ACIL ALLEN CONSULTING

REPORT TO
AUSTRALIAN ENERGY MARKET OPERATOR

8 JUNE 2017

PEAK DEMAND AND ENERGY FORECASTS

FOR THE SOUTH WEST INTERCONNECTED SYSTEM – WESTERN AUSTRALIA

C O N T E N T S

C O N T E N T S

FIGURES

C O N T E N T S

TABLES

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1 INTRODUCTION

ACIL Allen Consulting (ACIL Allen) has been commissioned by the Australian Energy Market Operator (AEMO) to produce 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.

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 for two years ahead.

Annual reserve capacity requirements 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 reserve capacity mechanism 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 2016-17 to 2026-27, 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 produced for the SWIS covering the time horizon from 2016-17 to 2026-27.

10%, 50% and 90% POE forecasts have been produced 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 used as 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 2015-16.

FIGURE 2.1 RESIDENTIAL ENERGY CONSUMPTION, 2006-07 TO 2015-16

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 for the next four years. In 2015-16, residential consumption was 5,139 GWh.

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

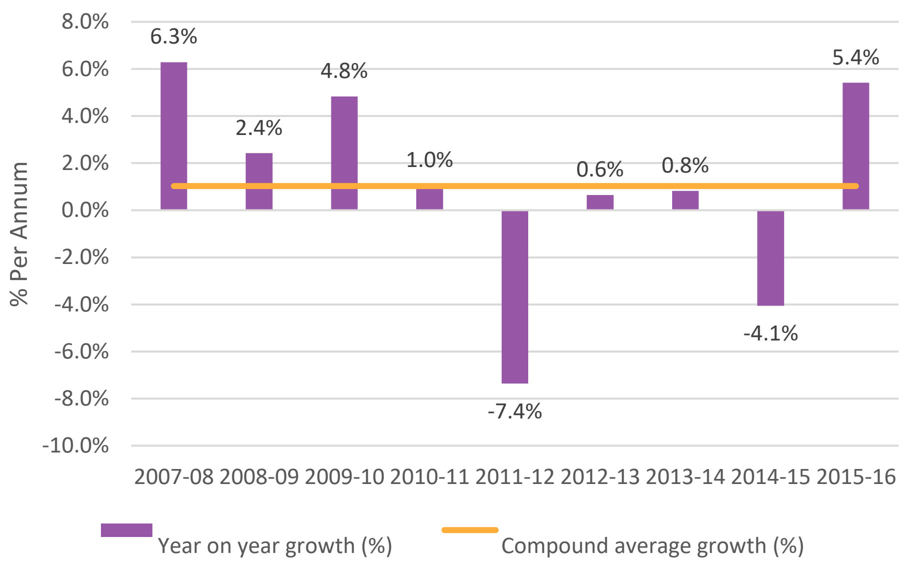
- slower economic growth
- higher electricity prices
- increased rooftop PV uptake.

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 obtained from AEMO. Residential rooftop PV systems generated 787 GWh of energy in 2015-16, having increased from just 277 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 2015-16



SOURCE: ACIL ALLEN

The compound average annual rate of growth in residential energy consumption between 2007-08 and 2015-16 was 1.0%.

2.1.2 Non-residential energy consumption[1]

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

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

Figure 2.3 shows the historical non-residential consumption in the SWIS from 2007-08 to 2015-16.

[1] 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.

Annual non-residential consumption increased steadily from 11,405 GWh in 2007-08 to 13,473 GWh in 2015-16.

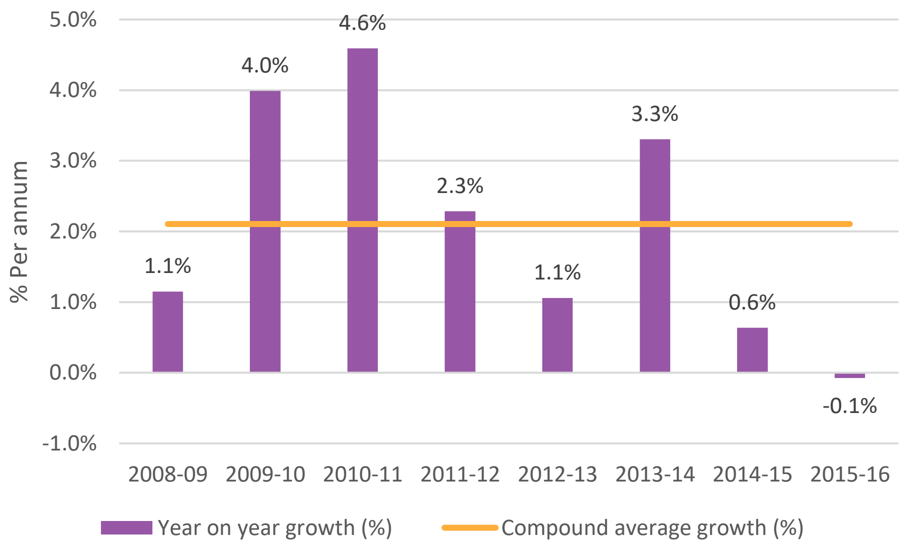
This is equivalent to a compound average rate of growth in non-residential energy consumption between 2007-08 and 2015-16 of 2.1%.

