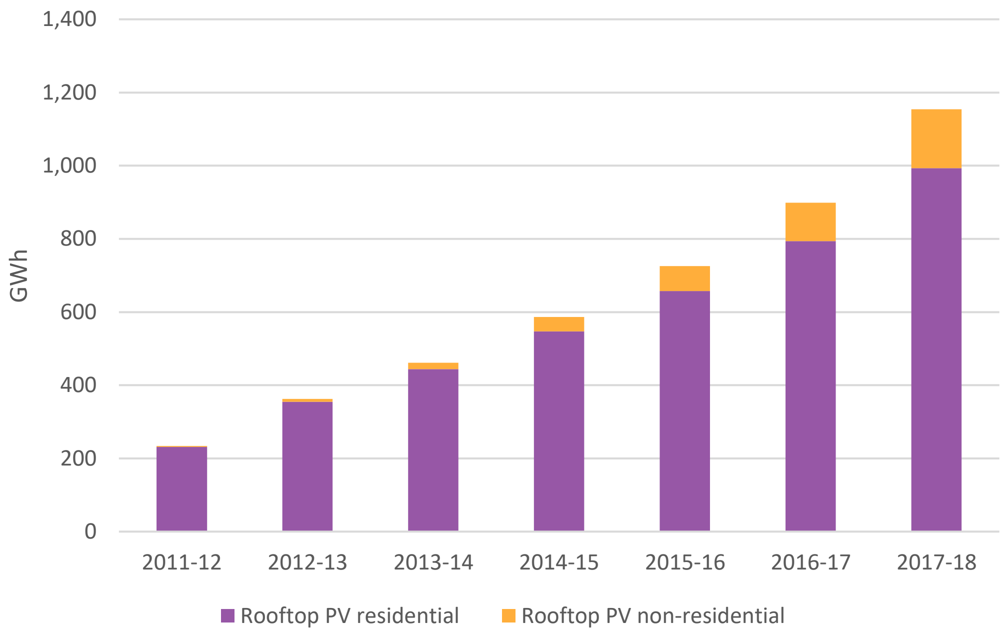
FIGURE 2.6 ANNUAL GROWTH IN TOTAL OPERATIONAL ENERGY CONSUMPTION



SOURCE: ACIL ALLEN

The impact of rooftop PV on operational energy consumption in the SWIS is shown in **Figure 2.7** below. The figure shows that in 2017-18, rooftop PV systems generated an estimated 1,154 GWh of energy, compared to 234 GWh in 2011-12.

FIGURE 2.7 IMPACT OF ROOFTOP PV ON ENERGY CONSUMPTION IN THE SWIS



SOURCE: CER DATA PROVIDED BY AEMO AND ACIL ALLEN CALCULATIONS

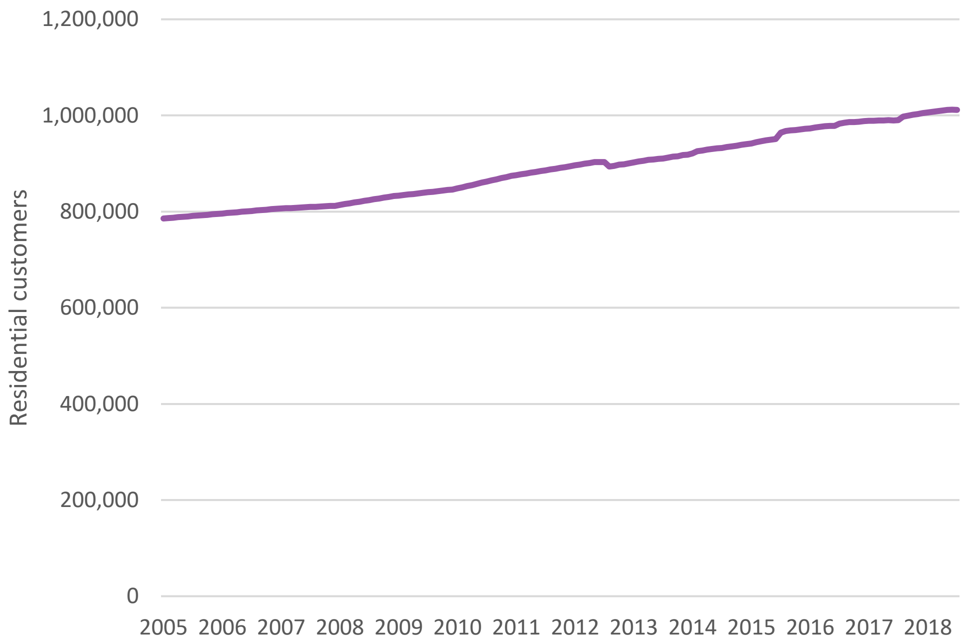
2.2 Residential customer numbers

Figure 2.8 shows the number of residential customers in the SWIS.

The figure indicates a steady increase in customer numbers over time. This is reflective of the number of households serviced by the network increasing. Since June 2006, growth in customer numbers has averaged 2% per annum.

As at December 2018, the SWIS had 1,012,013 residential customers, up from 795,186 in June 2006.

FIGURE 2.8 RESIDENTIAL CUSTOMER NUMBERS IN THE SWIS, JUNE 2005 TO DECEMBER 2018

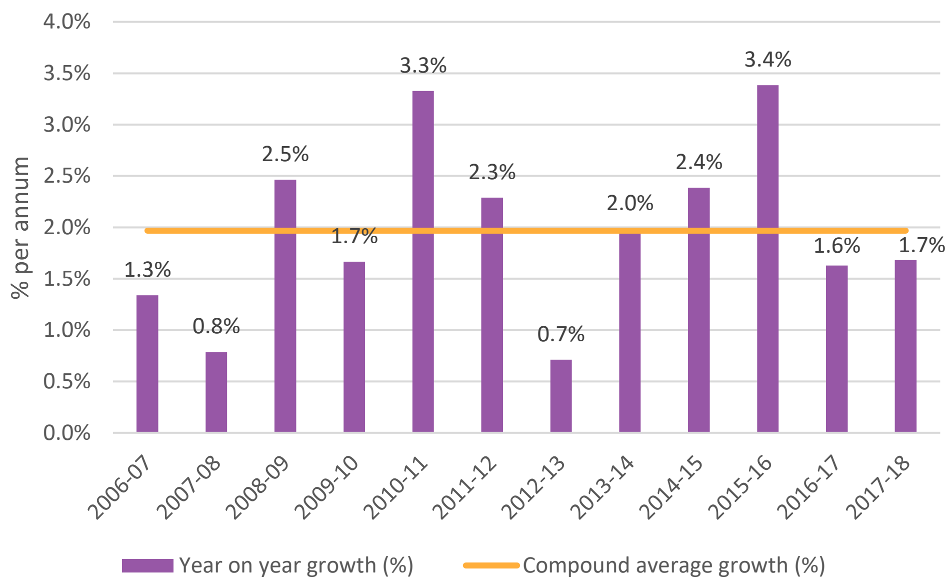


SOURCE: SYNERGY AND AEMO

Note: There is a dip in the time series from 2012 to 2016. This is most likely due to adjustments made to synergy's internal databases.

The year on year growth in residential customers is shown in **Figure 2.9** below. In 2017-18, growth in residential customer numbers was below average, rising by 1.7% compared to the long-term average of 2.0% per annum.

FIGURE 2.9 ANNUAL GROWTH IN RESIDENTIAL CUSTOMER NUMBERS



SOURCE: ACIL ALLEN

2.3 Peak demand

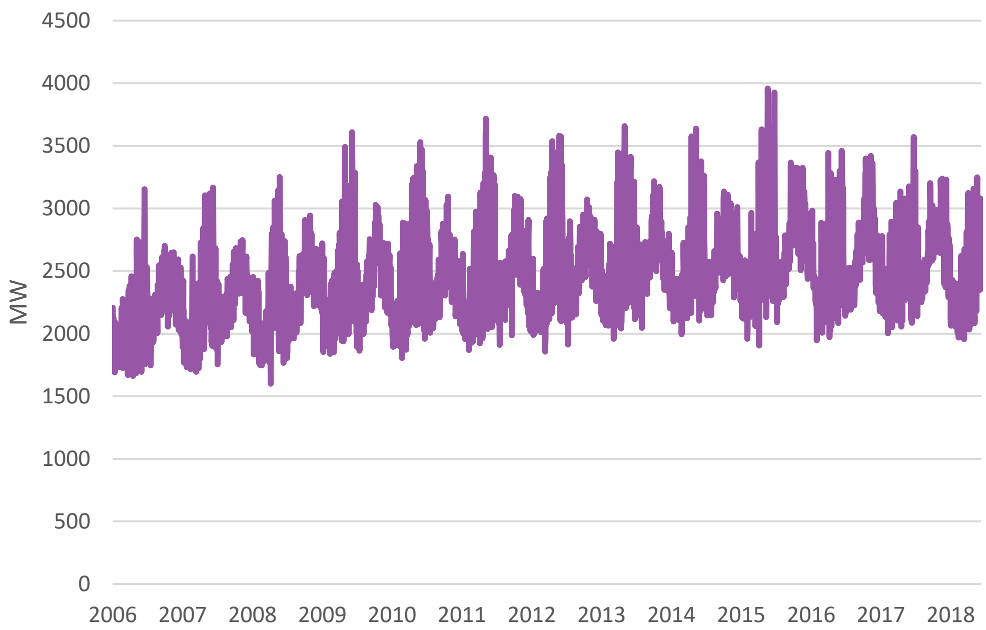
Figure 2.10 plots the daily peak demand in the SWIS between 21 September 2006 and 28 February 2019.

The figure shows that peak demand varies in line with weather conditions over the course of the year, with peak demand generally spiking in the summer months of January and February, as well as in the winter months of June and July. The summer peak is largely driven by cooling loads seeking to alleviate the impact of hot conditions, while the winter peaks are driven by heating loads.

Other cyclical behaviour is evident, including day of the week effects, with demand being higher on working days compared to weekends and public holidays. There are also variations across working days, with Fridays tending to exhibit lower levels of peak demand on average relative to other weekdays.

The figure also indicates a steady rising trend in peak demand over time, although this appears to have fallen back in the last few years.

FIGURE 2.10 DAILY PEAK DEMAND IN THE SWIS, SEPTEMBER 2006 TO FEBRUARY 2019



SOURCE: AEMO

Table 2.1 shows the summer peak demand in the SWIS from 2007-08 to 2018-19 along with the date and time of each peak event and the daily maximum, minimum and average temperature observed at the Perth Airport weather station. It can be observed that apart from the two most recent peaks which occurred in December and March respectively, the remaining peaks all occurred in January and February. The highest peak demand over the last 10 years was 4,004 MW which occurred on February 8 2016.

Another trend that can be observed is the tendency for the peak demand to occur later in the day, with the summer peak occurring at 3:00 pm in 2007-08, and at 5:30 pm in 2017-18 and 2018-19. This is largely due to the influence of increasing rooftop PV uptake, which generates more electricity during the early afternoon thus forcing the peak to shift to later in the day.

TABLE 2.1 SUMMER PEAK DEMAND, 2007-08 TO 2018-19

Year	Date	MW[3]	Time	Daily Max temp	Daily Min temp	Average temp
2007-08	28-02-08	3394	15:00	41.9	21.4	31.7
2008-09	11-02-09	3515	15:30	39.2	23.0	31.1
2009-10	25-02-10	3766	16:00	41.9	24.3	33.1
2010-11	16-02-11	3744	16:30	39.5	24.9	32.2
2011-12	25-01-12	3860	16:30	40.0	24.6	32.3
2012-13	12-02-13	3739	16:30	41.1	26.6	33.9
2013-14	20-01-14	3702	17:30	38.7	20.6	29.7
2014-15	05-01-15	3744	15:30	44.2	21.5	32.9
2015-16	08-02-16	4004	17:30	42.6	20.7	31.7
2016-17	21-12-16	3543	17:00	42.8	20.1	31.5
2017-18	13-03-18	3616	17:30	38.5	23.1	30.8
2018-19	7-02-19	3256	17:30	35.8	21.1	28.5

SOURCE: AEMO

The equivalent table for winter peak demand is shown in **Table 2.2**. In the case of winter, peak demand has increased from 2,705 in 2007 to 3,256 in 2018. All winter peaks have taken place in either June or July, except for the most recent winter peak which occurred in August. The most common time for the winter peak to occur is at 6pm with eight of the last twelve peaks all occurring at this time.

TABLE 2.2 WINTER PEAK DEMAND, 2007 TO 2018

Year	Date	MW[4]	Time	Daily Max temp	Daily Min temp	Average temp
2007	22-06-07	2705	17:30	18.2	7.3	12.8
2008	31-07-08	2774	18:30	13.7	6.5	10.1
2009	20-07-09	2943	18:00	14.6	8.3	11.5
2010	28-06-10	3029	18:00	15.5	1.8	8.7
2011	11-07-11	3095	18:00	12.8	10.1	11.5
2012	25-07-12	3100	18:30	16.1	-0.7	7.7
2013	08-07-13	3071	18:00	18.5	2.5	10.5
2014	23-06-14	3217	18:00	16.0	1.3	8.7
2015	23-06-15	3135	18:00	16.9	1.8	9.4
2016	07-06-16	3366	18:00	15.0	10.5	12.8
2017	31-07-17	3419	18:00	15.8	12.3	14.1
2018	9-08-18	3256	18:30	16.0	11.6	13.8

SOURCE: AEMO

[3] Any minor variations between the historical peak demands in this table and those presented in the 2019 WEM Electricity Statement of Opportunities are due to metering updates.
[4] Any minor variations between the historical peak demands in this table and those presented in the 2019 WEM Electricity Statement of Opportunities are due to metering updates.

MAIN DRIVERS OF ENERGY CONSUMPTION AND PEAK DEMAND

3

This section provides an overview of the history of likely drivers of energy consumption and peak demand in the SWIS. Data series that are discussed are:

- economic activity
- population growth
- weather
- rooftop PV
- battery storage
- electric vehicles
- block loads.

The historical data series presented in these sections were used as the dependent (X) variables in the regression models described in section 4 and 5. The projections of drivers presented in this section were used as inputs into the baseline forecasts.

3.1 Economic activity

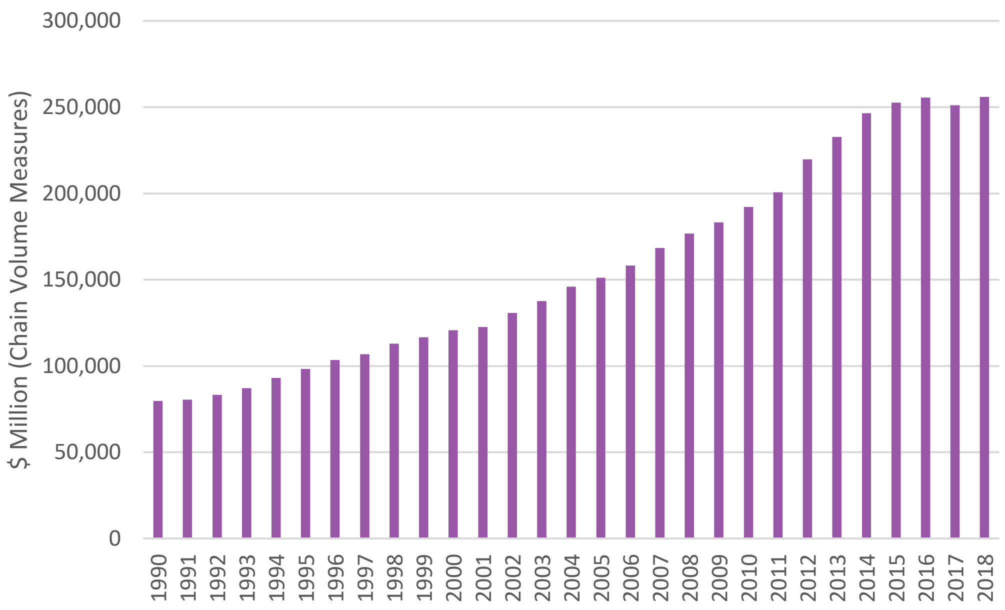
Growth in economic activity is a major driver of rising incomes. Consumption of electricity is, in part, driven by higher disposable incomes and subsequent demand for new electronic appliances and equipment, as well as increasing commercial and industrial activity.

In addition to this, there is typically some relationship between economic output and electricity consumption given that electricity is an important input into many industries.

Moreover, the ownership of appliances that can be used in peak demand conditions such as air-conditioners and electric space heaters will contribute significantly to peak demand.

Figure 3.1 shows the historical time series of WA economic activity, as measured by Gross State Product (GSP), for the financial years from 1989-90 to 2017-18.

FIGURE 3.1 WESTERN AUSTRALIAN GROSS STATE PRODUCT, 1989-90 TO 2017-18 $M (CHAIN VOLUME MEASURE)



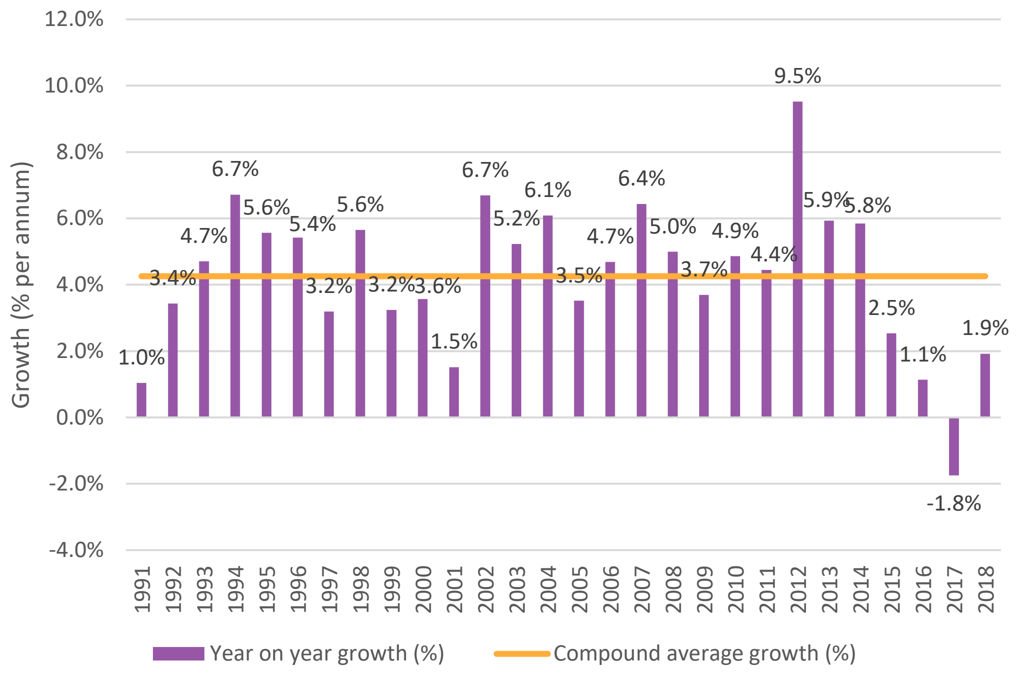
SOURCE: ABS, 5220.0 AUSTRALIAN NATIONAL ACCOUNTS: STATE ACCOUNTS

Western Australian economic growth has been positive in all years since 1990-91 except for 2016-17 where it declined by 1.8% (see **Figure 3.2**). In the most recent year economic growth rebounded to 1.9%.

Western Australian economic growth is characterised by cyclical periods of high growth followed by periods of subdued growth. Economic growth peaked at 6.7% in 1993-94, 6.7% in 2001-02, 6.4% in 2006-07 and 9.5% in 2011-12. Economic growth troughs occurred in 1990-91, 2000-01 and 2016-17.

Western Australian GSP growth has slowed significantly in the last three years as a result of declining aggregate demand and household incomes associated with the end of the mining boom. In 2015-16, economic growth was just 1.1% before contracting by 1.8% in 2016-17. This is compared to a long-term average of 4.3% per annum from 1990-91 to 2017-18.

FIGURE 3.2 YEAR ON YEAR GSP GROWTH, WESTERN AUSTRALIA 1990-91 TO 2017-18



SOURCE: ABS, 5220.0 AUSTRALIAN NATIONAL ACCOUNTS: STATE ACCOUNTS

Note: Any changes in this year's growth rates compared to last year's report are due to revisions made to the historical data by the ABS

3.1.1 Economic Growth forecasts

For the purposes of the modelling, independent economic growth forecasts were sourced by AEMO. Economic growth forecasts were sourced under expected, high and low scenarios. These are shown in **Table 3.1** below.

TABLE 3.1 FORECAST GSP GROWTH RATES 2018-19 TO 2028-29 , EXPECTED, HIGH AND LOW SCENARIOS

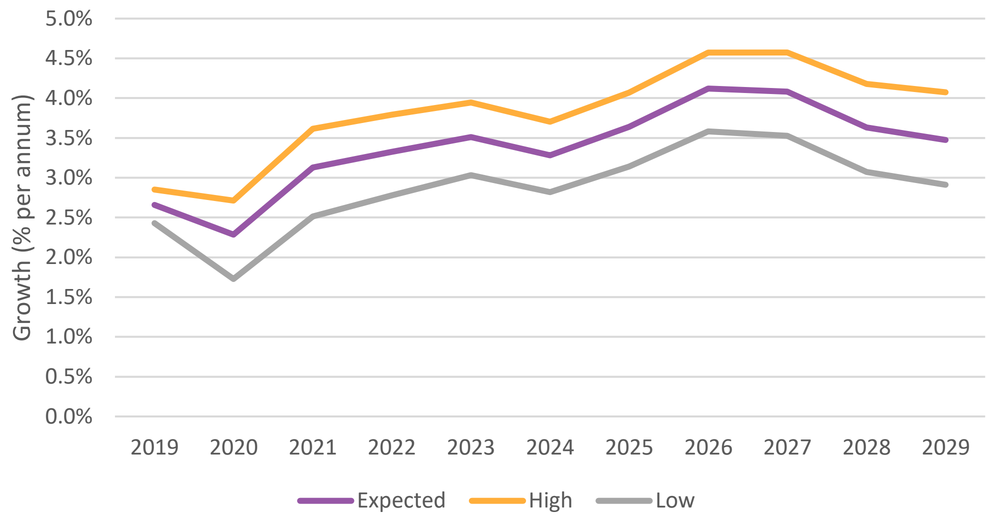
Year	GSP (expected)	GSP (high)	GSP (low)
2018-19	2.7%	2.9%	2.4%
2019-20	2.3%	2.7%	1.7%
2020-21	3.1%	3.6%	2.5%
2021-22	3.3%	3.8%	2.8%
2022-23	3.5%	3.9%	3.0%
2023-24	3.3%	3.7%	2.8%
2024-25	3.6%	4.1%	3.1%
2025-26	4.1%	4.6%	3.6%
2026-27	4.1%	4.6%	3.5%
2027-28	3.6%	4.2%	3.1%
2028-29	3.5%	4.1%	2.9%
CAGR (%)[5]	**3.6%**	**4.1%**	**3.0%**

SOURCE: AEMO

[5] This is the compound average annual growth rate from 2019-20 to 2028-29.