FIGURE 2.3 NON-RESIDENTIAL ENERGY CONSUMPTION, 2007-08 TO 2015-16

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 in excess of 4% was followed by a period of slower growth, particularly in the last two years when growth was 0.6% in 2014-15 and -0.1% in 2015-16. The last two years reflect slower economic conditions arising from the end of the mining boom and the associated loss of income and employment in the SWIS.

FIGURE 2.4 ANNUAL GROWTH IN NON-RESIDENTIAL ENERGY CONSUMPTION

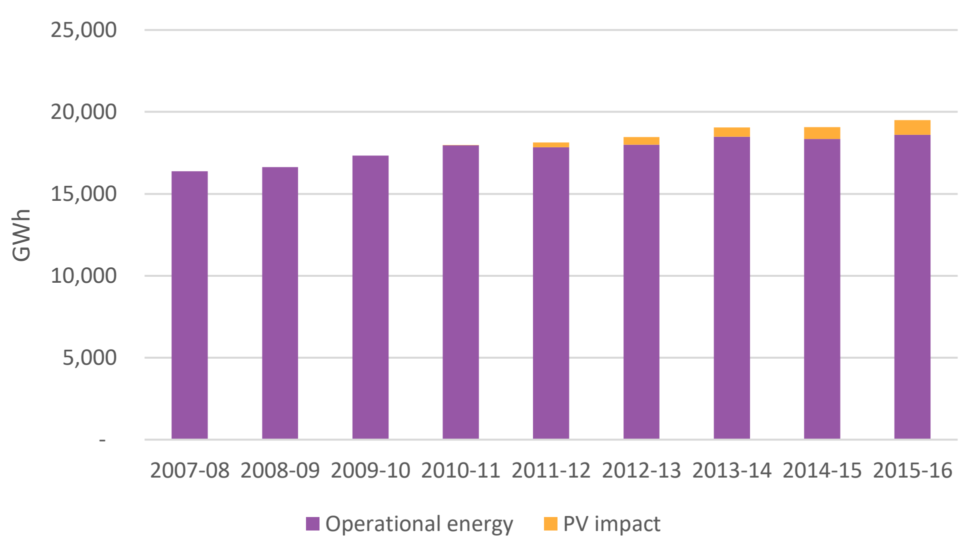


SOURCE: ACIL ALLEN

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 2015-16, total operational energy consumption in the SWIS increased from 16,387 GWh to 18,612 GWh.

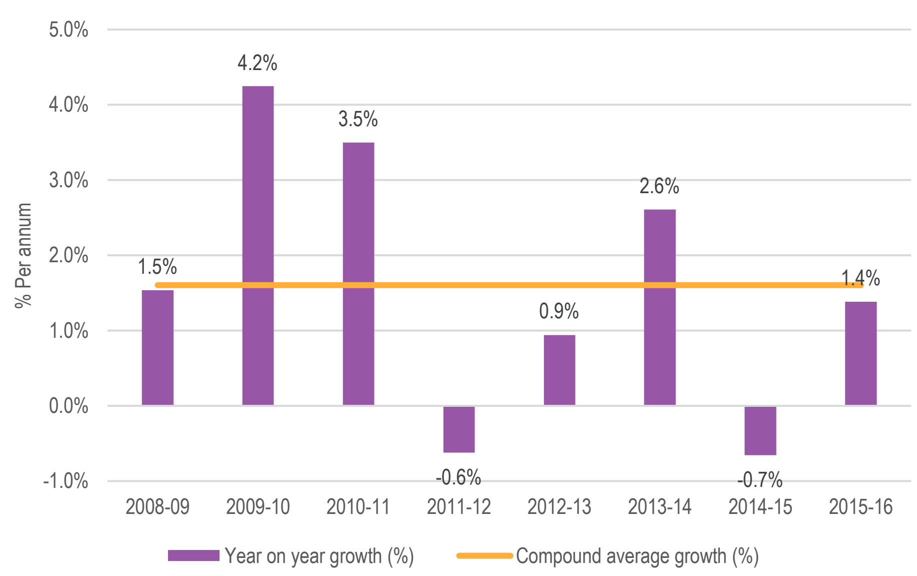
FIGURE 2.5 TOTAL OPERATIONAL ENERGY CONSUMPTION, 2007-08 TO 2015-16



SOURCE: SYNERGY AND AEMO

Over the last eight years, total operational energy consumption increased at a compound average growth rate of 1.6%. From 2008-09 to 2010-11, average annual growth in operational energy consumption was in excess of 3%. This was then followed by a five year period of below average growth with the exception of 2013-14, where growth exceeded the average over the whole period (see **Figure 2.6**).

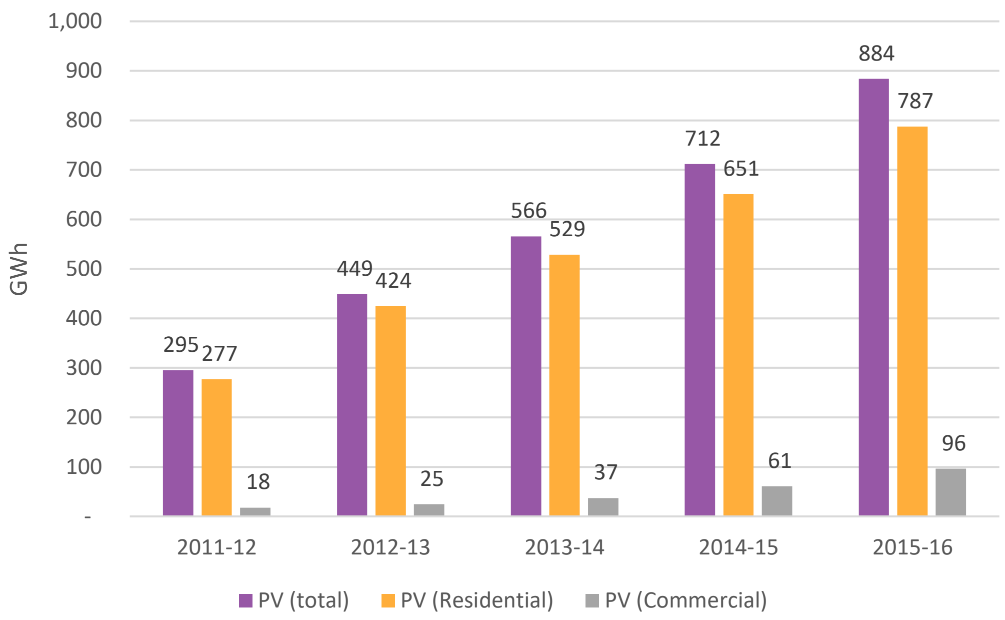
FIGURE 2.6 ANNUAL GROWTH IN TOTAL OPERATIONAL ENERGY CONSUMPTION



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 2015-16, rooftop PV systems generated 884 GWh of energy, compared to 295 GWh in 2011-12.

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



SOURCE: AEMO AND ACIL ALLEN CALCULATIONS

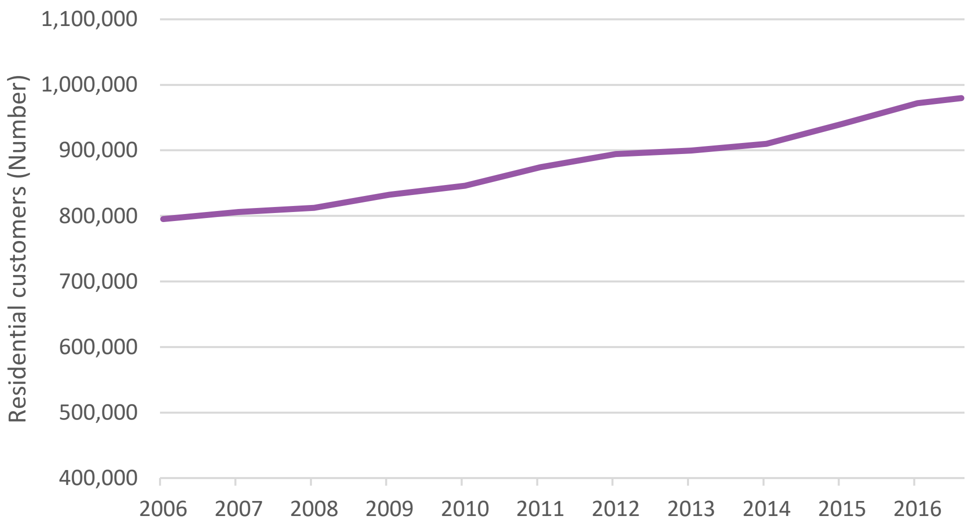
2.2 Residential customer numbers

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 cent per annum.