The same forecasts are presented graphically in **Figure 3.3** below.

FIGURE 3.3 FORECAST GSP GROWTH 2018-19 TO 2028-29, EXPECTED, HIGH AND LOW SCENARIOS

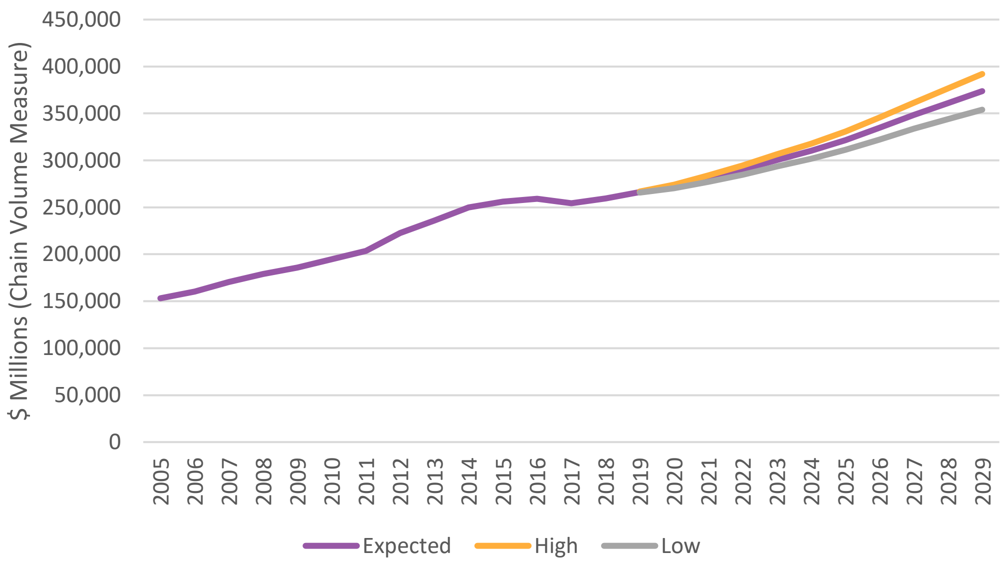


SOURCE: AEMO

Under the expected economic growth scenario, Western Australian GSP growth is forecast to average 3.6% per annum from 2019-20 to 2028-29. In 2018-19, economic conditions are expected to improve with growth increasing to 2.7% per annum after growth of 1.9% in 2017-18. GSP growth is expected to peak at 4.1% in 2025-26 and 2026-27. Under the high economic growth scenario, GSP is forecast to average 4.1% over the period from 2019-20 to 2028-29. Under the low economic growth scenario, GSP is forecast to average 3.0% over the same period.

Figure 3.4 presents the path of forecast Western Australian GSP under the three separate scenarios.

FIGURE 3.4 FORECAST WESTERN AUSTRALIAN GSP UNDER EXPECTED, HIGH AND LOW SCENARIOS



SOURCE: AEMO

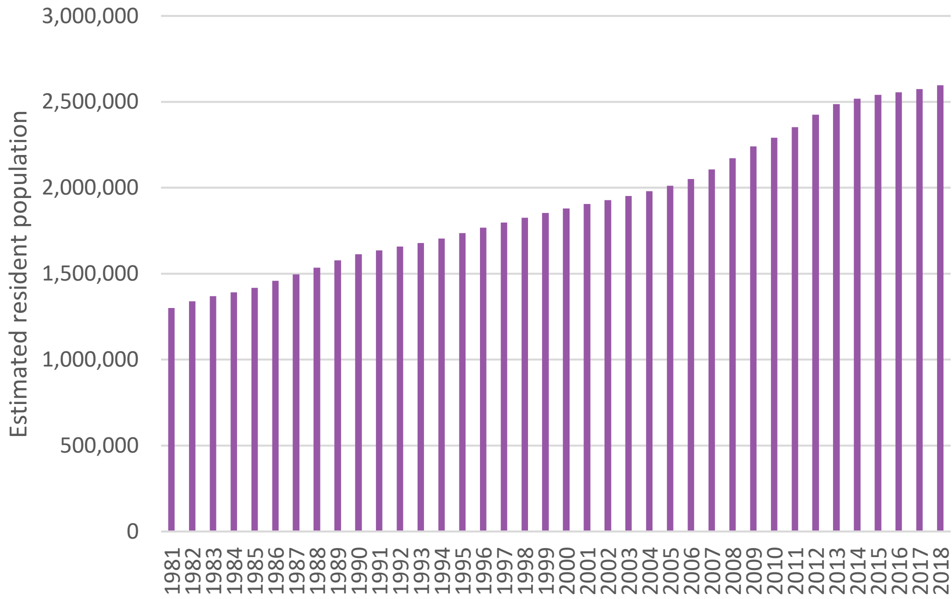
3.2 Population growth

Growth in customer numbers has been a key driver of electricity consumption. Increasing residential customer numbers are driven by household formation arising from population growth.

Figure 3.5 shows the long term Western Australian resident population from June 1981 to June 2018.

The figure shows a long steady increase in the estimated resident population of Western Australia. In June 2018, the estimated resident population of Western Australia had reached 2.6 million people.

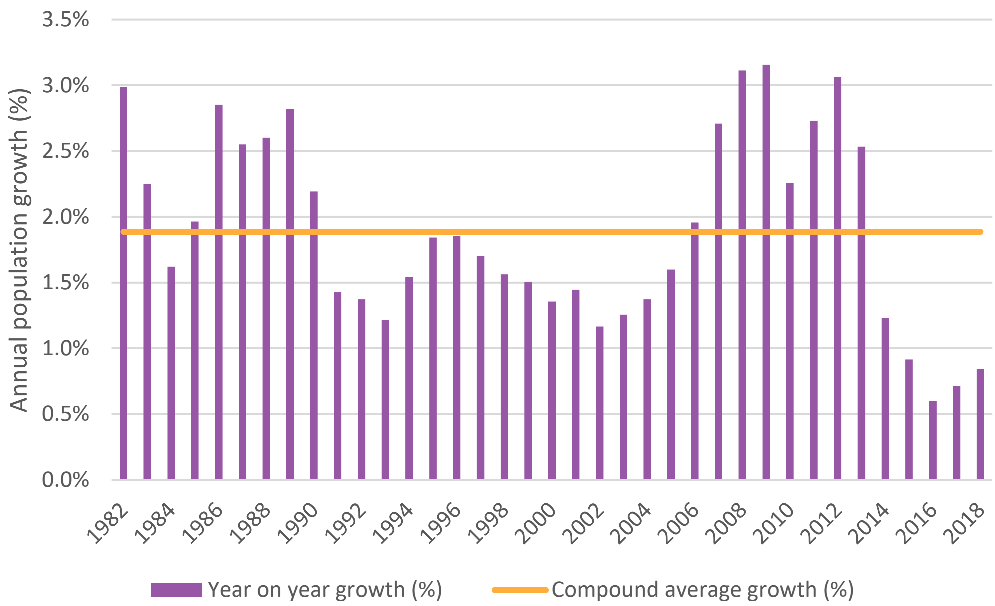
FIGURE 3.5 WESTERN AUSTRALIAN ESTIMATED RESIDENT POPULATION, 1981 TO 2018



SOURCE: ABS, 3101.0 AUSTRALIAN DEMOGRAPHIC STATISTICS

Growth in the population of Western Australia has followed a cyclical pattern largely in line with the state's economic fortunes (see **Figure 3.6**). Over the long term, Western Australian population growth has averaged 1.9% per annum. Over the last five years, Western Australian population growth has been below average. Population growth in 2015-16, 2016-17 and 2017-18 was 0.6%, 0.7% and 0.8% respectively.

FIGURE 3.6 ANNUAL POPULATION GROWTH, WESTERN AUSTRALIA, JUNE 1982 TO JUNE 2018



SOURCE: ABS, 3101.0 AUSTRALIAN DEMOGRAPHIC STATISTICS

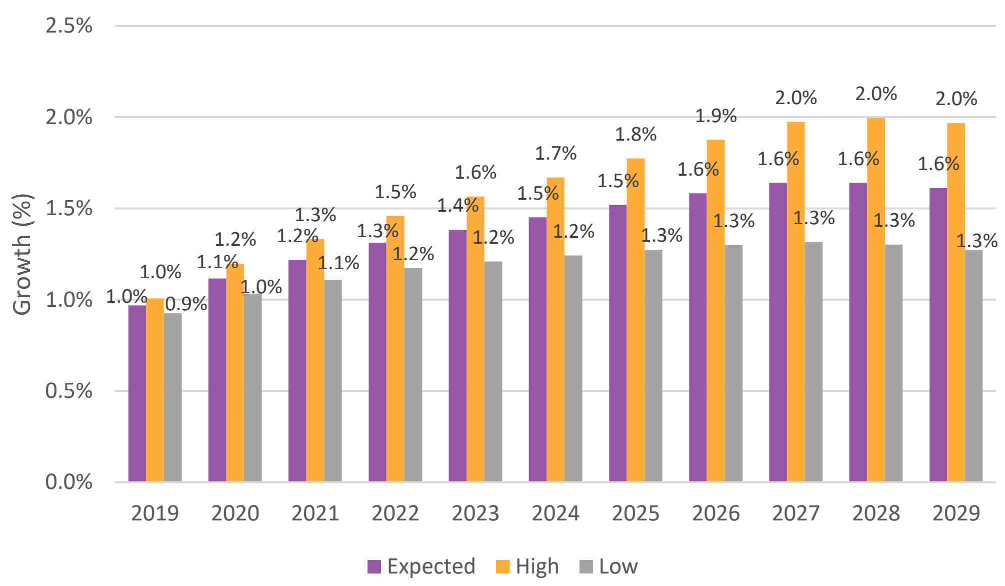
3.2.1 Population growth forecasts

For the purposes of projecting residential customer numbers in the SWIS, population forecasts were provided by AEMO. These were based on the ABS's A, B and C series projections with adjusted interstate migration flows for the latest ABS actuals.

Forecasts were provided under three separate scenarios, expected, high and low.

The forecast population growth rates under each scenario are shown in **Figure 3.7**.

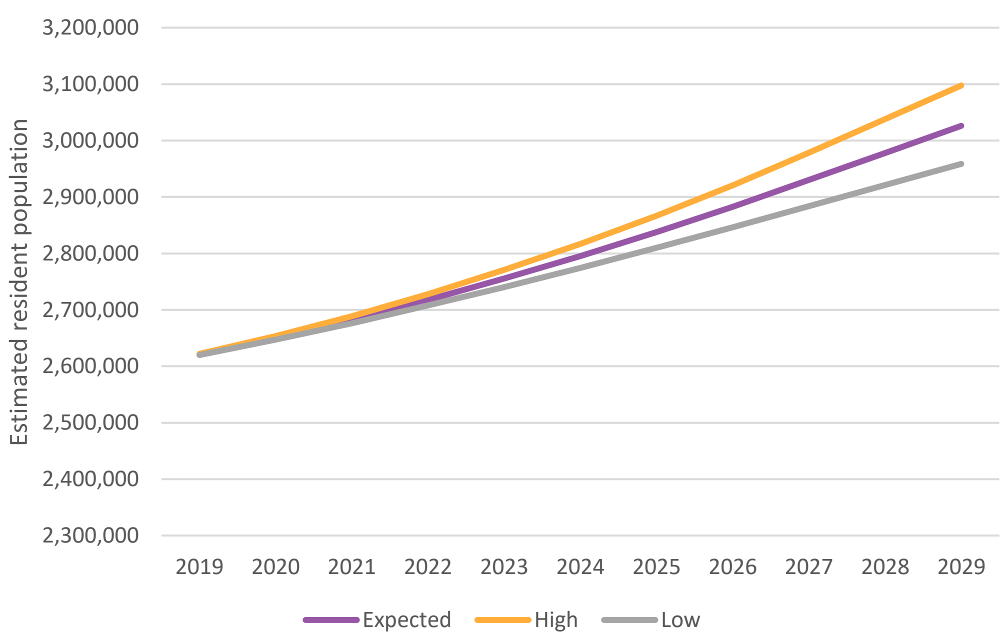
FIGURE 3.7 WESTERN AUSTRALIAN POPULATION GROWTH FORECASTS, EXPECTED, HIGH AND LOW SCENARIOS, BY FINANCIAL YEAR



SOURCE: AEMO AND ABS

The separate forecast growth rates are applied to the historical estimated resident population data obtained from the ABS to obtain a projection of Western Australia's estimated resident population under the expected, high and low scenarios. These are shown in **Figure 3.8** below.

FIGURE 3.8 FORECAST WESTERN AUSTRALIAN POPULATION, EXPECTED, HIGH AND LOW SCENARIOS, AS AT JUNE 30



SOURCE: ABS AND ACIL ALLEN CALCULATIONS

3.3 Rooftop PV and battery storage

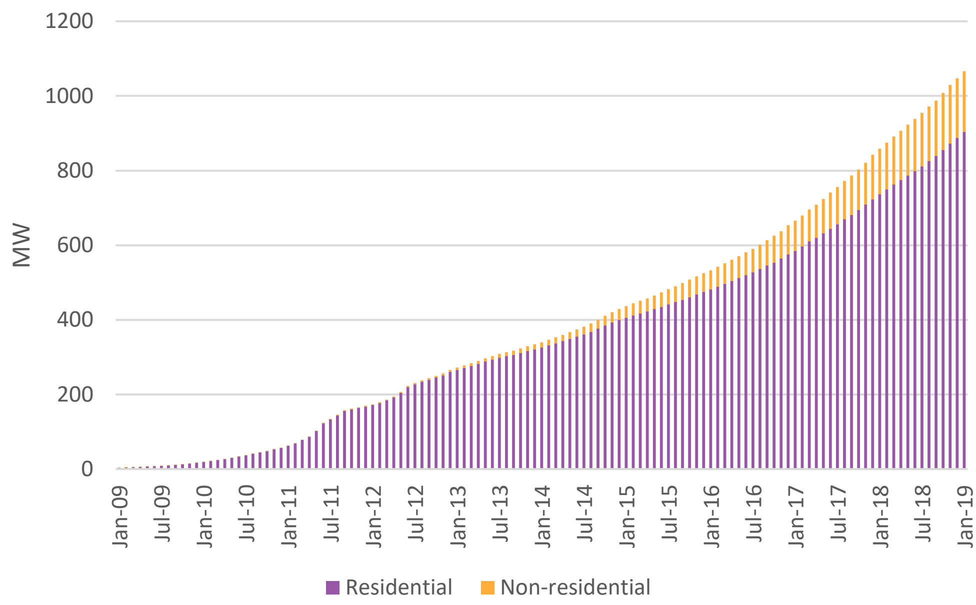
3.3.1 Rooftop PV uptake

The use of rooftop PV systems has increased dramatically in recent years. To date, this has mainly been in response to government incentives, rising electricity prices and falling system installation costs. Rooftop PV systems have a fairly straightforward impact on energy sales. Simply put, when the output of a PV system is used 'on site', it reduces the quantity of energy supplied by the wholesale market.

The rapid increase in installations of rooftop PV systems at the household level has not only changed the growth rate in energy and peak demand to be satisfied by centralised generation sources, it has also changed the shape of the daily demand profile by shifting the time of the peak demand from mid-afternoon to late-afternoon / early evening.

Standard regression techniques do not cope well with this change since it has occurred rapidly over a short period of time. Further, the effect of rooftop PV on peak demand at the margin will diminish over the next few years as the timing of the peak demand moves from daylight hours towards the evening. These sorts of changes are hard to properly characterise in a regression model. Therefore, we have removed the impact of rooftop PV from the estimated regression data and forecast the impact of rooftop PV independently.

FIGURE 3.9 HISTORICAL INSTALLED CAPACITY OF ROOFTOP PV, 2009 TO JANUARY 2019

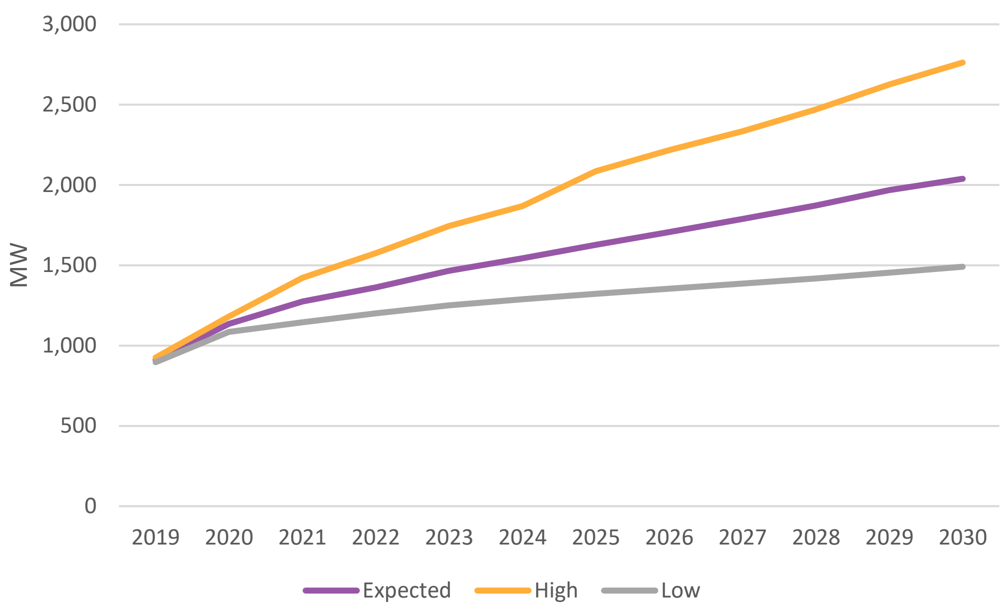


SOURCE: AEMO

Forecasts of rooftop PV capacity over the forecast period were provided by AEMO from another consultant.

Figure 3.10 shows the forecast uptake of residential rooftop PV under the three separate growth scenarios. Under the expected scenario, installed residential rooftop PV capacity is expected to reach 2,038 MW by June 2030. Under the high and low growth scenarios, residential rooftop PV capacity is forecast to reach 2,762 MW and 1,491 MW respectively.

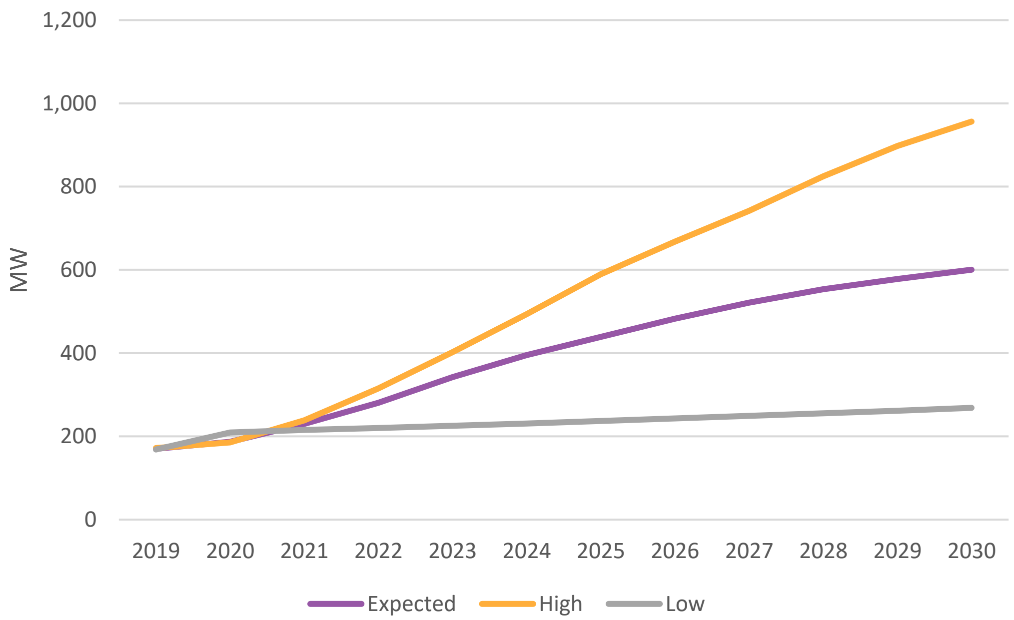
FIGURE 3.10 FORECAST RESIDENTIAL ROOFTOP PV CAPACITY AS AT JUNE 30, 2019 TO 2030



SOURCE: AEMO

Figure 3.11 shows the forecast uptake of non-residential rooftop PV under the three separate growth scenarios. Under the expected scenario, installed non-residential rooftop PV capacity is expected to reach 600 MW by June 2030. Under the high and low growth scenarios, non-residential rooftop PV capacity is forecast to reach 956 MW and 269 MW respectively.