As at January 2017, the SWIS had 979,748 residential customers, up from 795,186 in June 2006.

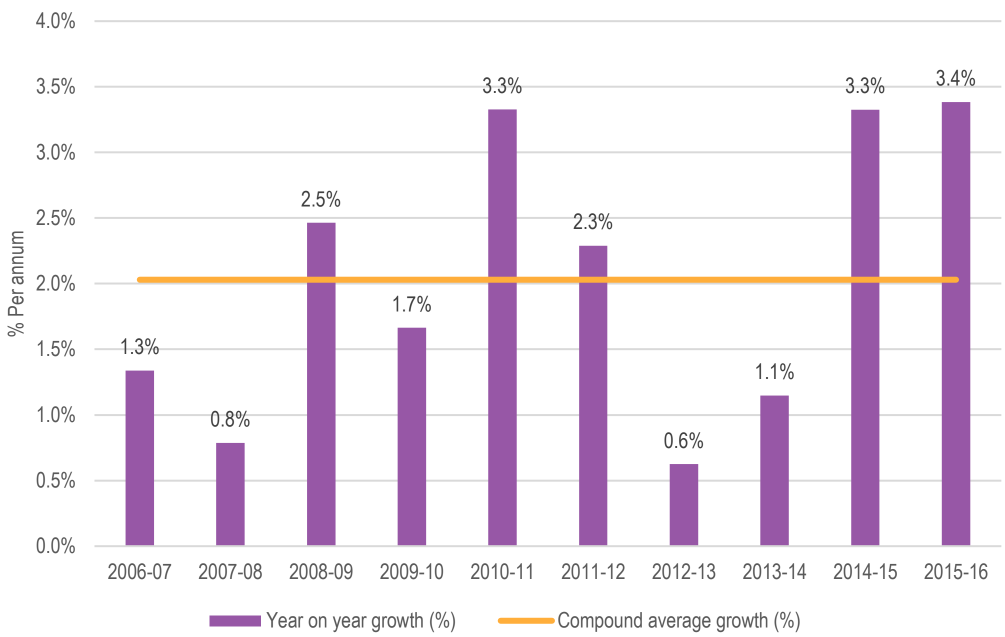
FIGURE 2.8 RESIDENTIAL CUSTOMER NUMBERS IN THE SWIS, JUNE 2006 TO JANUARY 2017



SOURCE: SYNERGY AND AEMO

The year on year growth in residential customers is shown in **Figure 2.9** below. The figure shows that growth has varied from a low of 0.6% in 2012-13 up to a 3.4% increase in 2015-16.

FIGURE 2.9 ANNUAL GROWTH IN RESIDENTIAL CUSTOMER NUMBERS



SOURCE: ACIL ALLEN

2.3 Peak demand

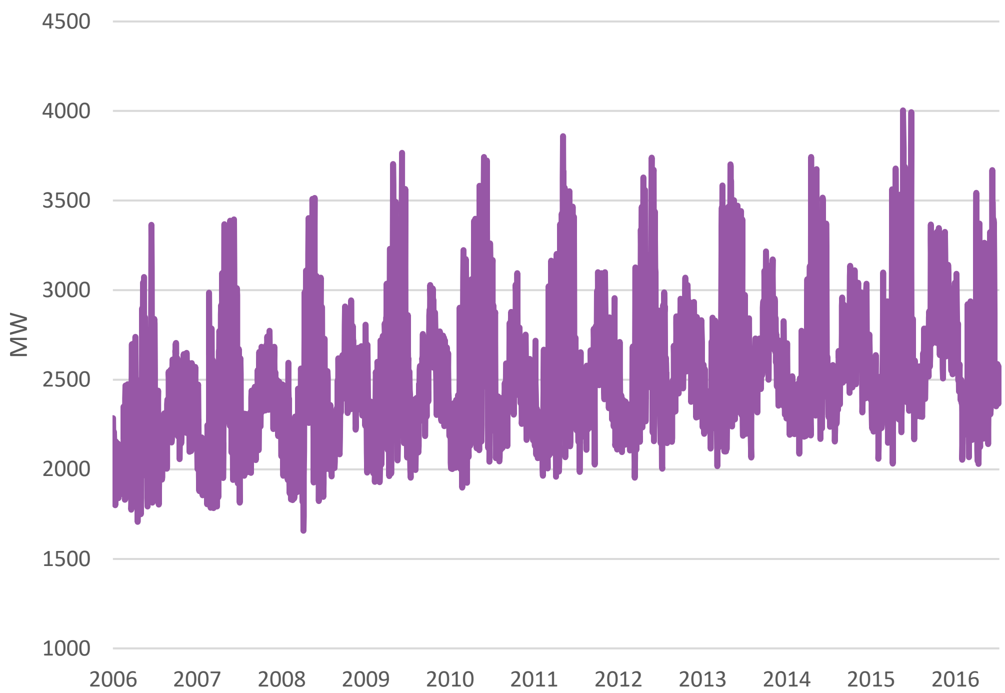
Figure 2.10 plots the daily peak demand in the SWIS from 21 September 2006 to 31 March 2017.