FIGURE 3.11 FORECAST NON-RESIDENTIAL ROOFTOP PV CAPACITY AS AT JUNE 30, 2019 TO 2030

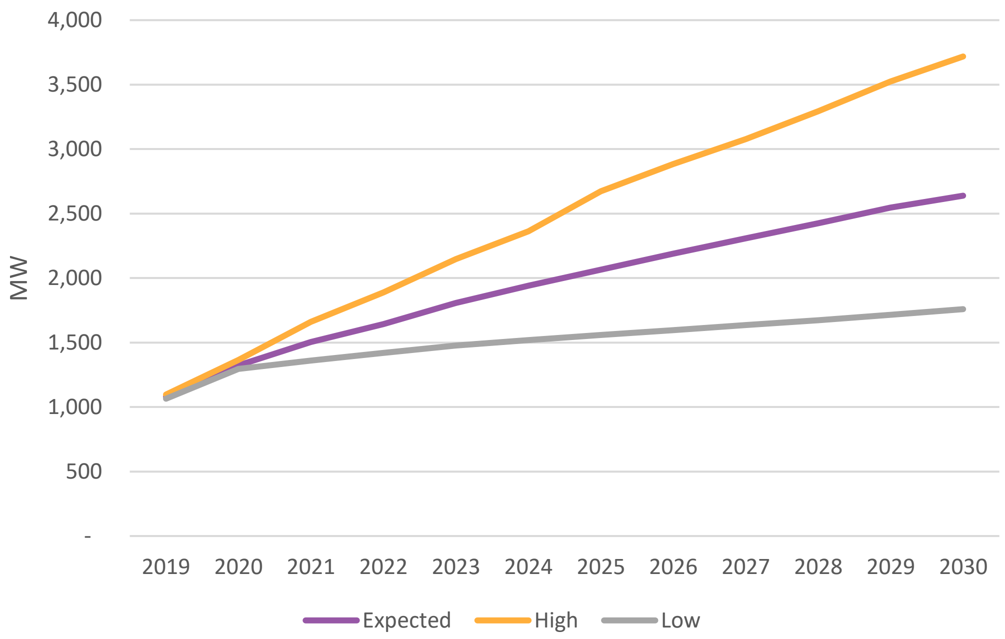


SOURCE: AEMO

Figure 3.12 shows the forecast uptake of total rooftop PV in the SWIS under the three separate growth scenarios. Under the expected scenario, installed rooftop PV capacity is expected to reach

2,639 MW by June 2030. Under the high and low growth scenarios, total rooftop PV capacity in the SWIS is forecast to reach 3,718 MW and 1,759 MW respectively.

FIGURE 3.12 FORECAST TOTAL ROOFTOP PV CAPACITY AS AT JUNE 30, 2019 TO 2030



SOURCE: CSIRO AND AEMO

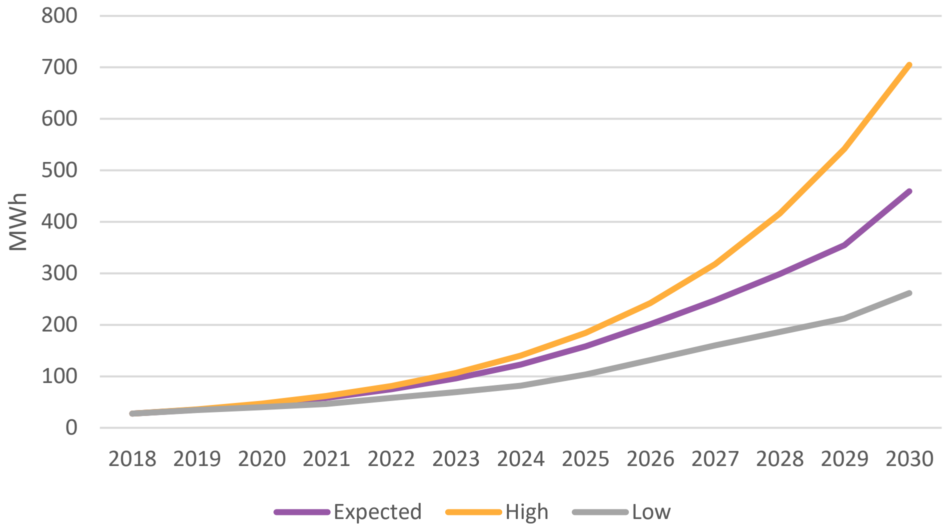
3.3.2 Battery storage

To date the deployment of home energy storage systems in Australia has been negligible. However, prices for battery technology are widely expected to reduce in the future and this could have major implications for battery uptake and the level of peak demand that is required to be met using network services. As with the reduction in cost of PV systems over the last decade, a reduction in cost of battery systems could be accelerated by a large scale, subsidy assisted, deployment of this technology as observed in Germany or other countries where there are currently subsidies for the installation of home energy storage systems.

Forecasts of the uptake of battery storage were provided by AEMO.

Figure 3.13 shows the forecast increase in residential storage capacity which is expected to reach 355 MWh by June 2029. Under the high and low growth scenarios, residential battery storage is forecast to reach 542 MWh and 212 MWh respectively by June 2029.

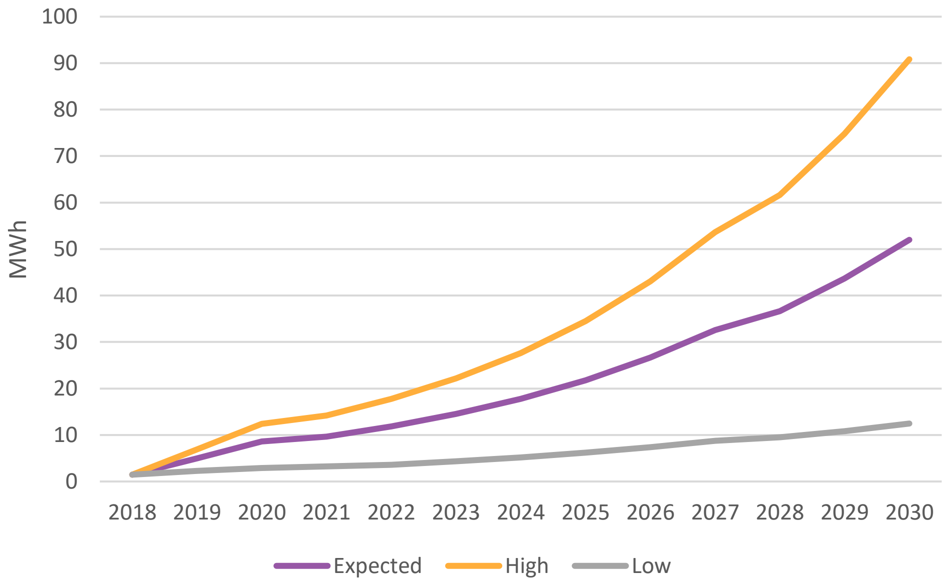
FIGURE 3.13 FORECAST RESIDENTIAL BATTERY STORAGE, EXPECTED, HIGH AND LOW SCENARIOS, AS AT JUNE 30



SOURCE: CSIRO AND AEMO

Figure 3.14 shows the forecast increase in non-residential storage capacity which is expected to reach 44 MWh by June 2029. Under the high and low growth scenarios, non-residential battery storage is forecast to reach 75 MWh and 11 MWh respectively by June 2029.

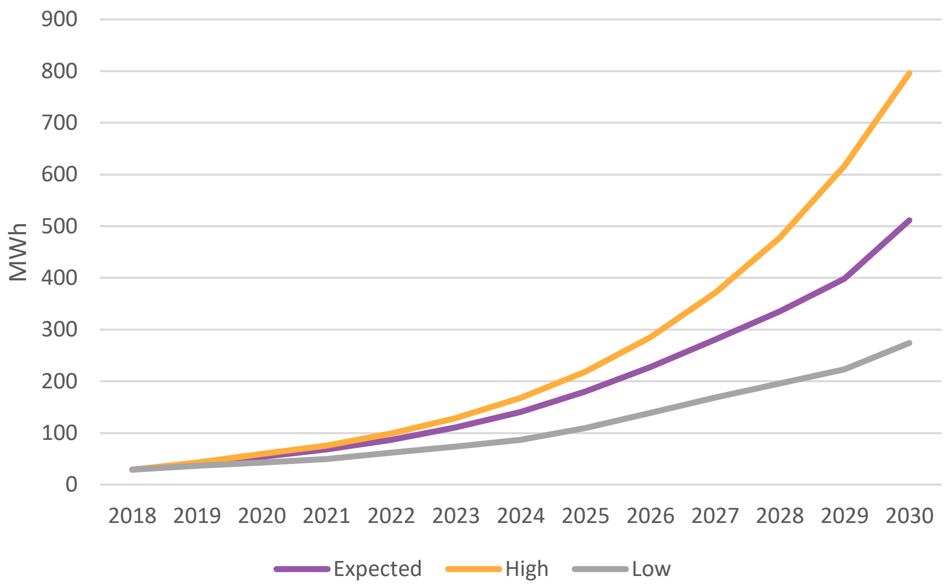
FIGURE 3.14 FORECAST NON-RESIDENTIAL BATTERY STORAGE, EXPECTED, HIGH AND LOW SCENARIOS, AS AT JUNE 30



SOURCE: CSIRO AND AEMO

Figure 3.15 shows the forecast increase in total storage capacity in the SWIS which is expected to reach 398 MWh by June 2029. Under the high and low growth scenarios, residential battery storage is forecast to reach 617 MWh and 223 MWh respectively by June 2029.

FIGURE 3.15 FORECAST TOTAL BATTERY STORAGE, EXPECTED, HIGH AND LOW SCENARIOS, AS AT JUNE 30



SOURCE: CSIRO AND AEMO

3.4 Electric vehicles (EV)

Forecasts of the energy impact arising from the uptake of electric vehicles in Western Australia were provided by sources internal to AEMO.

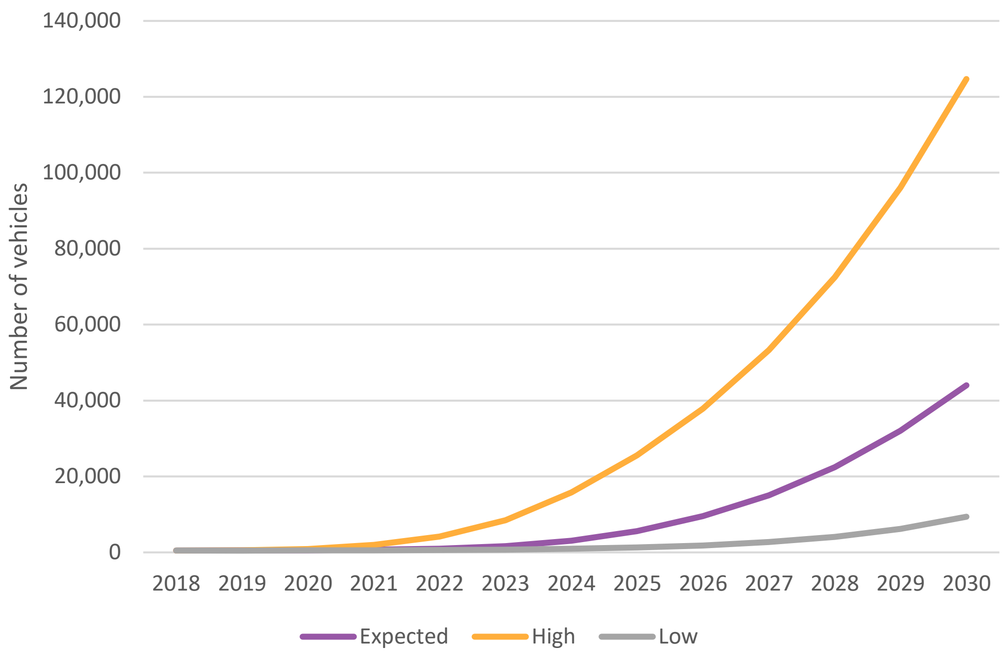
The main drivers that are likely to play a significant role in the future take up of electric vehicles are:

— vehicle prices
— petrol and electricity prices
— vehicle fuel efficiency
— running costs
— range
— charging convenience
— emissions standards.

As upfront electric vehicle (EV) prices continue to decline and the range that these EVs can travel before a recharge is required increases, it is reasonable to expect sales of EVs to increase.

The number of residential passenger vehicles under the expected scenario is forecast to be 32,055 in June 2029. Under the high and low scenarios, they are forecast to reach 96,104 and 6,204 vehicles respectively (see **Figure 3.16**).

FIGURE 3.16 FORECAST NUMBER OF RESIDENTIAL PASSENGER ELECTRIC VEHICLES, EXPECTED, HIGH AND LOW SCENARIOS, AS AT JUNE 30

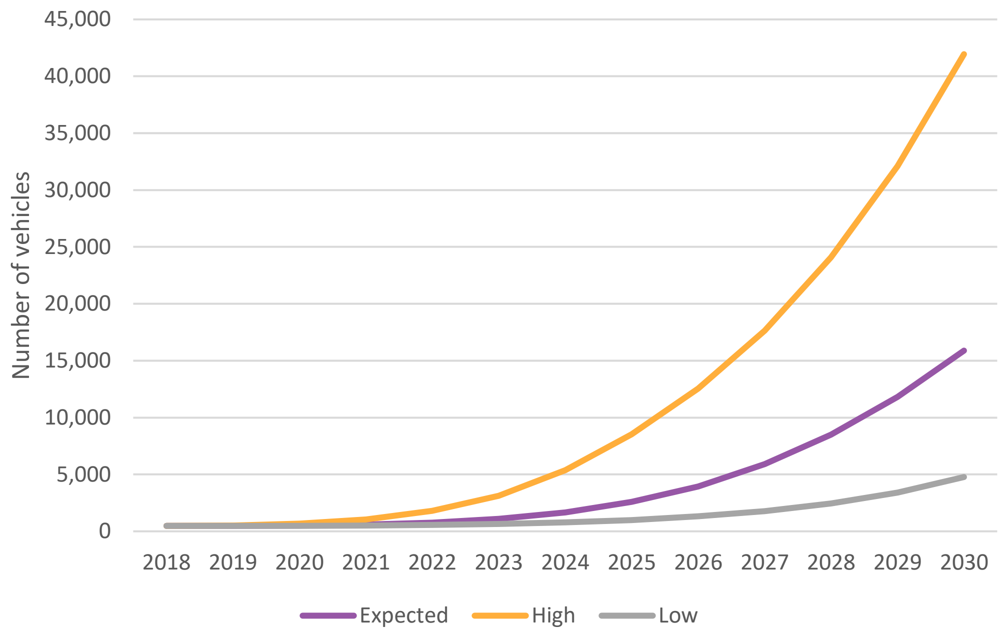


SOURCE: CSIRO AND AEMO

The number of non-residential or commercial vehicles[6] under the expected scenario is forecast to be 11,828 in June 2029. Under the high and low scenarios, they are forecast to reach 32,093 and 3,414 vehicles respectively (see **Figure 3.17**).

[6] Includes light commercial vehicles, trucks and buses.

FIGURE 3.17 FORECAST NUMBER OF NON-RESIDENTIAL ELECTRIC VEHICLES, EXPECTED, HIGH AND LOW SCENARIOS, AS AT JUNE 30



Note: Non-residential vehicles includes Light commercial vehicles, Trucks and Buses

SOURCE: CSIRO AND AEMO

3.5 Block loads

Apart from the normal organic growth which will occur at the system level there may also be larger discrete jumps in demand over time arising from block loads. Block loads arise as new major developments come online, such as when new commercial or industrial developments arise. Block loads show up as discrete jumps or relatively short ramps in peak demand and electricity consumption.

AEMO has advised of several new block loads that are expected to come online in the SWIS during the forecast period.

Demand and energy forecasts of the new block loads were developed by AEMO in consultation with Western Power.

Under the expected scenario, peak demand is forecast to increase by 84 MW as a result of new block loads, while energy is forecast to increase by 566,947 MWh over the forecast period. Under the high scenario, peak demand is forecast to increase by 108 MW and energy by 735,139 MWh as a result of new block loads over the forecast period, while under the low scenario, peak demand is forecast to increase by 40.5 MW and energy by 260,697 MWh.

3.6 Weather

3.6.1 Weather impact on peak demand

The weather is a key driver of peak demand in both summer and winter.

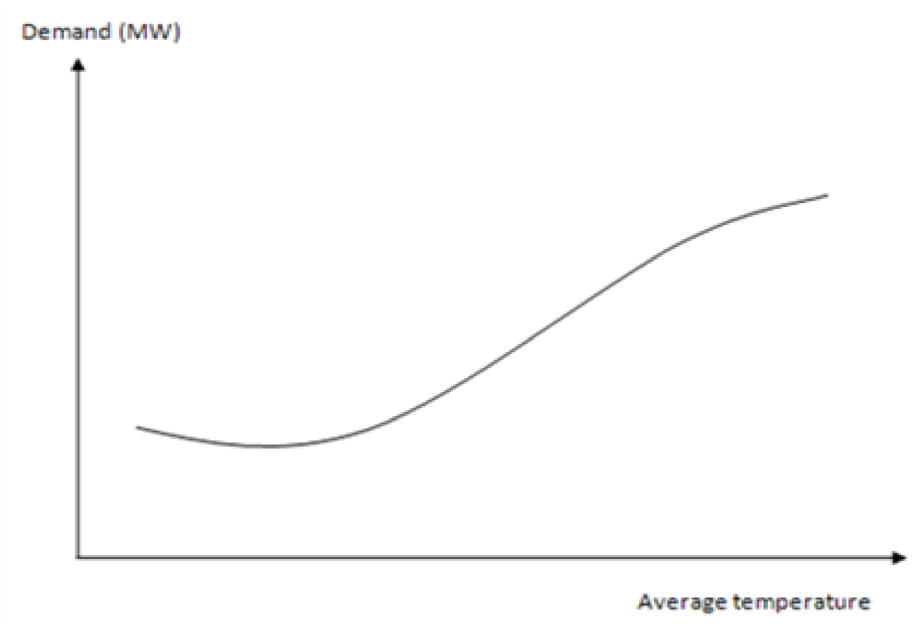
In winter, demand that varies with weather conditions is driven primarily by the ‘heating requirement’. Generally, cooler seasons would be associated with a greater heating requirement, and therefore a greater peak demand. In summer this pattern is reversed, with cooling becoming the driver of weather-related demand.

Establishing a relationship between peak load and weather will also enable weather normalisation to be applied and comparisons of peaks on a weather adjusted basis to be made.

The most important weather variable for the modelling of peak demand is temperature.

The relationship between temperature and daily peak demand is non-linear. This is because there is a range of temperatures where demand becomes unresponsive to changes in temperature. In the summer season models, this range will appear at the lower end of the temperature range, on milder days (see **Figure 3.18**).

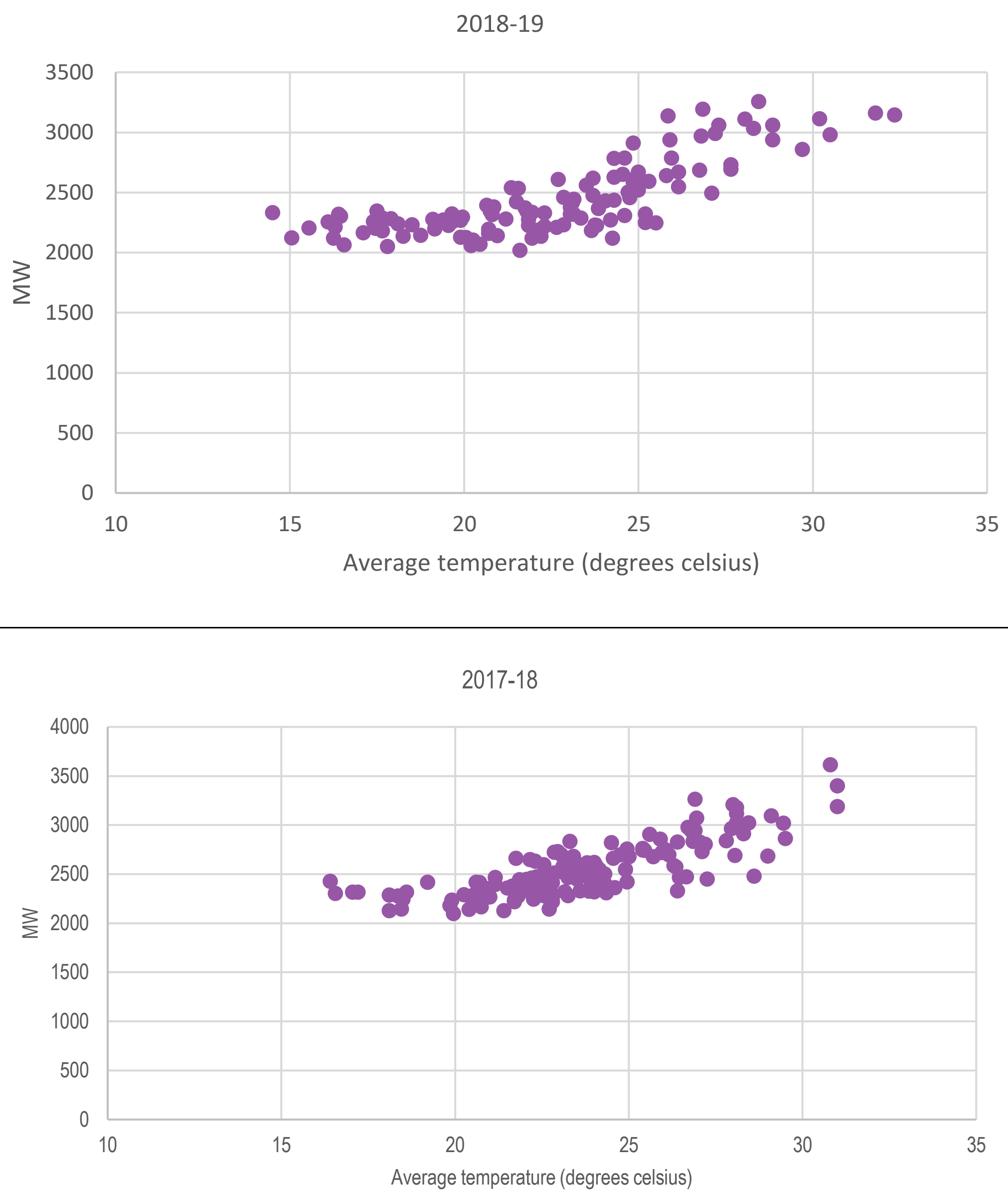
FIGURE 3.18 STYLISED RELATIONSHIP BETWEEN SUMMER DAILY PEAK DEMAND AND AVERAGE DAILY TEMPERATURE



There is also a point on the extreme right of the curve where demand becomes saturated at extremely hot temperatures. At this point, demand becomes unresponsive once again to changes in temperature. This saturation point is rarely observed in practice and corresponds to levels of demand that are well above the 10 POE level.

Figure 3.19 below shows the actual relationship between daily summer peak demand and average temperature for the last two summer seasons in the WEM. The stylised pattern described above is evident.

FIGURE 3.19 PEAK DEMAND (NOVEMBER TO APRIL) VERSUS AVERAGE TEMPERATURE, 2017-18 AND 2018-19



SOURCE: AEMO AND BUREAU OF METEOROLOGY, ACIL ALLEN CALCULATIONS

In the case of winter, the unresponsive part of the curve lies at the upper end of the temperature range, again on milder days (see **Figure 3.20**).

FIGURE 3.20 STYLISED RELATIONSHIP BETWEEN WINTER DAILY PEAK DEMAND AND AVERAGE DAILY TEMPERATURE

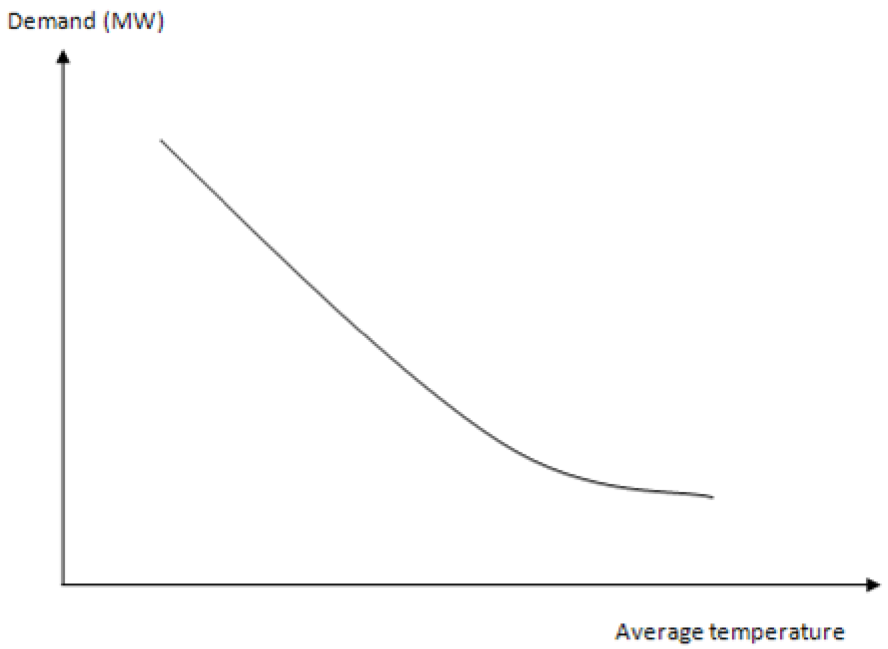
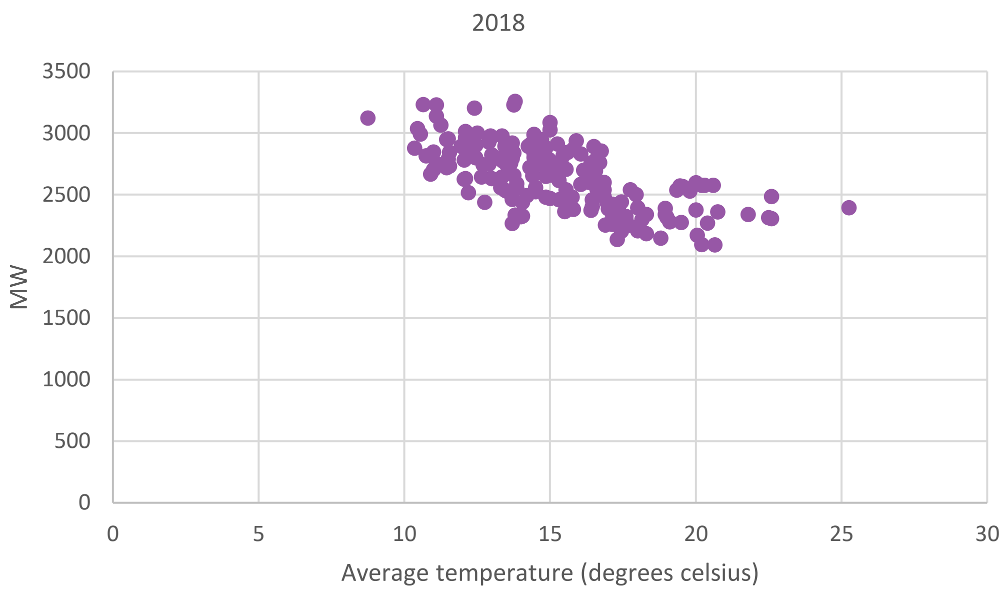
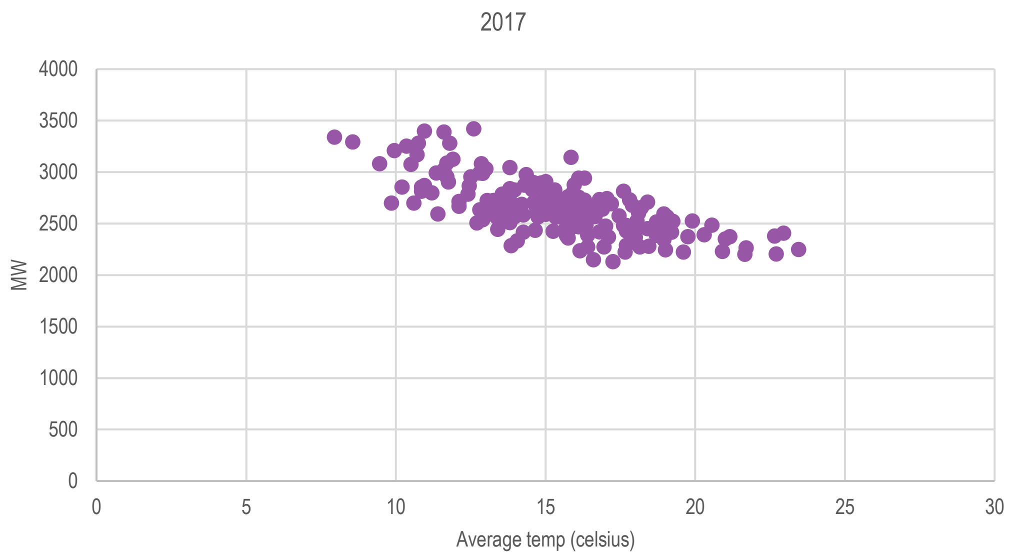


Figure 3.21 below shows the actual relationship between daily winter peak demand and average temperature for the last two seasons in the WEM.

FIGURE 3.21 PEAK WIINTER DEMAND VERSUS AVERAGE TEMPERATURE, 2017 AND 2018





SOURCE: AEMO AND BUREAU OF METEOROLOGY, ACIL ALLEN CALCULATIONS

Weather measurements were taken from the Perth Airport weather station, as reported by the Bureau of Meteorology website. The Perth Airport weather station was chosen because it has high quality data that is located close to the main population centres in the SWIS. Data from this weather station is also highly correlated with peak demand. Further discussion relating to the choice of weather station is provided in section 5.

3.6.2 Weather impact on energy consumption

The weather is a key driver of energy consumption.

Energy consumption will vary over time in response to variations in weather conditions. In order to capture the relationships that exist between energy consumption and its fundamental drivers, it is necessary to remove or control for the impact of weather across the seasons. Failure to do so will result in a model that is mis-specified and that may falsely attribute the impact of weather variation to other factors.

While a single extreme day is sufficient to result in a season peak demand, that day will make only a small contribution to total annual energy consumption. A measure of the overall hotness or mildness of a season is likely to be a better indicator of how temperature is affecting energy consumption. We assess the impact of average weather conditions with the concept of heating degree days and cooling degree days.

Heating degree days is a measure designed to reflect the amount of energy required to heat a home or business, while cooling degree days reflects how much energy is required to cool a home or business.

Data used in the models are the daily maximum and overnight minimum temperatures which are used to derive the number of heating degree days (HDD18) and cooling degree days (CDD24) and (CDD26) for each year.

The number of HDD18 in a given year is simply the sum of the difference between some measure of average ambient room temperature which we define as 18 degrees Celsius and the average daily temperature on each day. Any given day makes a contribution to the total number of heating degree days only if the average temperature[7] on that day is below 18 degrees. For example, if the average temperature today is 10 degrees Celsius, then the number of heating degree days contributed to the annual total from today is 8 (i.e. 18-10).

If the average temperature exceeds 18 on a given day then that day contributes zero to the total number of HDD18 for the year. The higher the number of HDD18 for a given year, the colder that year is.

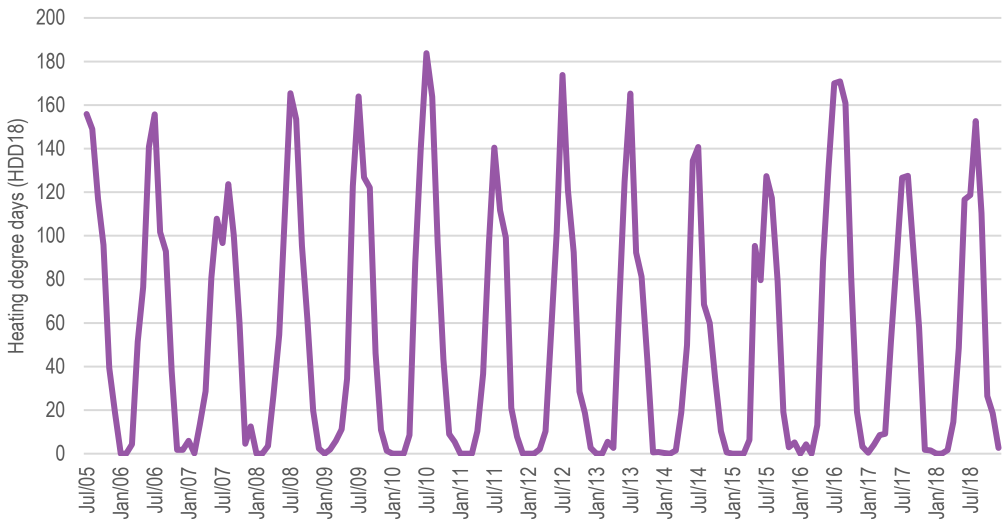
In the case of CDD24 and CDD26 the concept is the same, but the formula takes the sum of degrees that exceed some benchmark (in our case 24 and 26 degrees Celsius) for each day. It is therefore an indication of how hot a given year is, with a higher number of CDD24 or CDD26 reflecting a hotter season.

The temperature thresholds used were determined empirically by looking at the correlation between the different levels of HDD and CDD and monthly energy consumption. In the case of residential energy consumption, the two measures that best explained the variation in energy consumption were HDD18 and CDD26, while for non-residential energy consumption it was HDD18 and CDD24.

The historical heating degree days (HDD18) and cooling degree days (CDD24) and CDD26 series used in the energy regression models to control for weather variation are shown in **Figure 3.22**, **Figure 3.23** and **Figure 3.24** below. The figures show that heating degree days (HDD18) tend to peak in the coldest month of July, while cooling degree days (CDD24 and CDD26) tend to peak in January, reflecting the hotter weather conditions.

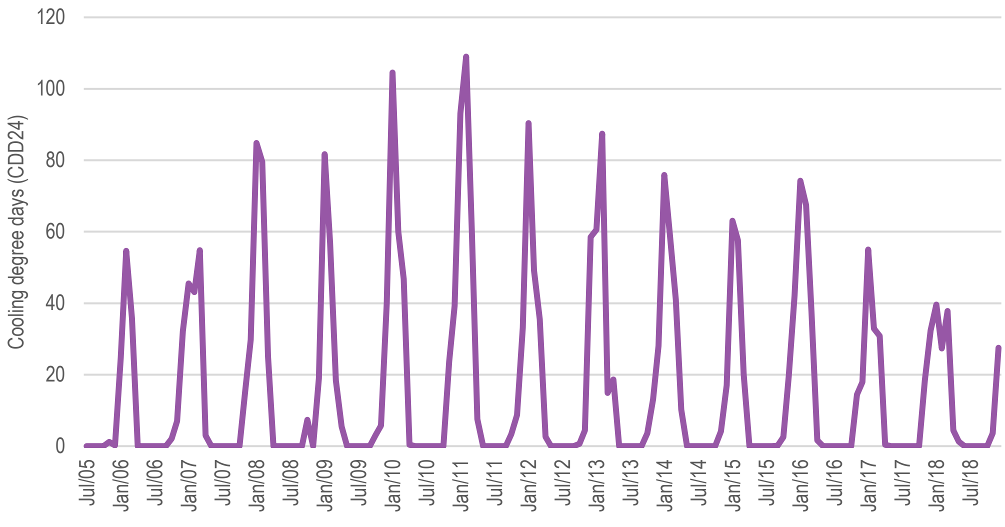
[7] Average temperature is defined as the sum of the daily overnight minimum temperature and daily maximum temperature divided by 2.

FIGURE 3.22 NUMBER OF HEATING DEGREE DAYS (HDD18) BY MONTH, JULY 2005 TO FEBRUARY 2019



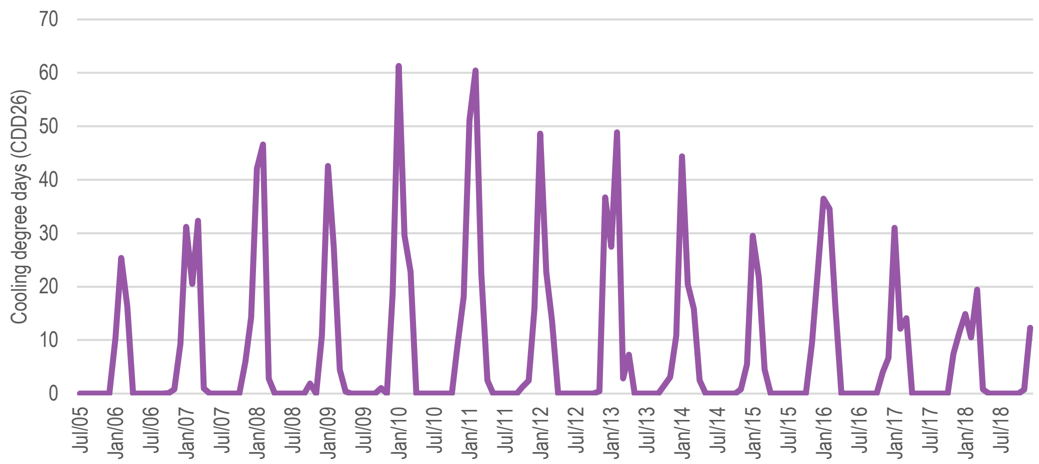
SOURCE: BUREAU OF METEOROLOGY AND ACIL ALLEN

FIGURE 3.23 NUMBER OF COOLING DEGREE DAYS (CDD24) BY MONTH, JULY 2005 TO FEBRUARY 2019



SOURCE: BUREAU OF METEOROLOGY AND ACIL ALLEN

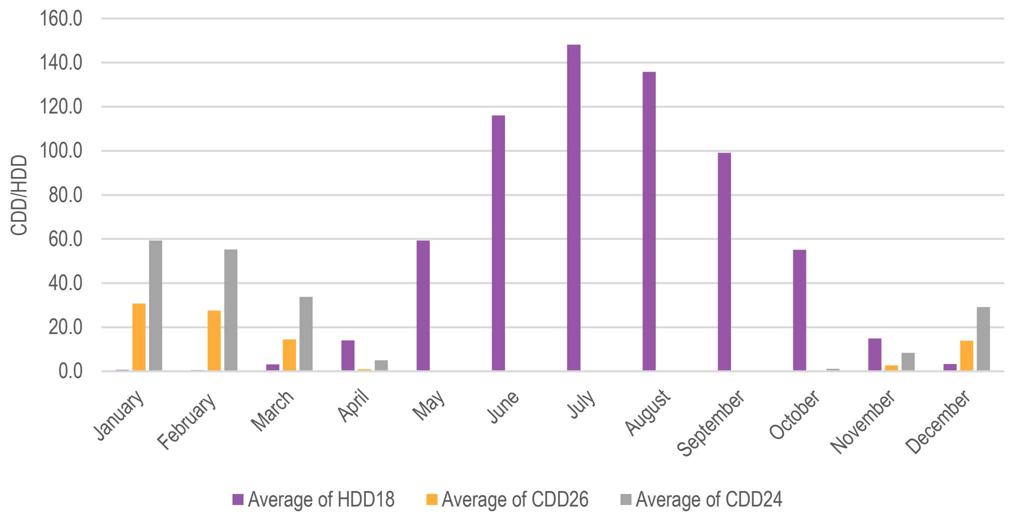
FIGURE 3.24 NUMBER OF COOLING DEGREE DAYS (CDD26) BY MONTH, JULY 2005 TO FEBRUARY 2019



SOURCE: BUREAU OF METEOROLOGY AND ACIL ALLEN

For the purposes of generating the forecasts, a long run monthly average was applied covering the period from January 1987 to December 2018. The average heating degree days and cooling degree days by month are shown in **Figure 3.25**.

FIGURE 3.25 HEATING DEGREE AND COOLING DEGREE DAYS IN THE FORECAST PERIOD



SOURCE: BUREAU OF METEOROLOGY AND ACIL ALLEN

4 ENERGY CONSUMPTION FORECASTING METHODOLOGY

4.1 Modelling approach

An econometric approach to forecasting energy consumption within the SWIS is adopted.

The econometric approach to forecasting sector energy consumption establishes a statistical relationship between energy use and those factors that influence it. By incorporating the major factors affecting the demand for energy, the econometric approach improves the forecaster's ability to explain changes in the structure of demand.

The approach sets the model coefficients so as to maximise parameter efficacy through a range of statistical tests using analysis of variation (ANOVA). Minimising the sum of the squared errors between the values predicted by the model and actual values forms the basis of least squares. Minimising the sum of squared errors is equivalent to maximising the R^2 (explanatory power) of the regression.

A key aspect of the approach involves identifying the key economic, demographic and weather parameters that are important drivers of energy consumption, and therefore necessary inclusions into any model that attempts to explain their historical contribution to energy consumption.

By establishing a statistical relationship between energy and its drivers, the econometric approach allows the forecaster to incorporate their view (or the views of other experts) on the future course of these drivers into the forecasts. This is not possible with simple trend analysis (which essentially assumes that drivers will not vary from past behaviour) and is the main advantage of this approach.

The modelling approach splits the total energy consumption into residential and non-residential customer classes and specifies separate econometric models for these.

The rationale for this is that the drivers of energy growth between customer segments are likely to differ as follows:

- consumption in the residential sector is likely to be closely correlated with population growth and household formation
- consumption in the non-residential sector tends to be driven more by overall economic growth than population growth

With these differences a forecasting methodology that models the different sectors independently of one another is likely to produce a superior set of forecasts than one which does not.

4.2 Forecasts to be produced

Operational energy consumption in the SWIS is forecast on a monthly and annual basis from 2018-19 to 2028-29, on both a Financial Year (July 1 to June 30) and Capacity Year (October 1 to September 30) basis. Forecasts are generated under expected, high and low economic growth scenarios. In addition, there are separate rooftop PV, block load and electric vehicle scenarios. In the case of electric vehicles and block loads, the high uptake case is added to the high economic growth scenario. This in our view, is reasonable as higher uptake of electric vehicles is likely to be associated with higher levels of economic and income growth. In the case of rooftop PV, the expected uptake case is applied to all three economic growth scenarios. The decision to do this was made last year in consultation with AEMO. We are taking a similar approach again this year.

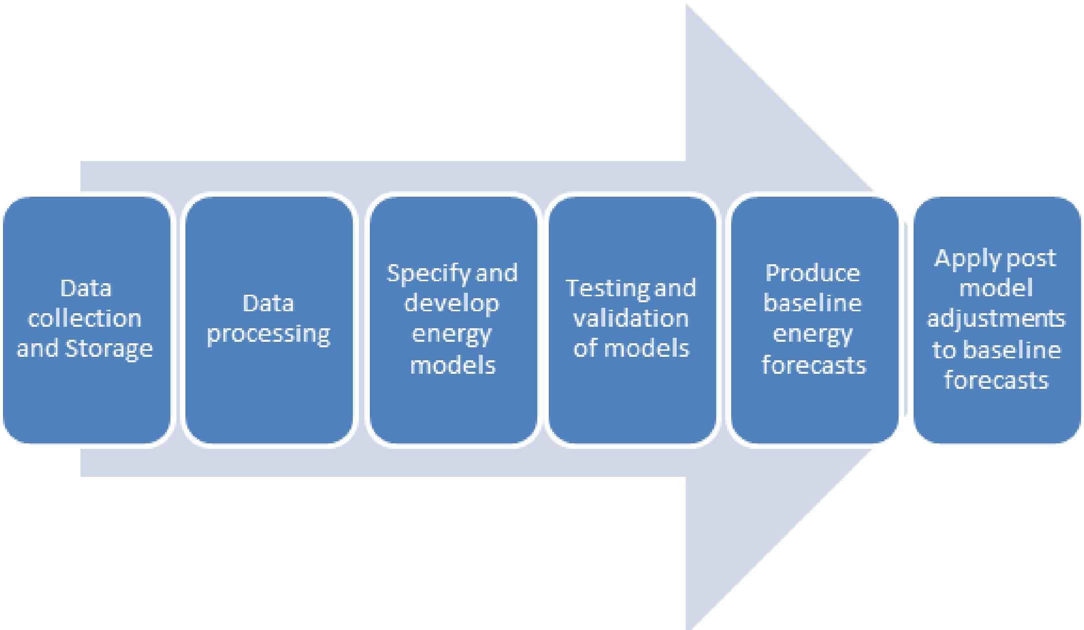
4.3 Model development and forecasting process

The model development process can be broken down into six separate steps shown in **Figure 4.1** below.

The major steps in the forecasting process are:

— data collection
— data processing
— model specification and estimation
— model validation and testing
— produce base line energy forecasts
— apply post model adjustments.

FIGURE 4.1 STEPS IN THE ENERGY FORECASTING PROCESS



4.4 Data collection

The first step in implementing the methodology was to collect the required data described in section 2 and section 3 of this document. The main sources of data were:

— energy consumption and customer numbers data from Synergy

- a rooftop PV capacity factor trace from AEMO
- historical and forecast rooftop PV uptake data from AEMO
- historical block load energy consumption from AEMO
- forecast energy consumption of new block loads under separate expected, high and low scenarios from AEMO
- forecast energy consumption of electric vehicles (EVs) under separate expected, high and low scenarios from AEMO
- economic growth forecasts under separate expected, high and low growth scenarios from AEMO
- population growth forecasts under separate expected, high and low growth scenarios from AEMO
- historical estimated resident population and WA Gross State Product (GSP) data from the Australian Bureau of Statistics (ABS)
- daily maximum and minimum temperature data for the Perth Airport weather station covering the period from January 1 1987, from the Bureau of Meteorology.

Model calibration

The models were calibrated using monthly time series dating back to July 2005 in the case of the residential data, and October 2006 in the case of the non-residential data. Both the residential and non-residential time series covered the period up to the end of December 2018.