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 caused 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. Moreover, 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 dropped back in the most recent year.

FIGURE 2.10 DAILY PEAK DEMAND IN THE SWIS, SEPTEMBER 2006 TO MARCH 2017



SOURCE: AEMO

Table 2.1 shows the summer peak demand in the SWIS from 2007-08 to 2016-17 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 most recent peak which occurred on the first day of March, the remaining peaks all occurred in January and February. The largest peak demand over the last 10 years of 4,013 MW occurred on February 8 2016.

Another trend that can be observed is the tendency for the peak demand to occur later in the day over time, with the summer peak occurring at 3:00 pm in 2007-08, and at 5:00 pm and 5:30pm in 2016-17 and 2015-16 respectively. This is due to the influence of increasing rooftop PV uptake, which generates more during the early afternoon thus forcing the peak to shift to later in the day.

TABLE 2.1 SUMMER PEAK DEMAND, 2007-08 TO 2016-17

Year	Date	MW	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	4013	17:30	42.6	20.7	31.7
2016-17	01-03-17	3670	17:00	38.1	20.3	29.2

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 3,366 in 2016. All winter peaks have taken place in either June or July, with the three most recent winter peaks occurring in June. The most common time for the winter peak to occur is at 6pm with seven of the last eight peaks all occurring at this time.

TABLE 2.2 WINTER PEAK DEMAND, 2007 TO 2016

Year	Date	MW[2]	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

SOURCE: AEMO

[2] Any minor variations between the historical peak demands in this table and those presented in the 2017 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

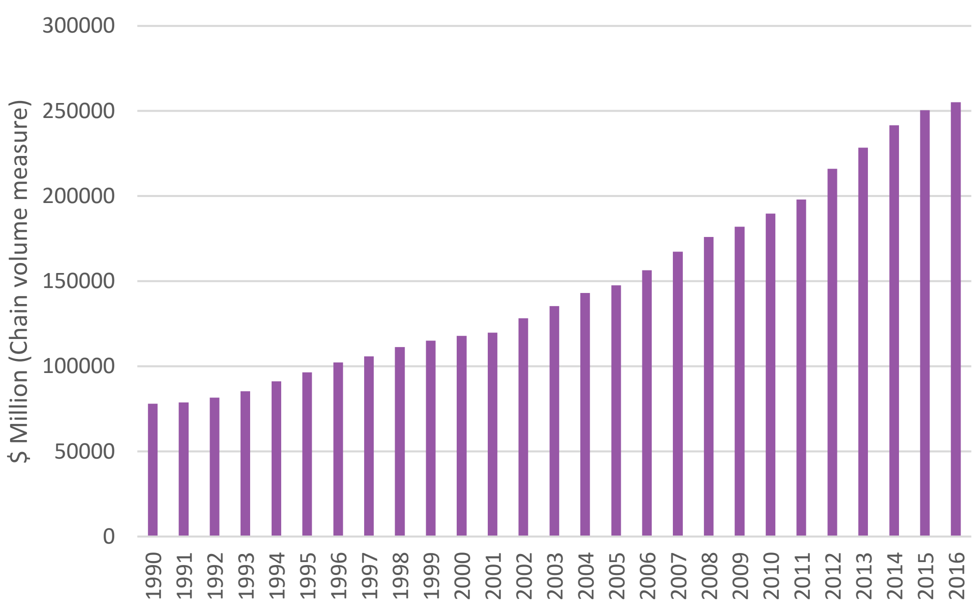
Growth in economic activity is a major driver of rising incomes. Consumption of electricity is, in part, driven by higher disposable incomes and subsequent demand for new electronic appliances and equipment, as well as increasing commercial and industrial activity.

In addition to this, there is typically a strong 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.

Table 3.1 shows the historical time series of WA economic activity, as measured by Gross State Product (GSP), from 1989-90 to 2015-16.

FIGURE 3.1 WESTERN AUSTRALIAN GROSS STATE PRODUCT, 1989-90 TO 2015-16 $M (CHAIN VOLUME MEASURE)

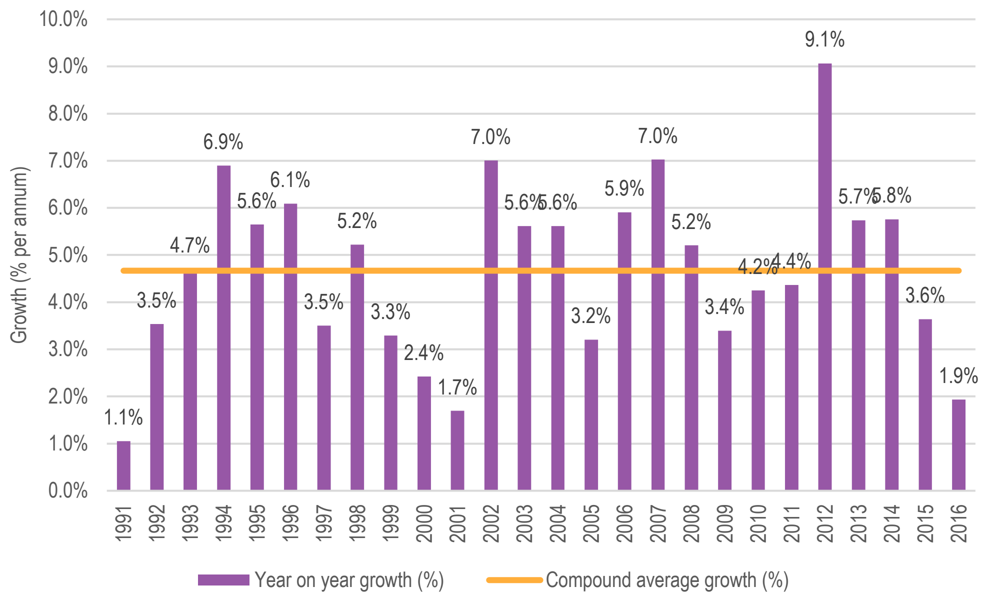


SOURCE: ABS, 5220.0 AUSTRALIAN NATIONAL ACCOUNTS: STATE ACCOUNTS

Western Australian economic growth has been positive in all years since 1990-91 (see **Figure 3.2**). Western Australian economic growth is characterised by cyclical periods of high growth followed by periods of subdued growth. Economic growth peaked at 6.9% in 1993-94, 7.0% in 2001-02, 7.0% in 2006-07 and 9.1% in 2011-12. Economic growth troughs occurred in 1990-91, 2000-01 and 2015-16.

Western Australian GSP growth has slowed significantly in the last two 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 1.9%. This is compared to a long term average of 4.7% per annum from 1990-91 to 2015-16.

FIGURE 3.2 YEAR ON YEAR GSP GROWTH, WESTERN AUSTRALIA 1990-91 TO 2015-16



SOURCE: ABS, 5220.0 AUSTRALIAN NATIONAL ACCOUNTS: STATE ACCOUNTS

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.

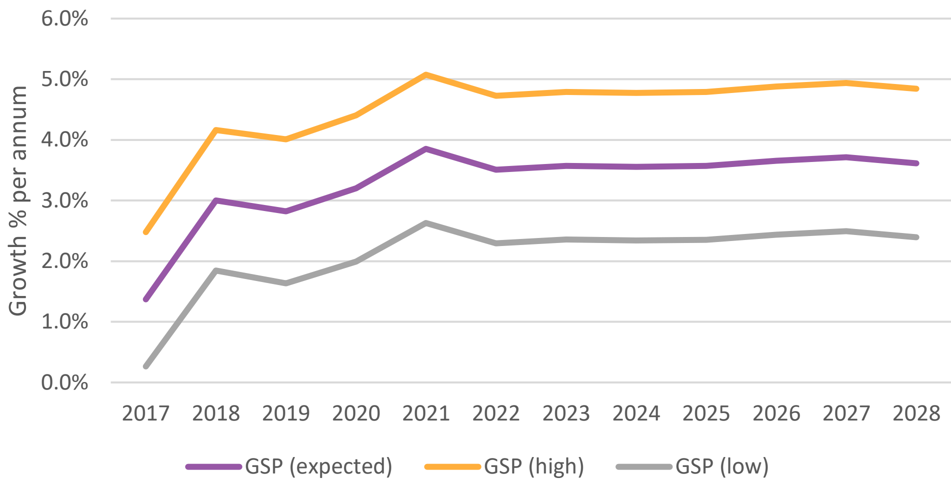
TABLE 3.1 FORECAST GSP GROWTH 2016-17 TO 2027-28, EXPECTED, HIGH AND LOW SCENARIOS