4.5 Data processing

Before any energy regression models could be estimated, some intermediate processing was required to render the data suitable to be used in the modelling process.

Key aspects of the intermediate data processing included:

- creation of time series that could be used to estimate the underlying econometric relationships
- checking the continuity of the data, identifying any discrete jumps in the time series which may arise due to system changes or changes in the way customers are classified. These shifts, when detected were corrected for through the appropriate use of dummy variables in the specified models
- checking for measurement errors in the data
- converting the data into monthly time series where necessary. This was done for the historical GSP and population series which are annual and quarterly respectively. The conversion was done using interpolation
- adjusting the baseline historical energy consumption data to remove the impact of rooftop PV and historical block loads (in excess of 20 MW) before the calibration of the baseline energy models. Rooftop PV and block loads are then forecast separately and then added back as post model adjustments
- transformation of the daily air temperature data into the heating degree day (HDD18) and cooling degree day (CDD24 and CDD26) variables
- checking and imputing for missing data where necessary.

4.6 Model specification and estimation

4.6.1 Specification and estimation of the residential consumption models

For the residential customer class, consumption forecasts were derived from two independent components:

1. residential customer numbers
2. average consumption per customer.

The outputs of these two components were multiplied together to provide the baseline forecast of residential energy consumption.

Residential customers

In the case of residential customer numbers, a simple linear regression between residential customers and WA population was estimated in the form of equation (1) below:

$$\textbf{(1)}\quad Customers_t = \alpha + \beta_1 \times Population_t + \beta_2 \times Discontinuity\ dummy_t + \varepsilon_t$$

Where α is a constant, β_1 represents the responsiveness of the number of customers in the SWIS to changes in the WA population and ε is the error term. The dummy variable is included to capture a large discrete jump in residential customer numbers between December 2015 and January 2016.

We note that we are using the entire Western Australian population as a proxy for the SWIS. The model therefore reflects the degree of correlation between customers in the SWIS and the WA population, rather than the population of the SWIS. This is not an issue as the vast majority of Western Australians live within the SWIS, and changes in the WA population are dominated by the SWIS.

The estimated coefficients from the regression model are shown in **Table 4.1**.

TABLE 4.1 RESIDENTIAL CUSTOMER REGRESSION RESULTS

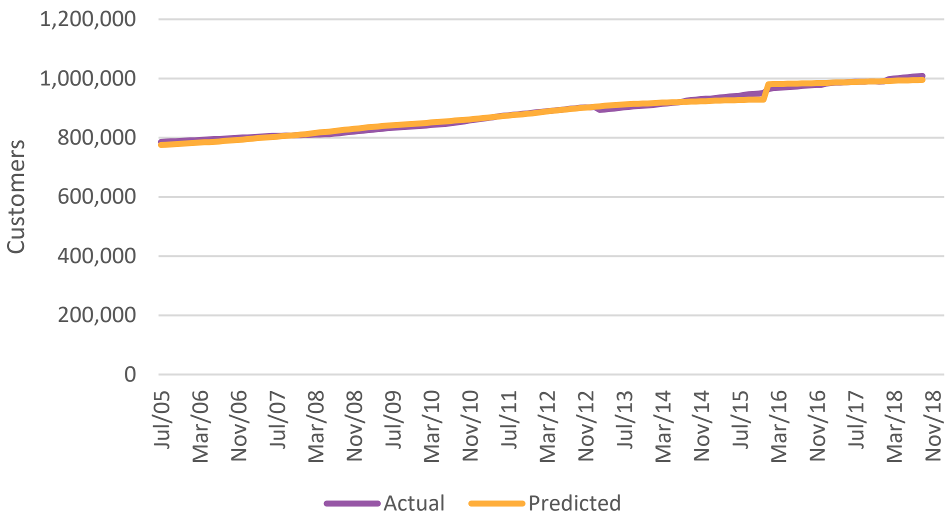
Variable	Coefficient	Std. Err.	t statistic	P>t
Population	0.2875	0.0043	66.7027	0.0000
Discontinuity dummy	51048.7825	1970.0605	25.9123	0.0000
Constant	196486.2109	9967.8364	19.7120	0.0000
R-squared	0.986			

SOURCE: ACIL ALLEN

The coefficient on population can be interpreted as meaning that for every additional person added to Western Australia's resident population there are an additional 0.288 residential customers in the SWIS. The dummy variable is included in the regression from January 2016 onwards to capture a discontinuity in the residential customer numbers when the number of customers jumps from 950,768 in December 2015 to 964,331 in January 2016. This change over a single month is too large to be plausible. While we do not know the exact cause, a possible explanation could be a change in Synergy's internal systems.

Figure 4.2 shows the actual residential customer numbers against the regression models predicted values.

FIGURE 4.2 RESIDENTIAL CUSTOMER NUMBERS, PREDICTED VERSUS ACTUAL



SOURCE: ACIL ALLEN

Residential consumption per customer

Household income is considered to be a driver of residential consumption per customer. Gross state product (GSP) is a good proxy for income and is more commonly forecast than income. GSP was included in the model for residential consumption per customer after being converted to a monthly basis. The coefficient on GSP was found to be statistically insignificant and so was excluded from the final specification.

The potential impact of weather is measured by the CDD26 and HDD18 variables. Moreover, seasonal variation in residential energy consumption per customer is captured through the inclusion of monthly dummy variables. The consumption per residential household in this model is actually latent or underlying consumption (i.e. metered consumption plus PV output).

The estimated regression (not including the monthly dummies) is represented by equation (2) below.

(2) $$\text{Energy per customer}_t = \alpha + \beta_1 \times \text{HDD18}_t + \beta_2 \times \text{CDD26}_t + \varepsilon_t$$

The estimated coefficients of the residential consumption per customer model are shown in **Table 4.2**.

TABLE 4.2 RESIDENTIAL CONSUMPTION PER CUSTOMER REGRESSION RESULTS

Variable	Coefficient	Std. Err.	t statistic	P>t
Heating degree days (18)	0.0004	0.0000	8.9633	0.0000
Cooling degree days (26)	0.0021	0.0002	9.8758	0.0000
Feb	-0.0275	0.0076	-3.6017	0.0004
Apr	-0.0432	0.0081	-5.3242	0.0000
Sep	-0.0539	0.0072	-7.5180	0.0000
Oct	-0.0489	0.0074	-6.5744	0.0000
Nov	-0.0452	0.0078	-5.7760	0.0000
May	-0.0343	0.0075	-4.5906	0.0000
Jun	-0.0260	0.0075	-3.4888	0.0006

Variable	Coefficient	Std. Err.	t statistic	P>t
Constant	0.4205	0.0073	57.8558	0.0000
R-squared	0.7458			

SOURCE: ACIL ALLEN

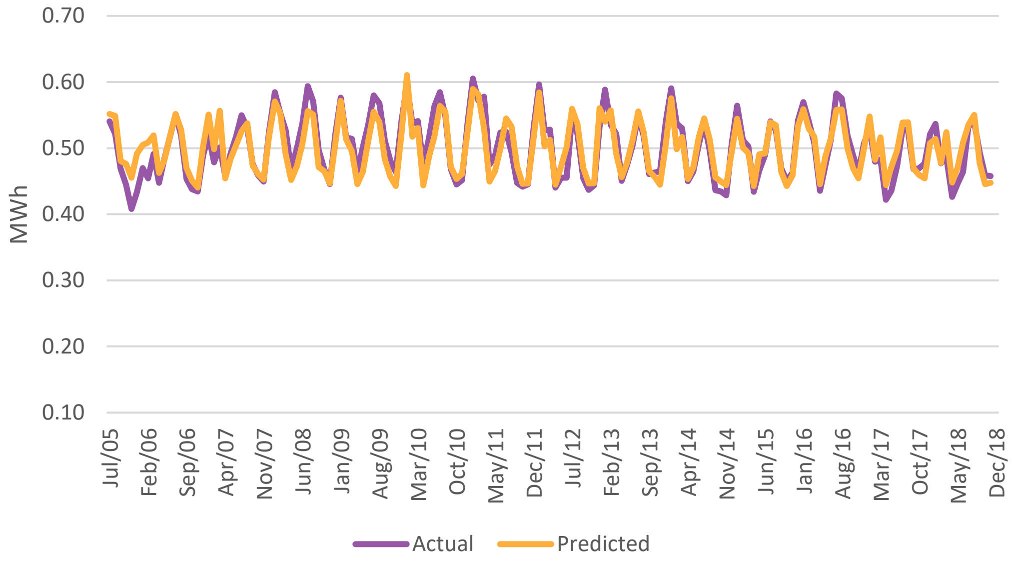
The coefficients can be interpreted as follows:

— each additional 100 HDDs increases energy consumption per customer by 0.044 MWh per month
— each additional 100 CDDs increases energy consumption per customer by 0.208 MWh per month
— in the case of February, April, September, October and November, May and June monthly consumption per customer is lower on average compared to the other months not included in the model (for which a statistically significant relationship could not be established)
— in February, average consumption per customer is 0.027 MWh below the months excluded from the model
  – This is due to the fact that February contains fewer days than the other months of the year
— in April, average consumption per customer is 0.043 MWh below the months excluded from the model
— in September, average consumption per customer is 0.054 MWh below the months excluded from the model
— in October, average consumption per customer is 0.049 MWh below the months excluded from the model
— in November, average consumption per customer is 0.045 MWh below the months excluded from the model.
— in May, average consumption per customer is 0.034 MWh below the months excluded from the model.
— in June, average consumption per customer is 0.026 MWh below the months excluded from the model.

The estimated R^2 of the regression which measures the goodness of fit of the model was 74.6%, which means that over 74% of the variation in the historical data was explained by the model.

Figure 4.3 shows the actual historical average residential consumption per customer numbers against the regression models predicted values.

FIGURE 4.3 MONTHLY RESIDENTIAL CONSUMPTION PER CUSTOMER, PREDICTED VERSUS ACTUAL, MWH



SOURCE: ACIL ALLEN

The chart shows that residential consumption per customer has been relatively flat over the estimation period.

Another variable that was tested in the modelling process was the real retail price of electricity. This was found to be statistically insignificant and excluded from the model. One possible explanation for this is that by removing the impact of rooftop PV from the dependent variable we have also removed the impact of prices, as they are highly correlated, with the onset of rapid PV uptake corresponding with rising retail electricity prices. It is important to note that while we do not directly account for the impact of retail electricity prices on energy consumption, they do play an indirect role through the rooftop PV capacity forecasts which are added to the forecast as a post model adjustment.

4.6.2 Specification and estimation of the non-residential energy consumption models

Total non-residential consumption was modelled as a function of heating degree and cooling degree days as well as a number of monthly dummy variables to capture seasonal variation in non-residential energy consumption. GSP was initially included as an explanatory variable but was found to be statistically insignificant. This is different from last year's specification where GSP was included in the model. This result is largely due to the removal of historical block loads from the dataset and base forecasts, which is a change in the methodology compared to last year. By removing historical block loads from the dataset we are ensuring that there is no double counting when we add new block loads to the base forecasts as post-model adjustments.

A single monthly econometric model was estimated shown in equation (3) below (not including the monthly dummies).

(3) $$Non\text{-}residential\ consumption_t = \alpha + \beta_1 \times HDD18_t + \beta_2 \times CDD24_t + \varepsilon_t$$

The estimated coefficients are shown in **Table 4.3** below.

TABLE 4.3 NON-RESIDENTIAL CONSUMPTION REGRESSION RESULTS

Variable	Coefficient	Std. Err.	t statistic	P>t
Heating degree days (18)	200.93	72.72	2.76	0.01
Cooling degree days (24)	2272.39	125.08	18.17	0.00
Feb	-26197.73	9433.00	-2.78	0.01
Mar	39898.41	8716.88	4.58	0.00
May	19179.20	8592.68	2.23	0.03
Apr	-22056.70	9076.33	-2.43	0.02
Jul	48349.35	10638.40	4.54	0.00
Aug	27500.85	9841.60	2.79	0.01
Constant	822175.21	5811.42	141.48	0.00
R-squared	0.91			

SOURCE: ACIL ALLEN

The estimated regression had an R^2 of 91%, indicating that over 90% of the historical variation in the data could be accounted for by the estimated model.

The coefficients can be interpreted as follows:

— each additional 100 HDDs increases non-residential energy consumption by 20,093 MWh per month

— each additional 100 CDDs increases non-residential energy consumption by 227,239 MWh per month

— in the case of March, May, July and August monthly non-residential consumption is higher on average compared to the excluded months of December, January, June, September, October and November (for which a statistically significant relationship could not be established)

— in February non-residential energy consumption is 26,198 MWh lower on average than the months excluded from the model

  – Just as in the residential consumption per customer model, this is a result of the fact that February contains fewer days than the other months

— in March non-residential energy consumption is 39,898 MWh higher on average than the months excluded from the model

— in April non-residential energy consumption is 22,057 MWh lower on average than the months excluded from the model

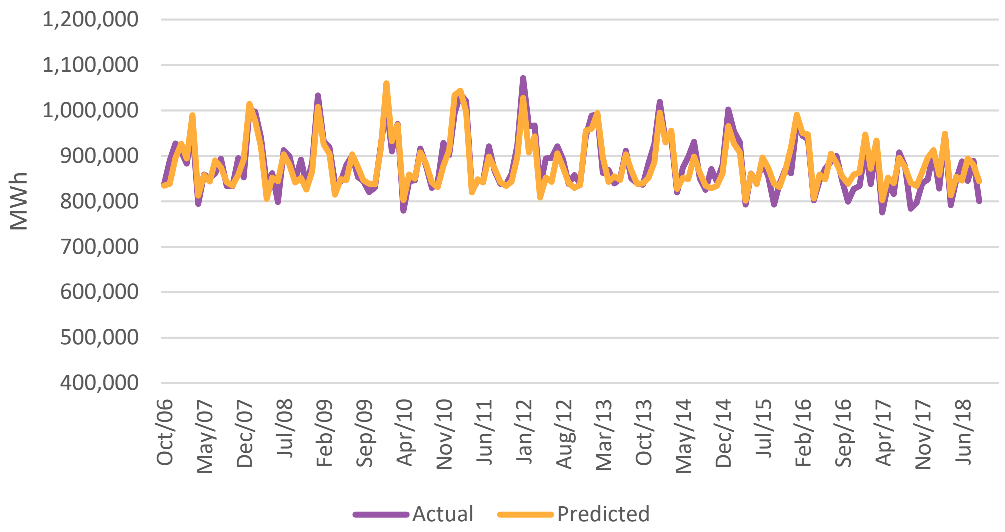
— in May non-residential energy consumption is 19,179 MWh higher on average than the months excluded from the model

— in July non-residential energy consumption is 48,349 MWh higher on average than the months excluded from the model

— in August non-residential energy consumption is 27,501 MWh higher on average than the months excluded from the model

Figure 4.4 shows the historical monthly non-residential consumption against the regression models predicted values.

FIGURE 4.4 NON-RESIDENTIAL ENERGY CONSUMPTION, PREDICTED VERSUS ACTUAL, MWH



SOURCE: ACIL ALLEN

4.7 Model testing and validation

The specified and estimated econometric models have been validated using standard statistical diagnostic tools.

The main methods of model validation used are:

— the theoretical basis of the coefficient size and sign
— the goodness of fit of the regression
— the statistical significance of the explanatory variables
— unit root testing and testing for stationarity to minimise the risk of spurious regression coefficients
— testing for the presence of heteroscedasticity and multicollinearity

The choice of model variables has been based on theoretical considerations of key drivers to explain the measured variation in energy consumption. As a consequence, some sense of the likely size and direction of model coefficients is possible. Where a variable produced an effect contrary to that understood by economic theory it was excluded from any model specification.

The most commonly used measure of the goodness of fit of the regression model to the observed data is R^2. In the model validation process, the R^2 is considered as part of a suite of statistical tools available. Emphasis is placed on the overall fit of the models as well as on the statistical significance of individual explanatory variables.

4.8 Post model adjustments

It was also necessary to make additional adjustments arising from factors that were not included in the baseline econometric models. The post model adjustments applied to the energy consumption forecasts were for rising uptake of rooftop PV, new block loads and the increasing energy consumption over time due to the uptake of electric vehicles.

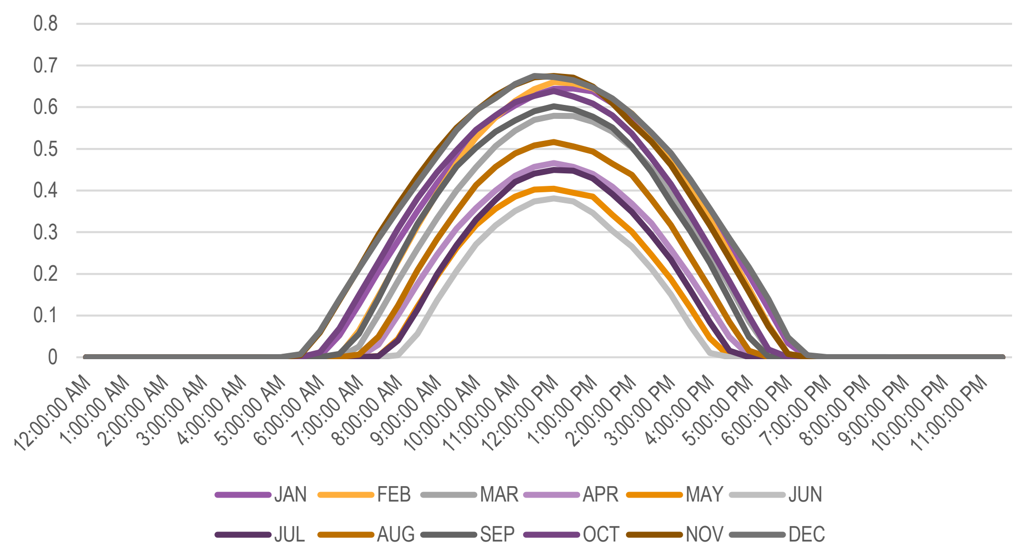
4.8.1 Rooftop PV adjustment

As mentioned previously, the dependent variables in the baseline econometric models were stripped of any impact of rooftop PV before the models were calibrated.

This means that the impact of rooftop PV needs to be re-introduced into the baseline econometric forecasts to generate the final forecasts. This was done by applying average rooftop PV capacity factors for a subset of customers in the SWIS. The behaviour of these customers was assumed to apply to all the rooftop PV capacity in the SWIS at any point in time.

For the purposes of estimating the contribution of rooftop PV over the forecast horizon, a load trace covering the period from June 1 2011 to February 21 2019 was averaged by month to generate twelve separate load traces. These are shown in **Figure 4.5** below. From the figure it is evident that rooftop PV systems are operating at peak output during the early afternoon hours, with the summer months of December, January and February generating more output than the other months.

FIGURE 4.5 AVERAGE DAILY ROOFTOP PV CAPACITY FACTORS BY MONTH



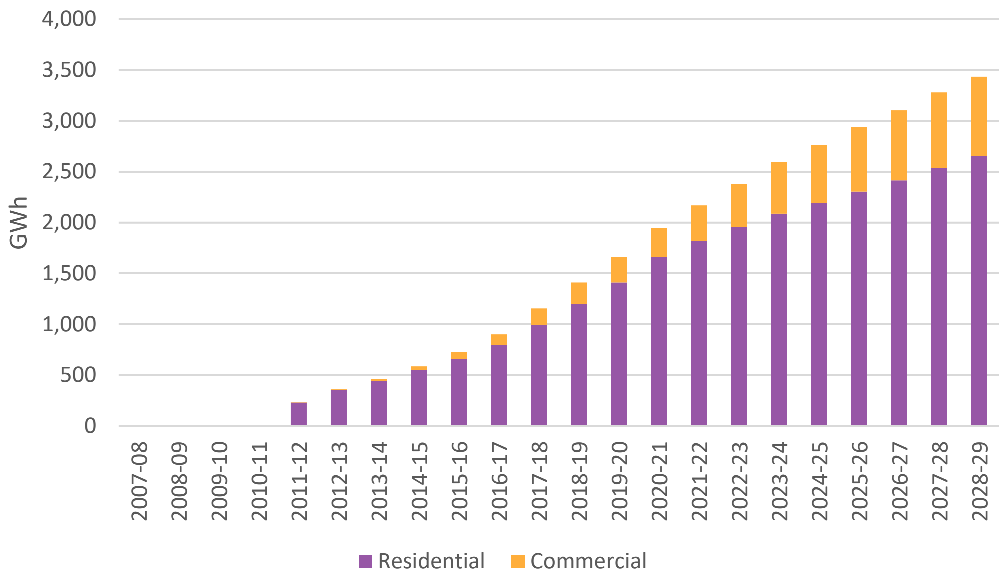
SOURCE: AEMO AND ACIL ALLEN

In order to estimate the amount of energy generated on a daily basis, the load trace for each half hour was multiplied by the forecast daily rooftop PV capacity and then this total was divided by 2 to adjust for the fact that we are aggregating by each half hour. Once the level of daily rooftop PV energy generation was calculated, it was aggregated up to the monthly level and deducted from the baseline econometric forecasts of monthly residential and non-residential consumption.

Figure 4.6 presents the total energy generated by rooftop PV systems under each of the three scenarios. Under the expected scenario, rooftop PV generation is forecast to reach 3,432 GWh by 2028-29. Of this, 2,653 GWh will be generated by the residential sector, while 779 GWh will be generated by the non-residential sector.

We note that, in line with last year, the expected rooftop PV scenario is also applied to all the high, expected and low economic growth scenarios.

FIGURE 4.6 FORECAST GENERATION OF ROOFTOP PV SYSTEMS, UNDER ALL SCENARIOS, GWH



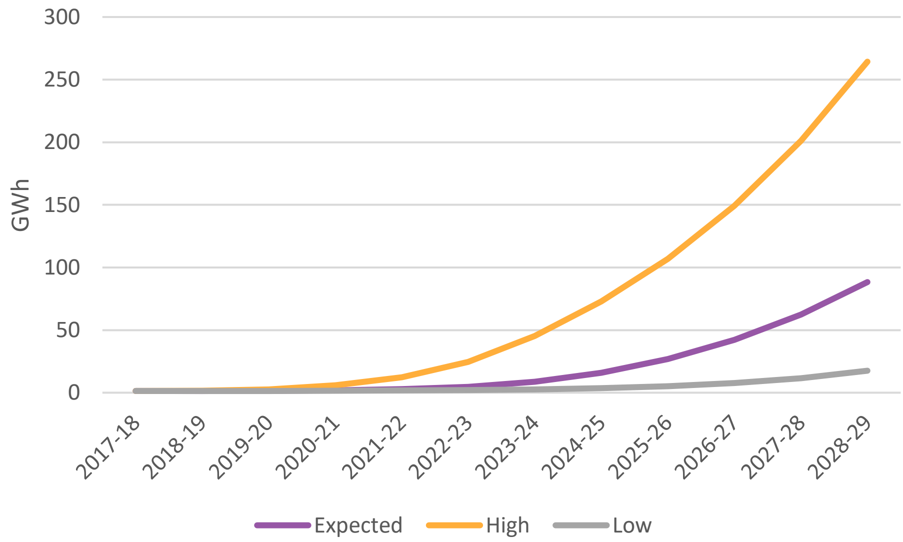
SOURCE: AEMO AND ACIL ALLEN

4.8.2 Electric vehicle adjustment

Another post-model adjustment required as part of the energy forecasting methodology is to add on the impact of electric vehicles. Forecasts of the energy impact of electric vehicles were provided by AEMO.

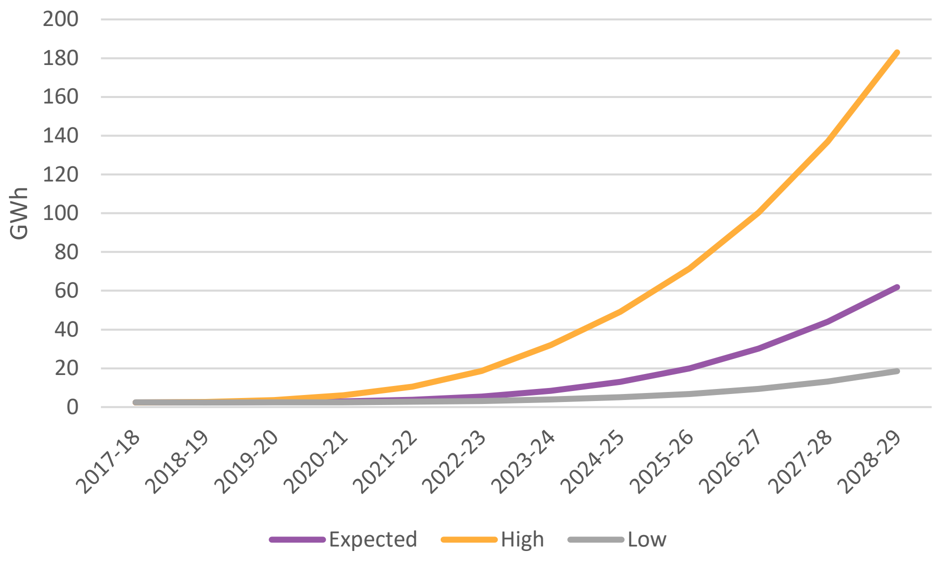
These forecasts are presented in **Figure 4.7** and **Figure 4.8** below for the residential and non-residential sectors respectively, and in **Figure 4.9** for the total across the SWIS.

FIGURE 4.7 FORECAST RESIDENTIAL ENERGY CONSUMPTION OF ELECTRIC VEHICLES, GWH



SOURCE: AEMO AND CSIRO

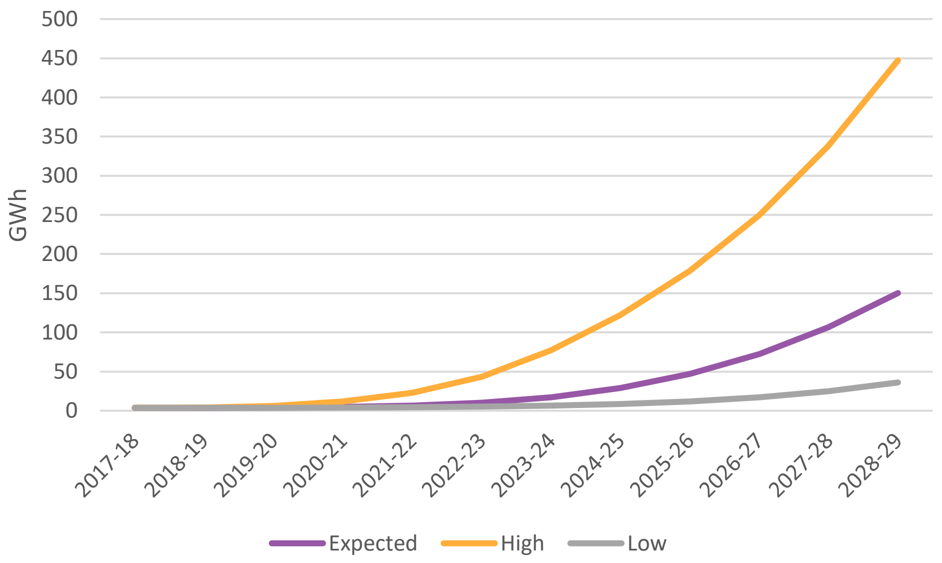
FIGURE 4.8 FORECAST NON-RESIDENTIAL ENERGY CONSUMPTION OF ELECTRIC VEHICLES, GWH



SOURCE: AEMO AND CSIRO

Under the expected scenario, total energy consumption of electric vehicles in the SWIS is forecast to be 150 GWh by 2028-29. This increases to 447 GWh under the high scenario and declines to just 36 GWh under the low scenario.

FIGURE 4.9 FORECAST TOTAL ENERGY CONSUMPTION OF ELECTRIC VEHICLES, GWH



SOURCE: AEMO AND CSIRO

4.8.3 Block loads

A final post model adjustment is made for the addition of new block loads in excess of 20 MW under the three separate scenarios. This is in addition to the historical block loads that are also added back as part of the post model adjustment process.

Under the expected scenario, the total impact of block loads is forecast to reach 3,668 GWh in 2028-29 (see **Figure 4.10**). This includes both the existing historical loads as well as new loads coming online during the forecast period.

Under the high scenario, the total impact of block loads is forecast to reach 3,836 GWh, while under the low scenario the impact of block loads is forecast to be 3,361 GWh by 2028-29.

FIGURE 4.10 HISTORICAL AND PROJECTED BLOCK LOADS IN THE SWIS, GWH

SOURCE: AEMO

5 PEAK DEMAND FORECASTING METHODOLOGY

5.1 Modelling approach

Just as in the energy consumption forecasting methodology, an econometric approach to forecasting peak demand within the SWIS was adopted. This approach establishes a statistical relationship between daily peak demand and those key economic, demographic and weather factors that drive it and then uses the estimated relationships to generate forecasts of peak demand. Separate regression models were specified and estimated for the hotter (summer) and colder months (winter) of the year.

These estimated statistical relationships were used in conjunction with a long run weather series comprising 30 years of data to conduct a stochastic analysis. This was used to weather normalise the peak demand forecasts. This is described further in section 5.7.

5.1.1 Forecasts to be produced

Forecast horizon and frequency

Peak demand in the SWIS was forecast on a seasonal basis (summer and winter) covering a forecast horizon from the 2019-20 to 2028-29 Capacity Years in the case of summer and 2019 to 2028 for winter. Forecasts were produced under 10 POE, 50 POE and 90 POE weather conditions as well as under expected, high and low economic growth scenarios.

5.2 Model development and forecasting process

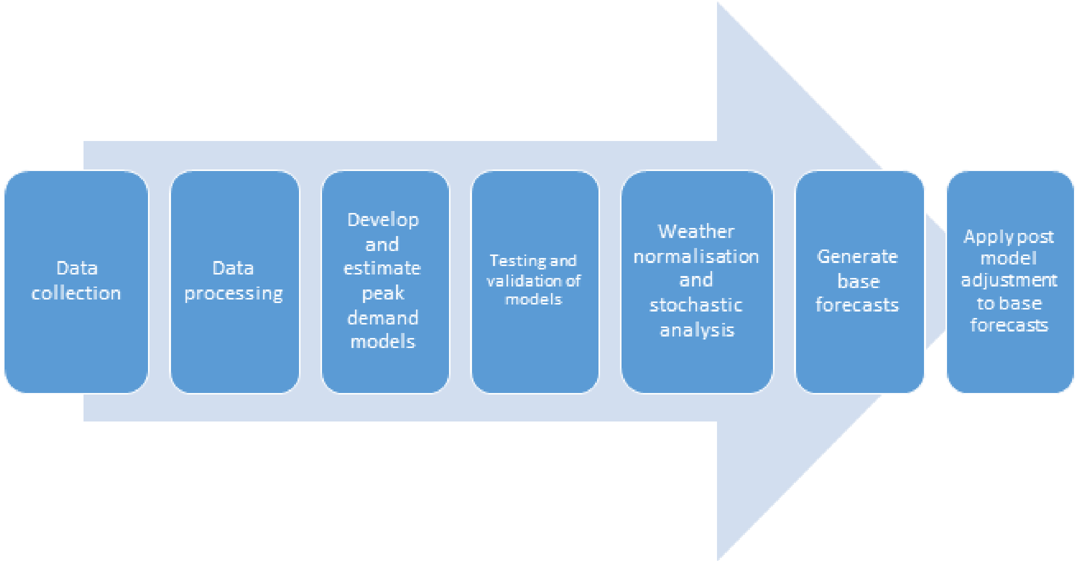
The steps required in peak demand forecasting process are shown in **Figure 5.1** below.

These steps can be broken down as follows:

- data collection
- data processing
- base model specification and estimation
- model testing and validation
- weather normalisation and stochastic analysis
- base forecast generation
- post model adjustments.

While these steps follow a similar structure to the energy forecasting methodology, a key extra step in the peak demand methodology is weather normalisation, which is the most complex and important step in the peak demand methodology.

FIGURE 5.1 STEPS IN THE PEAK DEMAND FORECASTING PROCESS



5.3 Data collection and storage

The data used in the peak demand modelling process were:

- half hourly electricity sent out demand data from WA market commencement
- a rooftop PV load trace and historical rooftop PV capacity
- details of any block loads expected over the forecast horizon
- economic growth forecasts under separate expected, high and low growth scenarios
- historical WA GSP data
- daily maximum and minimum temperature data for the Perth Airport weather station covering the period from January 1 1987.

Model calibration

The models were calibrated using daily time series dating from September 21 2006 to February 28 2019.

5.4 Data processing

There were several important data processing steps required before the peak demand modelling could proceed. These are described below.

5.4.1 Prepare peak demand time series for regression analysis

The first step in the data preparation process was to create a time series data set suitable for conducting a regression analysis. This involved the following:

- extracting peak summer and winter demands with associated date / time stamp
- extracting daily peak demand for inclusion in the regression dataset
- creating an underlying daily peak demand series with the impact of block loads and rooftop PV removed (to be re-introduced as a post model adjustment). This was done by using a half hourly load trace to estimate the contribution of rooftop PV in each half hour
- creation of seasonal, day of the week and monthly dummy variables

- addition of other explanatory variables to the daily dataset such as economic activity and temperature variables
- checking for, identifying and rectifying any errors in the data or missing data.

5.4.2 Removing weekends, other non-working days and Christmas holiday period from the dataset

Peak demand is typically lower on weekends, non-working days and holiday periods. For this reason, any estimated regression model will need to account for this characteristic of the data. The regression data set was adjusted by:

- removing weekends from the dataset
- removing other non-working days such as public holidays (eg: Australia Day)
- removing the Christmas holiday period starting from December 22nd and ending on January 4th of each summer.

An additional adjustment was to remove the milder days from the modelling data sets before any regressions were estimated. This was done to remove the flat or non-responsive part of the relationship between daily peak demand and temperature. When we do this we are left with a relationship that is approximately linear.

A threshold average temperature of 21 degrees Celsius was applied to both the estimated regression models. In the case of the summer model, those days where the average temperature did not exceed 21 degrees were omitted from the regression. In the case of the winter model, milder days where the average temperature exceeded 21 degrees Celsius were omitted from the regression. This threshold was determined by visually inspecting the historical relationship between daily peak demand and average temperature.

The truncation of the available data set through the removal of non-working days, holiday periods and milder days does not result in any adverse consequences for the model estimation process. There is more than sufficient data remaining to allow for accurate estimation of the model parameters.

5.4.3 Choosing an appropriate weather station

The key weather inputs into the peak demand modelling process are the daily maximum and daily minimum temperature.

The modelling process required the use of suitable weather series to relate daily movements in system maximum demand with respect to weather variation. Weather data (daily maximum and minimum temperature) were used in the process in two ways. First, they were used in the regression model to relate maximum demand to the weather drivers. They were also used to construct the long run weather series to derive the desired POE demand.

While there were a large number of potential weather stations available for use it is important to note that the vast majority of these were unsuitable for one of two reasons:

- they didn’t have a sufficiently long time series to allow an accurate representation of the distribution of possible maximum demands in the weather correction process. Because we were interested in calculating the 10 POE maximum demand, which is by definition exceeded only once every 10 years on average, it was necessary to have a large sample of weather years available. It is our view that 30 years of weather data is the minimum number of years required to adequately capture the underlying distribution of possible outcomes
- they were missing a significant number of values (more than 1% to 2%).

Weather time series data were obtained from the Bureau of Meteorology (BOM).

The two candidate weather stations that were considered as part of this modelling exercise were:

- 009225 Perth Metro
- 009201 Perth Airport.

The time series data from Perth Airport date back to 1944, while Perth Metro contains data dating back to 1994 only.

The main factors that determined the best choice of weather station to use were:

- the degree of correlation between data from that weather station and peak demand
- the degree of proximity to major population centres
- the quality of data at the weather station such that there are few missing observations
- the length of time series available is long enough to gain a reasonable long run view of weather behaviour at that particular location.

Both the Perth Metro and Perth Airport time series are of high quality with virtually no missing data over the relevant periods.

While temperature data from both weather stations provided good explanatory power of movements in daily peak demand subject to the necessary quality standard, we opted to use the data from the Perth Airport weather station on the basis that we require a minimum of 30 years of historical data to adequately describe the long run weather distribution in the stochastic modelling. While the Perth Airport data goes back to before the start of 1987, which is our minimum time series requirement, the Perth Metro data falls short by about seven years.

5.5 Specification and estimation of the baseline peak demand models

The methodology adopted by ACIL Allen to forecast peak demand is a multiple regression approach. In the case of peak demand, two separate regression models were estimated, one for the warmer months of the year (to which we refer as the summer model) and one for the colder months (to which we refer as the winter model).

Separate regression models are necessary to capture the different relationship between daily peak demand and temperature in the summer and winter seasons. Higher peak demands in the summer are driven by cooling loads which increase in response to hot weather conditions. On the other hand, peak demand increases in the winter months due to cold weather conditions which drive heating loads. For the summer model, we expect a positive relationship between peak demand and temperature while the winter model is expected to produce a negative relationship.

After careful observation of the data, we chose to split the year into November to April for the summer model and May to October for the winter model.

There has been a change in the summer base model specification this year compared to last year. First the underlying daily peak demand series was adjusted to be the level of demand at the interval starting at 5:30 pm, which is the time interval at which the summer peaks have generally been occurring and the time at which these peaks are assumed to continue to occur during the forecast period. In last year's model, the alternative daily peak demand series was simply the new peak on that day, which often occurred at different time to the actual peak. In making the post model adjustment for rooftop PV, it was not entirely clear that the time shift in the peak resulting from rooftop PV was being captured in a way that was without error or bias.

By altering the model to use the adjusted daily demand at the same time every day, we remove the impact of the time shift associated with increasing rooftop PV capacity and avoid any ambiguity about how to correctly account for rooftop PV going forward into the forecast period. This is not an issue with the winter model, as rooftop PV plays a negligible role and the time of the winter peak has remained generally stable over time, occurring at around 6pm since the beginning of the sample period.

An additional change also involves the removal of historical block loads from the historical peak demand series before estimating the baseline econometric models. This was done for both the summer and winter models and reduces the risk of double counting future block loads that are added to the forecasts as post model adjustments. If the historical block loads were not removed from the regression data set, then the base line forecasts would contain additional growth that could be attributed to the historical block loads. Adding new block loads as post model adjustments in instance would in all likelihood result in double counting the new loads which are also captured in the base line forecasts.

5.5.1 System level maximum demand - summer

At the system level, daily summer peak demand was modelled from a dataset showing daily maximum demand for all 'non-mild' days.[8] The model expresses daily peak demand as a function of the following factors:

- **GSP_t:** gross state product
- **Min_t:** minimum daily temperature
- **Max_t:** maximum daily temperature
- **Max_{t-1}:** maximum daily temperature on the previous day
- **Max_{t-2}:** maximum daily temperature on two days prior
- **$November_t$:** dummy variable, equal to '1' if month is November, '0' otherwise
- **$December_t$:** dummy variable, equal to '1' if month is December, '0' otherwise
- **$January_t$:** dummy variable, equal to '1' if month is January, '0' otherwise
- **$March_t$:** dummy variable, equal to '1' if month is March, '0' otherwise
- **$April_t$:** dummy variable, equal to '1' if month is April, '0' otherwise
- **$Friday_t$:** dummy variable, equal to '1' if day is Friday, '0' otherwise.

This specification provided a good balance between explanatory power, sensible coefficients, and model parsimony. The final model is shown in equation (4). The error term in the model is represented by ε_t.

$$MD_t = -825.38 + 0.002 \times GSP_t + 64.65 \times Max_t + 30.36 \times Min_t + 3.85 \times Max_{t-1} + 7.58 \times Max_{t-2} - 68.87 \times Friday_t - 173.22 \times November_t - 101.51 \times December_t - 66.52 \times January_t - 74.74 \times March_t - 136.53 \times April_t + \varepsilon_t \quad (4)$$

Table 5.1 summarises the coefficients estimated using this specification.

TABLE 5.1 SYSTEM PEAK DEMAND MODEL (SUMMER), ESTIMATED COEFFICIENTS

Variable	Coefficient	Standard error	t-statistic	p-value
GSP	0.002	0.000	10.944	0.000
MAX_t	64.647	1.498	43.154	0.000
MIN_t	30.361	2.116	14.350	0.000
MAX_{t-1}	3.848	1.841	2.091	0.037
MAX_{t-2}	7.575	1.498	5.058	0.000
FRI	-68.870	12.902	-5.338	0.000
NOV	-173.223	17.998	-9.625	0.000
DEC	-101.514	18.040	-5.627	0.000
JAN	-66.523	14.534	-4.577	0.000
MAR	-74.742	15.131	-4.940	0.000
APR	-136.528	21.218	-6.435	0.000
Constant	-825.378	71.605	-11.527	0.000
R^2 (Adjusted):	0.835	Standard error of regression:	151.68	

SOURCE: ACIL ALLEN

The coefficient on GSP is positive, meaning that as the economy grows, the forecast peak demand increases also. For every $100 million increase in GSP, summer peak demand increases by 0.2 MW.

There is also a positive relationship between daily maximum and minimum temperature and peak demand. For every 1 degree Celsius increase in the daily maximum temperature, peak demand

[8] 'non-mild' days means that weekends, public holidays and days with mild temperatures were omitted.

increases by 65 MW, while a degree increase in the overnight minimum temperature increases peak demand by 30 MW.

The coefficients on lagged temperature are positive, meaning that as temperature increases over several days, peak demand is forecast to increase also. Moreover, peak demand is 69 MW lower on average on Fridays compared to the other days of the week.

5.5.2 System level maximum demand - winter

For winter system level forecasts, peak demand was modelled as a function of the following factors:

— **GSP_t:** gross state product

— **Max_t:** maximum daily temperature

— **Min_t:** minimum daily temperature

— **Max_{t-1}:** maximum daily temperature on the previous day

— **$Friday_t$:** dummy variable, equal to '1' if day is Friday, '0' otherwise

— **May:** dummy variable, equal to '1' if month is May, '0' otherwise

— **August:** dummy variable, equal to '1' if month is August, '0' otherwise

— **September:** dummy variable, equal to '1' if month is September, '0' otherwise

— **October:** dummy variable, equal to '1' if month is October, '0' otherwise.

This specification provided a good balance between explanatory power, sensible coefficients, and model parsimony. The final model is shown in equation (5). The error term in the model is represented by ε_t.

$$MD_t = 3129.43 + 0.001 \times GSP_t - 31.84 \times Max_t - 8.44 \times Min_t - 5.05 \times Max_{t-1} - 95.68 \times Friday_t - 111.48 \times May_t - 68.20 \times August_t - 176.03 \times September_t - 288.95 \times October_t + \varepsilon_t \quad (5)$$

Table 5.2 summarises the coefficients estimated using this specification.

TABLE 5.2 SYSTEM PEAK DEMAND MODEL (WINTER), ESTIMATED COEFFICIENTS

Variable	Coefficient	Standard error	t-statistic	p-value
GSP	0.001	0.000	11.612	0.000
MAX_t	-31.841	1.082	-29.430	0.000
MIN_t	-8.436	0.768	-10.989	0.000
MAX_{t-1}	-5.054	1.066	-4.743	0.000
FRI	-95.680	5.881	-16.268	0.000
MAY	-111.475	7.829	-14.239	0.000
AUG	-68.196	6.986	-9.762	0.000
SEP	-176.034	7.289	-24.152	0.000
OCT	-288.945	8.368	-34.532	0.000
Constant	3129.426	25.756	121.502	0.000
R^2 (Adjusted):	0.824	Standard error of regression:	92.2	

SOURCE: ACIL ALLEN

The positive coefficient on GSP suggests that peak demand increases with higher levels of economic activity. For every $100 million increase in GSP, winter peak demand increases by 0.1 MW.

The negative coefficients on the daily maximum and minimum temperature variables indicate that as temperature drops in the colder months, peak demand increases due to rising heating loads. For every 1 degree decline in the daily maximum temperature, winter peak demand increases by 32 MW, while a 1 degree decline in the daily overnight minimum raises winter peak demand by 8 MW.

A negative coefficient on lagged temperature implies an impact of sequences of cold days, in the same way as sequences of hot days increase electricity demand in summer.

Finally, daily peak demand in was found to be lower in May, August, September and October on average, relative to June and July. As with the summer model, demand is forecast to be lower on Friday than on other weekdays.