Year	GSP (expected)	GSP (high)	GSP (low)
2016-17	1.4%	2.5%	0.3%
2017-18	3.0%	4.2%	1.8%
2018-19	2.8%	4.0%	1.6%
2019-20	3.2%	4.4%	2.0%
2020-21	3.9%	5.1%	2.6%
2021-22	3.5%	4.7%	2.3%
2022-23	3.6%	4.8%	2.4%
2023-24	3.6%	4.8%	2.3%
2024-25	3.6%	4.8%	2.4%
2025-26	3.7%	4.9%	2.4%
2026-27	3.7%	4.9%	2.5%
2027-28	3.6%	4.8%	2.4%
Average	**3.3%**	**4.5%**	**2.1%**

SOURCE: AEMO

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

FIGURE 3.3 FORECAST GSP GROWTH 2016-17 TO 2027-28, EXPECTED, HIGH AND LOW SCENARIOS

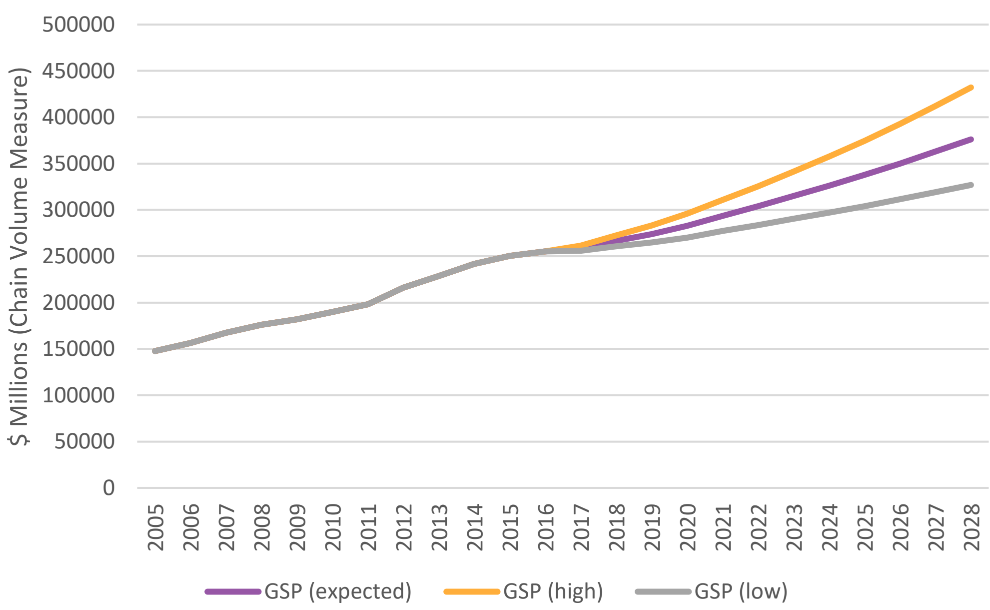


SOURCE: AEMO

Under the expected economic growth scenario, Western Australian GSP growth is expected to average 3.3% per annum. In 2016-17, sluggish economic conditions are expected to continue with growth falling to 1.4% per annum. From 2017-18, GSP growth is forecast to recover before peaking at 3.9% in 2020-21. Under the high economic growth scenario GSP is forecast to average 4.5% over the forecast horizon. Under the low economic growth scenario, GSP is forecast to average just 2.1% 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 SCEANARIOS