5.6 Model validation and testing

As in the case of the energy consumption models, the estimated peak demand models were validated and tested in the following ways;

— confirmation that established relationships fit with theory (direction and significance of the coefficients)
— assessment of the statistical significance of explanatory variables
— assessment of goodness of fit
— in-sample forecasting performance of the model against actual data
— unit root testing and testing for stationarity
— testing for the presence of heterocedasticity and multicollinearity

5.7 Weather normalisation and stochastic analysis

A stochastic analysis was conducted on the calibrated summer and winter demand models to generate a distribution of seasonal peak demands. The 10, 50 and 90 POE peak demand was derived from this distribution. The 50 POE level of demand corresponds to the level of demand that is exceeded in 1 out of every 2 years. The 10 POE level of demand is exceeded in 1 out of every 10 years.

The process for generating peak demand forecasts for summer and winter was to use the models described above to estimate daily peak demands for each forecast year. The estimated daily peak demands were calculated by:

— using historical temperature data from each day for a period of 30 years
— using the values of other drivers relating to that forecast year
— generating a draw from a normal distribution with mean zero and standard deviation equal to the standard error of the estimated regression and adding it to the daily demand.

The peak demand for each year of temperature data was stored and the process simulated 100 times.

The 10, 50 and 90 POE peak demand levels were then determined by considering percentiles of the 3,000 simulated peak demand values in each forecast year. We obtain 3,000 years simulated peak demand values because we use 30 years of data simulated 100 times (30×100=3,000).

The error term of each calibrated regression model was factored into the stochastic analysis to capture the tendency for the estimated regression models to under predict the seasonal peak demand. This is because the peak demand is also influenced by other random factors that are unrelated to temperature. So by adding a stochastic term to each fitted daily peak demand this tendency to under predict peak demand is removed.

5.8 Apply post model adjustments

As in the cast of the energy consumption methodology, there were a number of post model adjustments that needed to be added back to the peak demand econometric forecasts as these were excluded from the baseline models. These are discussed further below.

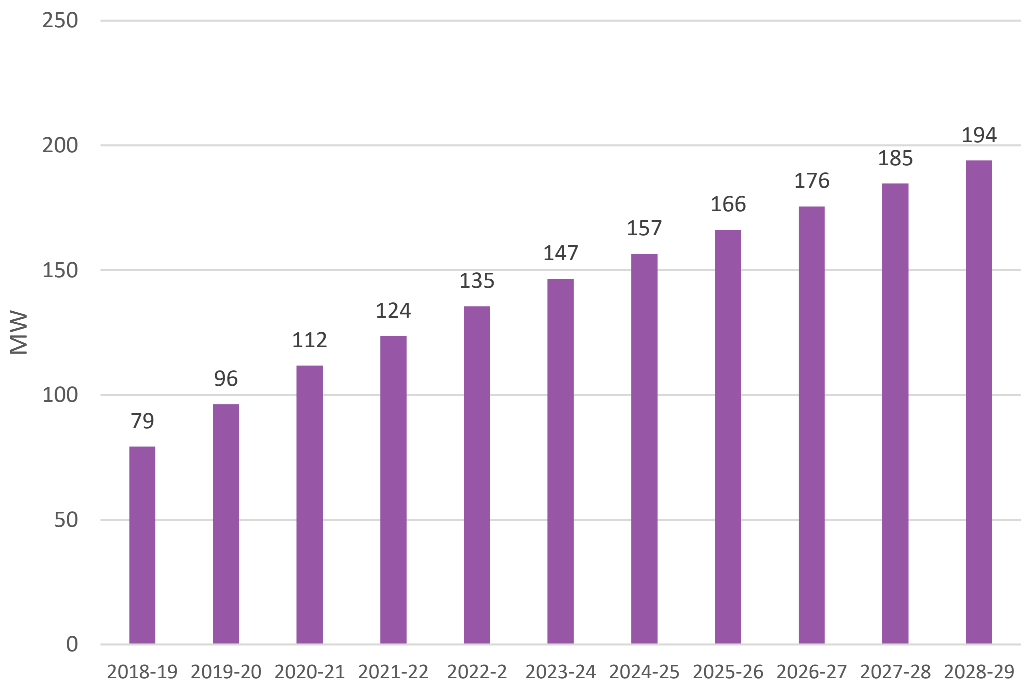
5.8.1 Rooftop PV

The contribution of rooftop PV to the summer peak demand was calculated by applying a PV capacity factor to forecast rooftop PV capacity. The capacity factors were calculated by averaging a rooftop PV load trace September 2011 to June 2019 by month. The capacity factor that was applied during the forecast period is the average for February for the interval from 5:30pm to 6:00 pm. This was 0.0775 at the interval commencing 5:30 pm.

Figure 5.2 shows the impact of rooftop PV on summer peak demand over the forecast period. By the summer of 2028-29, summer peak demand is reduced by 194 MW by rooftop PV across all three scenarios.

There is no adjustment made to winter peak demand for rooftop PV, as the contribution of rooftop solar at the typical time and month of the winter peak is negligible. Winter peak demand tends to occur around 6pm or 6:30pm in June or July.

FIGURE 5.2 FORECAST IMPACT OF ROOFTOP PV ON SUMMER PEAK DEMAND, UNDER ALL SCENARIOS, MW



SOURCE: AEMO AND ACIL ALLEN

5.8.2 Battery storage

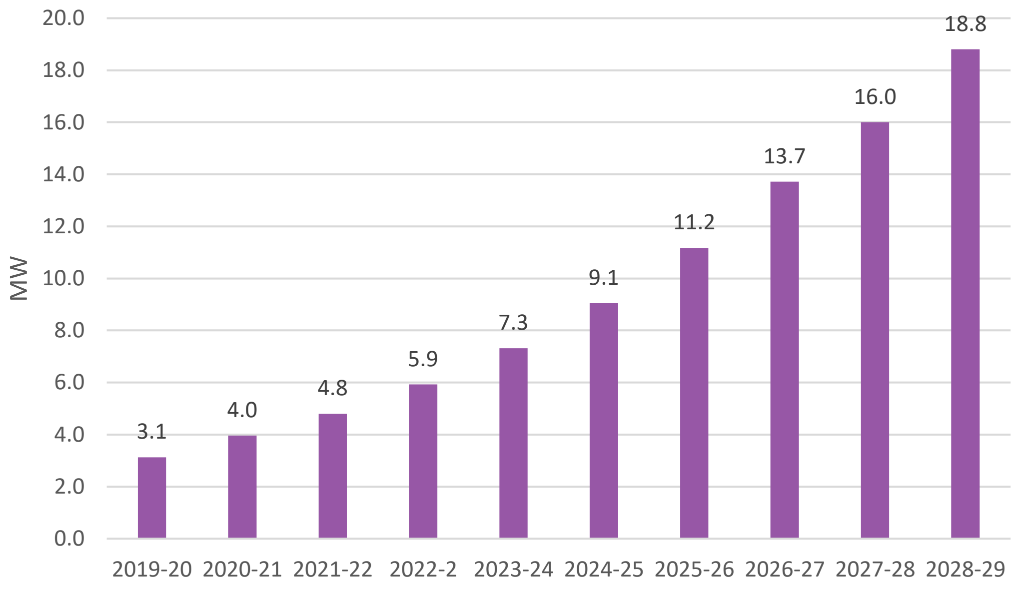
Battery storage is expected to reduce both the summer and winter peak demand over time as the installed capacity of systems increases.

In calculating the impact of new battery storage systems on summer and winter peak demand, a number of discharge factors were calculated by CSIRO and provided to ACIL Allen. These discharge factors were then multiplied by the battery capacity (measured in MWs) to obtain an impact on peak demand from both residential and commercial systems.

In the case of summer, the discharge factors applied were the February average at the interval starting 5:30 pm. For residential the discharge factor applied was 0.033, while for the commercial sector it was 0.916. The factors were then multiplied by the separate residential and commercial projections of battery storage capacity to obtain the impact on peak demand. In the case of winter, the discharge factors applied were the average in July at 6:00 pm. These are 0.383 for residential systems and 0.529 for commercial systems. The expected battery storage scenario is applied to all three economic growth scenarios.

The forecast impact of battery storage on summer peak demand is shown in **Figure 5.3**. Under all three scenarios, battery storage systems are forecast to reduce peak demand by 18.8 MW in 2028-29. This calculation is based on the level of installed battery storage in February of each year of the forecast period. Even with the fast rate of growth in battery storage systems, storage is expected to make only a small impact on overall peak demand.

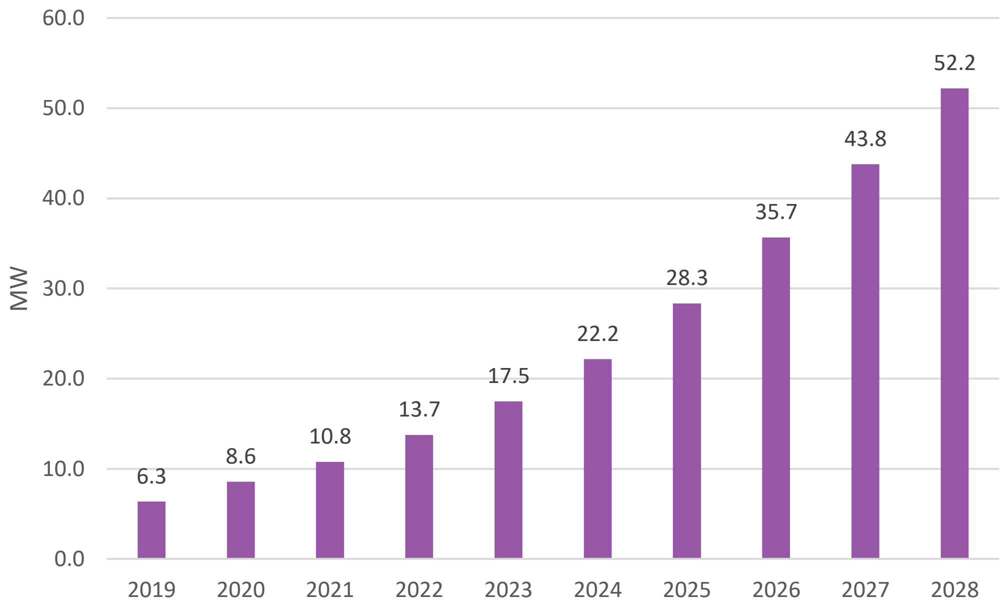
FIGURE 5.3 FORECAST OF BATTERY STORAGE IMPACT ON PEAK SUMMER DEMAND, EXPECTED, HIGH AND LOW SCENARIOS, MW



SOURCE: ACIL ALLEN AND AEMO

Figure 5.4 shows the impact of battery storage systems on winter peak demand under all three scenarios. Under all three scenarios, battery storage systems are forecast to reduce peak demand by 52.2 MW in 2028.

FIGURE 5.4 FORECAST OF BATTERY STORAGE IMPACT ON PEAK WINTER DEMAND, EXPECTED, HIGH AND LOW SCENARIOS, MW



SOURCE: ACIL ALLEN AND AEMO

5.8.3 Block loads

In section 3.5 we outlined the impact of several block loads that were expected to come online in the SWIS over the forecast period. These were added to the baseline econometric summer and winter peak demand forecasts.

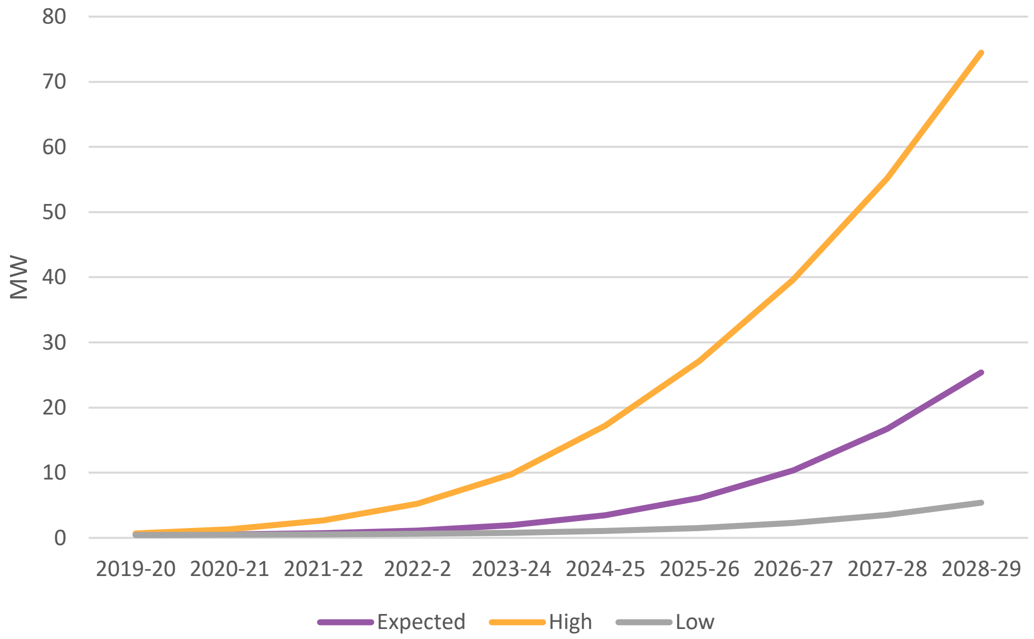
Under the expected scenario, there are a total of three new large loads forecast to increase peak demand by 84 MW (after accounting for diversity). Under the high scenario, a peak demand is forecast to increase by 108 MW, while under the low scenario, peak demand is forecast to increase by 40.5 MW over the forecast period.

5.8.4 Electric vehicles

In order to calculate the impact of electric vehicles on summer and winter peak demands, the projected number of vehicles over time (where vehicles are split into passenger vehicles, light commercial vehicles, trucks and buses) was multiplied by a set of charging profiles for each vehicle type and tariff at the time of the system peak. In the case of summer, the EV charge profiles applied were the February average at the interval commencing 5:30 pm, while for winter, the EV charge profiles applied were the July average at the interval commencing at 6:00 pm.

Under the expected scenario, electric vehicles are forecast to add 25 MW to summer peak demand by 2028-29 (see **Figure 5.5**). Under the high scenario this increases to 74 MW, while under the low scenario, electric vehicles contribute a very modest 5 MW to summer peak demand by 2028-29.

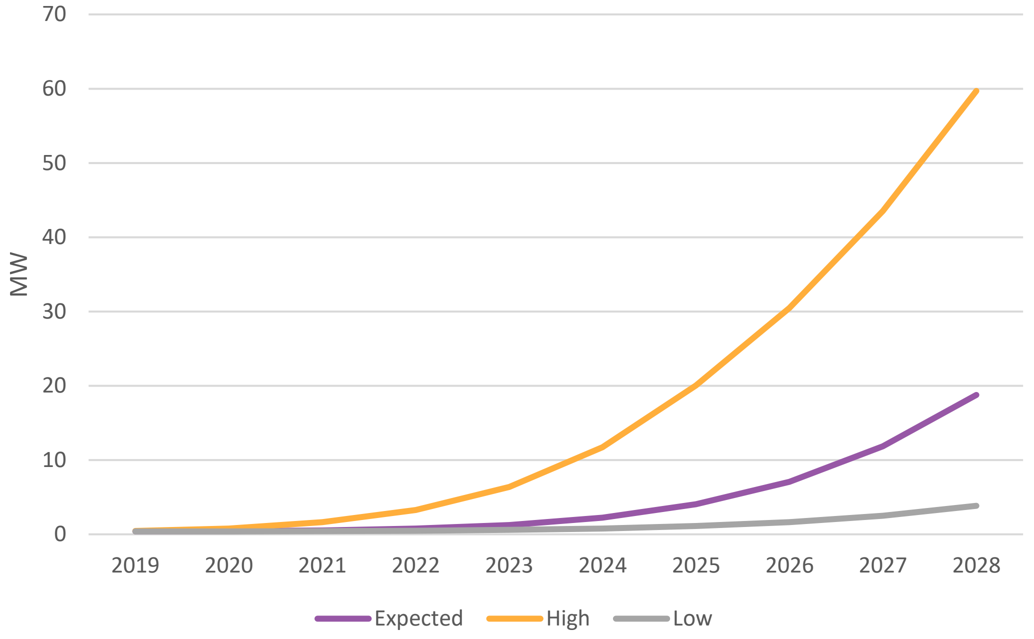
FIGURE 5.5 IMPACT OF ELECTRIC VEHICLE UPTAKE ON SUMMER PEAK DEMAND, EXPECTED, HIGH AND LOW SCENARIOS



SOURCE: ACIL ALLEN , CSIRO AND AEMO

In the case of winter, electric vehicles are forecast to add 19 MW to winter peak demand by 2028 under the expected scenario (see **Figure 5.6**). This increases to 60 MW under the high scenario, while under the low scenario, electric vehicles add just 4 MW to winter peak demand by the end of the forecast period.

FIGURE 5.6 IMPACT OF ELECTRIC VEHICLE UPTAKE ON WINTER PEAK DEMAND, EXPECTED, HIGH AND LOW SCENARIOS



SOURCE: ACIL ALLEN AND AEMO

6

OPERATIONAL ENERGY FORECASTS

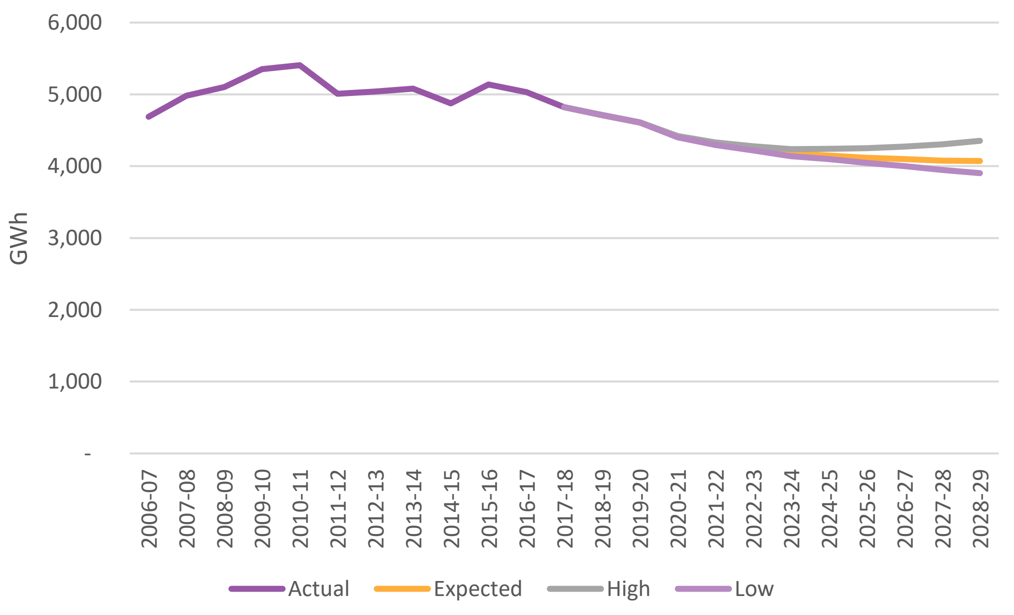
In this section we present the final energy consumption forecasts generated after applying the methodology described in the previous sections of this report.

Section 6.1 relates to forecasts of residential energy consumption. Section 6.2 relates to forecasts of non-residential energy consumption, and section 6.3 relates to total operational energy consumption in the SWIS.

6.1 Residential energy consumption

Figure 6.1 shows historical and forecast residential energy consumption from 2018-19 to 2028-29. The figure shows that residential energy consumption is expected to continue along a gentle downward trend before stabilising towards the end of the forecast period.

FIGURE 6.1 ACTUAL AND FORECAST RESIDENTIAL ENERGY CONSUMPTION, UNDER EXPECTED, HIGH AND LOW SCENARIOS, BY FINANCIAL YEAR



SOURCE: ACIL ALLEN

Under the expected scenario, residential energy consumption is forecast to grow at -1.5% per annum from 2018-19 to 2028-29. This increases to -0.8% per annum in the high scenario and falls to -1.9% per annum in the low scenario.

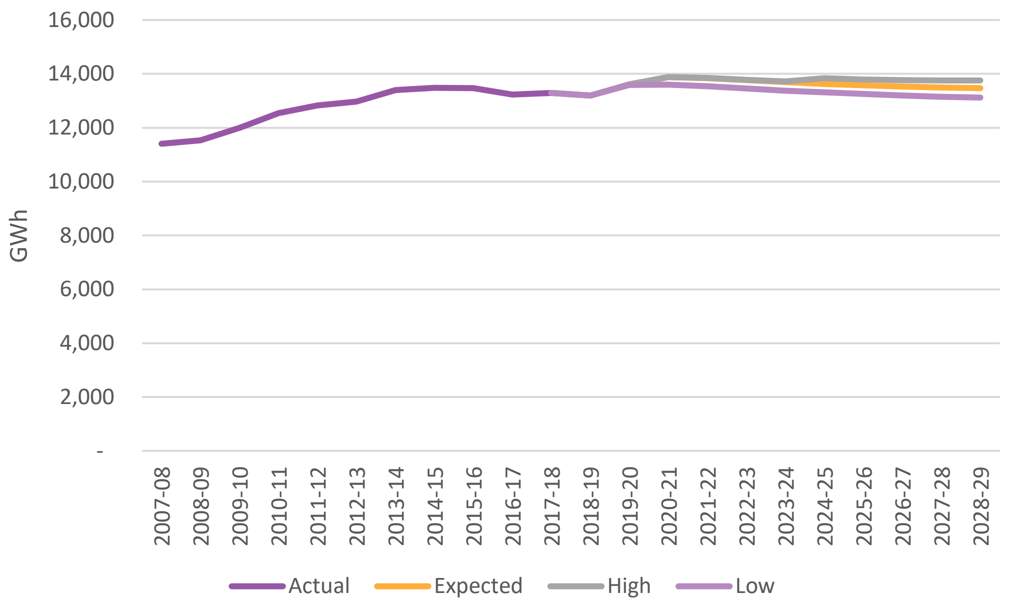
Residential consumption is forecast to reach 4,072 GWh by 2028-29, compared to 4,353 GWh in the high scenario and 3,903 GWh in the low scenario. The main cause of the slow growth in residential consumption is the continued rapid uptake of rooftop PV systems which are expected to maintain a strong rate of growth over the whole forecast horizon.

6.2 Non-residential energy consumption

Non-residential energy consumption is forecast to be relatively stable over the forecast period. This very much in line with the historical performance of this sector over the last five years.

Figure 6.2 shows historical and forecast non-residential energy consumption from 2018-19 to 2028-29.

FIGURE 6.2 ACTUAL AND FORECAST NON-RESIDENTIAL ENERGY CONSUMPTION, UNDER EXPECTED, HIGH AND LOW SCENARIOS



SOURCE: ACIL ALLEN

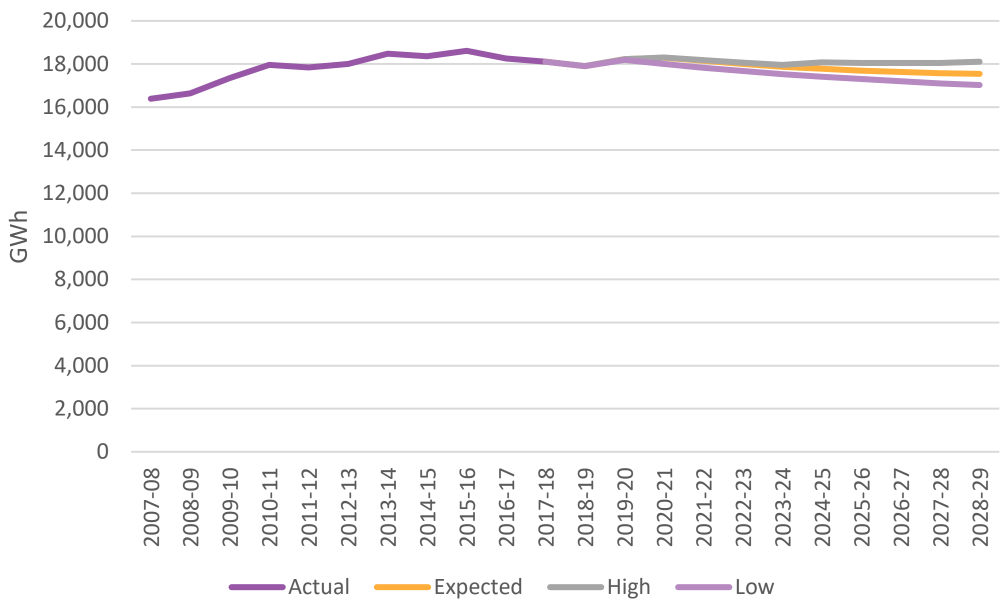
Under the expected growth scenario, non-residential energy consumption is forecast to increase from 13,194 GWh in 2018-19 to 13,470 GWh in 2028-29. This is equivalent to an average annual compound rate of growth of 0.2% per annum.

Under the high growth scenario, non-residential consumption is forecast to reach 13,760 GWh in 2028-29, equivalent to an average annual rate of growth of 0.4%. Under the low economic growth scenario, non-residential energy consumption is forecast to grow at -0.1% per annum, falling to 13,121 GWh by 2028-29.

6.3 Total operational energy consumption in the SWIS

Figure 6.3 shows historical and forecast total operational energy consumption in the SWIS from 2018-19 to 2028-29.

FIGURE 6.3 ACTUAL AND FORECAST TOTAL OPERATIONAL ENERGY CONSUMPTION, UNDER EXPECTED, HIGH AND LOW SCENARIOS



SOURCE: ACIL ALLEN

The same forecasts are also presented in **Table 6.1**. The total operational energy forecasts for the SWIS were obtained by aggregating the residential and non-residential energy consumption forecasts in the previous sections.

TABLE 6.1 FORECAST TOTAL OPERATIONAL ENERGY CONSUMPTION, EXPECTED, HIGH AND LOW

Financial year	Actual	Forecast (Expected)	Forecast (High)	Forecast (Low)
2008-09	16,639			
2009-10	17,346			
2010-11	17,952			
2011-12	17,841			
2012-13	18,009			
2013-14	18,479			
2014-15	18,358			
2015-16	18,612			
2016-17	18,262			
2017-18	18,109			
2018-19		17,906	17,906	17,906
2019-20		18,221	18,225	18,191
2020-21		18,289	18,302	18,004
2021-22		18,151	18,179	17,832
2022-23		18,008	18,059	17,679
2023-24		17,864	17,952	17,521

Financial year	Actual	Forecast (Expected)	Forecast (High)	Forecast (Low)
2024-25		17,775	18,075	17,412
2025-26		17,694	18,045	17,304
2026-27		17,629	18,041	17,204
2027-28		17,569	18,054	17,101
2028-29		17,543	18,112	17,024
Average annual growth rate (p.a.)[9]		**-0.20%**	**0.11%**	**-0.50%**

SOURCE: ACIL ALLEN

Under the expected growth scenario, total operational energy consumption in the SWIS is forecast to decline slightly from 17,906 GWh in 2017-18 to 17,543 GWh in 2028-29. This is equivalent to an average compound rate of growth of -0.2% per annum. This rate of growth is considerably slower than that observed historically, where total operational energy consumption grew at 1.0% per annum in the ten years from 2007-08 to 2017-18. This is very much due to the impact of very high rooftop PV uptake.

Under the high growth scenario, operational energy consumption is forecast to reach 18,112 GWh by 2028-29, equivalent to an average compound rate of growth of 0.1% per annum from 2018-19. On the other hand, if the low growth scenario prevails, total operational energy consumption in the SWIS is forecast to grow at -0.5% per annum.

[9] The average annual growth rate is calculated as the compound annual growth rate over the 10 year period from 2018-19 to 2028-29.

7 PEAK DEMAND FORECASTS

This section summarises the forecasts of peak demand for both summer and winter in the SWIS.

Section 7.1 relates to the forecasts of summer peak demand. Section 7.2 relates to forecasts of winter peak demand.

7.1 Summer peak demand forecasts in the SWIS

The forecasts of summer peak demand in the SWIS are shown in **Table 7.1**. This shows the 10 POE, 50 POE and 90 POE peak demand forecasts for each of the expected, high and low growth scenarios.

TABLE 7.1 SUMMER PEAK DEMAND FORECAST, MW, 10POE, 50POE AND 90POE, EXPECTED, HIGH AND LOW SCENARIOS

	Expected scenario			High scenario			Low scenario		
	90 POE	50 POE	10 POE	90 POE	50 POE	10 POE	90 POE	50 POE	10 POE
2018-19	3507	3732	3986	3501	3729	3981	3507	3730	3981
2019-20	3536	3758	4007	3556	3778	4024	3518	3743	4002
2020-21	3589	3813	4063	3601	3831	4090	3526	3756	4005
2021-22	3597	3819	4075	3609	3835	4092	3533	3751	4002
2022-23	3597	3822	4074	3614	3837	4097	3532	3758	4004
2023-24	3606	3826	4078	3622	3852	4099	3534	3755	4011
2024-25	3608	3832	4079	3668	3898	4146	3535	3756	4012
2025-26	3625	3847	4092	3692	3916	4160	3540	3765	4013
2026-27	3641	3860	4117	3720	3943	4191	3547	3781	4029
2027-28	3648	3876	4128	3756	3974	4217	3557	3784	4032
2028-29	3672	3897	4152	3783	4007	4256	3568	3789	4038
5 year average growth[10]	**0.56%**	**0.50%**	**0.46%**	**0.68%**	**0.65%**	**0.59%**	**0.15%**	**0.14%**	**0.15%**
10 year average growth[11]	**0.46%**	**0.43%**	**0.41%**	**0.78%**	**0.72%**	**0.67%**	**0.17%**	**0.16%**	**0.14%**

SOURCE: ACIL ALLEN

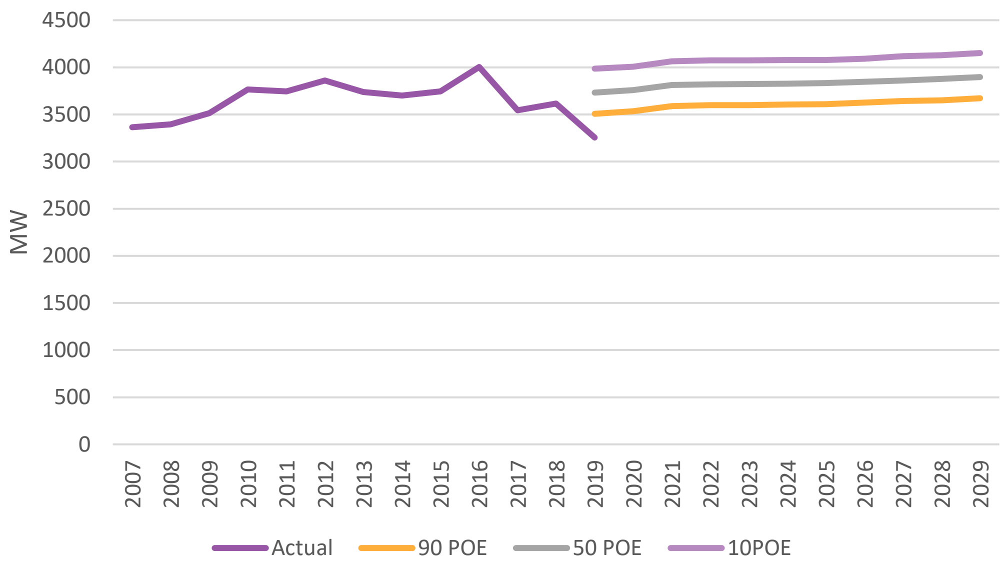
[10] The 5 year average growth rate covers the 5 year period from 2018-19 to 2023-24.
[11] The 10 year average growth rate covers the period from 2018-19 to 2028-29.

The results in the table are also presented graphically in the next four figures.

Figure 7.1, **Figure 7.2**, and **Figure 7.3** show the summer peak demand forecasts under each of the expected, high and low growth scenarios respectively. Under the expected scenario, both the 10POE and 50 POE forecast summer peak demand is expected to grow at 0.4% per annum over the period from 2018-19 to 2028-29. Under this scenario, the 10 POE summer peak demand is forecast to reach 4,152 MW in 2028-29, while the 50 POE summer demand will reach 3,897 MW over the same period.

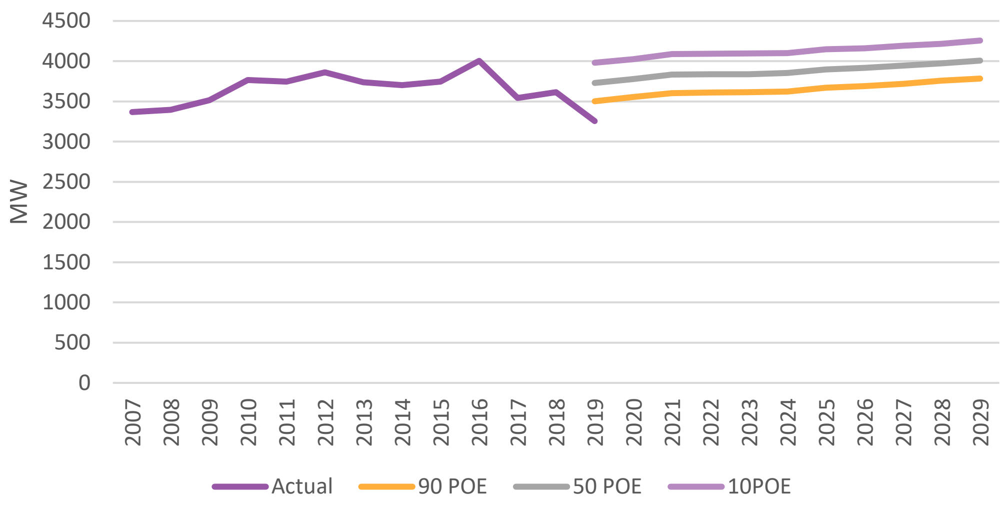
Under the high scenario, both the 10 POE and 50 POE summer peak demand are forecast to grow at a faster rate of 0.7% per annum over the 10 year forecast period. In the low growth scenario, summer peak demand is forecast to grow more slowly, increasing by just 0.1% per annum in the case of both the 10 and 50 POE peak demand.

FIGURE 7.1 SUMMER PEAK DEMAND FORECAST, MW, 10POE, 50POE AND 90POE, EXPECTED SCENARIO



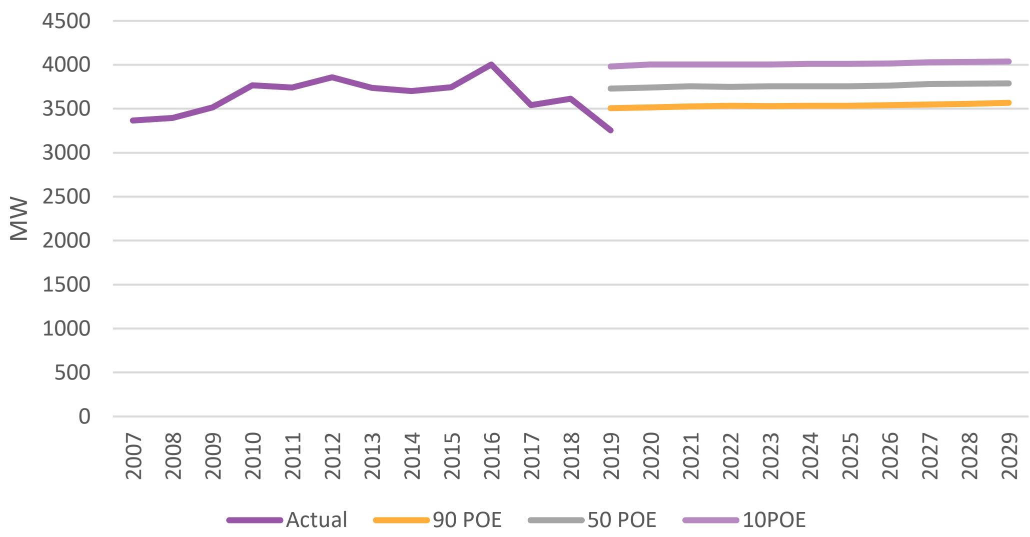
SOURCE: ACIL ALLEN

FIGURE 7.2 SUMMER PEAK DEMAND FORECAST, MW, 10POE, 50POE AND 90POE, HIGH SCENARIO



SOURCE: ACIL ALLEN

FIGURE 7.3 SUMMER PEAK DEMAND FORECAST, MW, 10POE, 50POE AND 90POE, LOW SCENARIO



SOURCE: ACIL ALLEN

7.2 Winter peak demand forecasts in the SWIS

The forecasts of winter peak demand in the SWIS are shown in **Table 7.2**. This shows the 10 POE, 50 POE and 90 POE peak demand forecasts for each of the expected, high and low growth scenarios.

TABLE 7.2 WINTER PEAK DEMAND FORECAST, MW, 10POE, 50POE AND 90POE, EXPECTED, HIGH AND LOW SCENARIOS

	Expected scenario			High scenario			Low scenario		
	90 POE	50 POE	10 POE	90 POE	50 POE	10 POE	90 POE	50 POE	10 POE
2018	3122	3193	3280	3122	3193	3280	3122	3194	3280
2019	3154	3226	3316	3161	3233	3321	3150	3219	3308
2020	3204	3276	3363	3217	3285	3372	3166	3237	3325
2021	3219	3289	3374	3229	3298	3386	3179	3250	3340
2022	3222	3292	3382	3237	3307	3395	3183	3253	3341
2023	3229	3299	3385	3247	3314	3399	3184	3256	3341
2024	3235	3304	3391	3278	3349	3438	3188	3258	3342
2025	3237	3307	3395	3291	3360	3451	3187	3258	3345
2026	3245	3313	3403	3305	3376	3463	3192	3260	3347
2027	3251	3322	3408	3324	3395	3486	3195	3262	3347
2028	3262	3331	3417	3346	3416	3502	3193	3266	3350
5 year average growth[12]	**0.68%**	**0.66%**	**0.63%**	**0.79%**	**0.75%**	**0.72%**	**0.39%**	**0.38%**	**0.37%**
10 year average growth[13]	**0.44%**	**0.42%**	**0.41%**	**0.70%**	**0.68%**	**0.66%**	**0.22%**	**0.22%**	**0.21%**

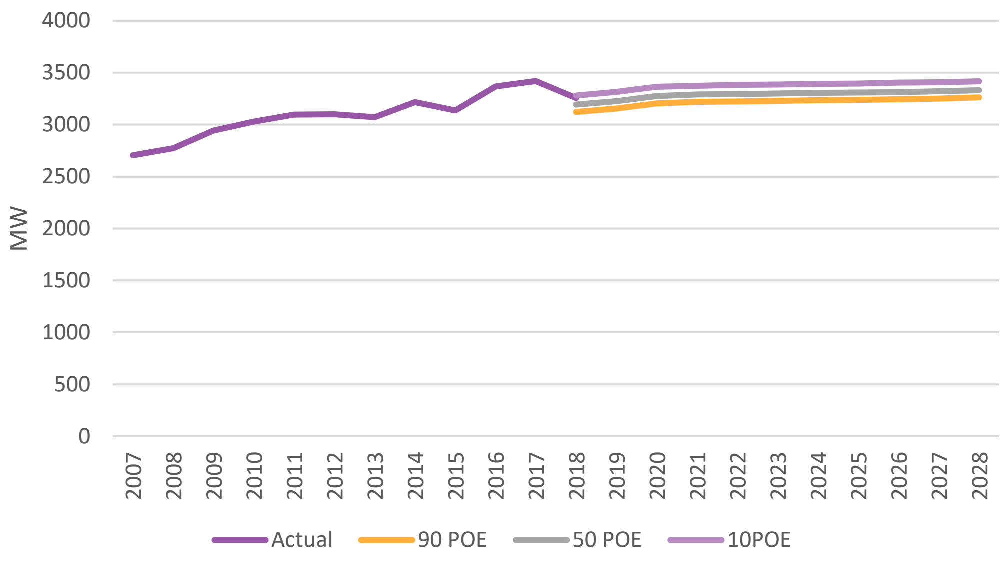
SOURCE: ACIL ALLEN

Figure 7.4, **Figure 7.5** and **Figure 7.6** show the winter peak demand forecasts graphically under each of the expected, high and low scenarios respectively.

Under the expected growth scenario, both the 50 POE and 10 POE winter peak demand are forecast to grow at 0.4% per annum over the period from 2018 to 2028. Under this scenario the 10 POE winter demand is forecast to reach 3,417 MW in 2028, while the 50 POE is forecast to reach 3,331 MW over the same period.

[12] The 5 year average growth rate covers the 5 year period from 2018 to 2023.
[13] The 10 year average growth rate covers the 10 year period from 2018 to 2028.

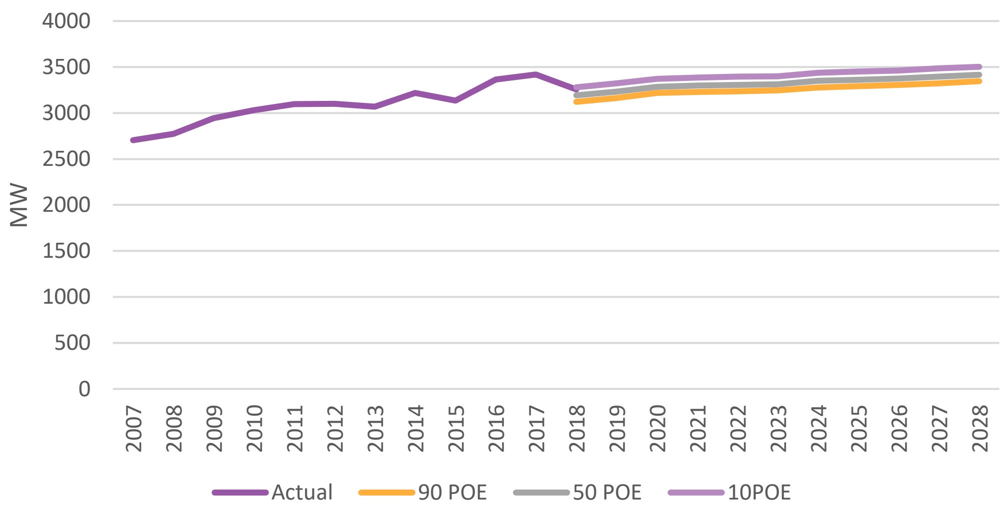
FIGURE 7.4 WINTER PEAK DEMAND FORECAST, MW, 10POE, 50POE AND 90POE, EXPECTED SCENARIO



SOURCE: ACIL ALLEN

Under the high growth scenario, both the 10 POE and 50 POE winter peak demand is forecast to grow by 0.7% per annum over the next 10 years, with the 10 POE and 50 POE reaching 3,502 MW and 3,416 MW by 2028 respectively.

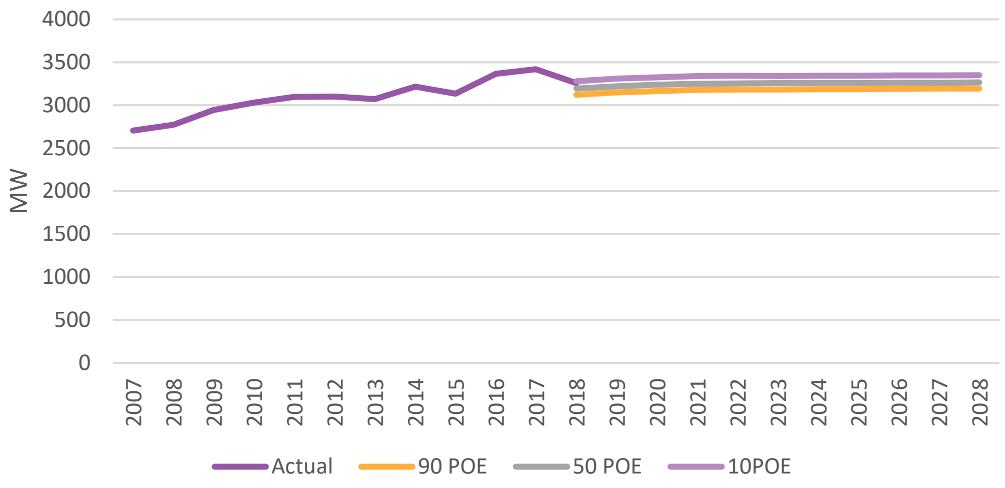
FIGURE 7.5 WINTER PEAK DEMAND FORECAST, MW, 10POE, 50POE AND 90POE, HIGH SCENARIO



SOURCE: ACIL ALLEN

Under the low growth scenario, both the 10 POE and 50 POE winter peak demand is forecast to grow by 0.2% per annum over the next 10 years, with the 10 POE and 50 POE reaching 3,350 MW and 3,266 MW respectively by 2028.

FIGURE 7.6 WINTER PEAK DEMAND FORECAST, MW, 10POE, 50POE AND 90POE, LOW SCENARIO



SOURCE: ACIL ALLEN