SOURCE: AEMO

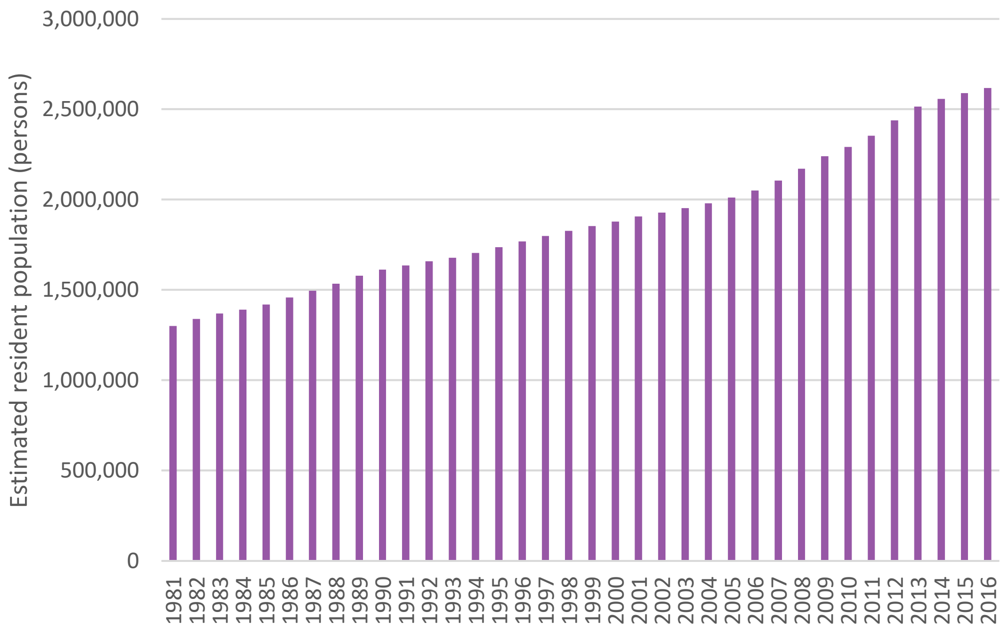
3.2 Population growth

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 2016.

The figure shows a long steady increase in the estimated resident population of Western Australia. In June 2016, the estimated resident population of Western Australia had reached 2.6 million people.

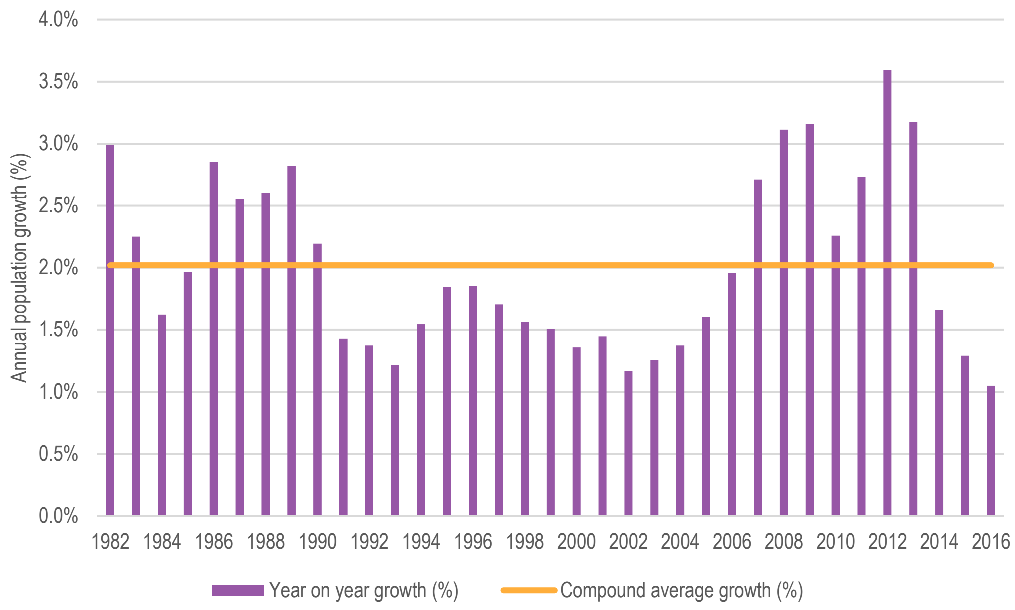
FIGURE 3.5 WESTERN AUSTRALIAN ESTIMATED RESIDENT POPULATION, 1981 TO 2016



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 2.0% per annum. In the last three years, Western Australian population growth has been below average, with growth in 2013-14, 2014-15 and 2015-16 of 1.7%, 1.3% and 1.0% respectively.

FIGURE 3.6 ANNUAL POPULATION GROWTH, WESTERN AUSTRALIA, JUNE 1982 TO JUNE 2016



SOURCE: ABS, 3101.0 AUSTRALIAN DEMOGRAPHIC STATISTICS

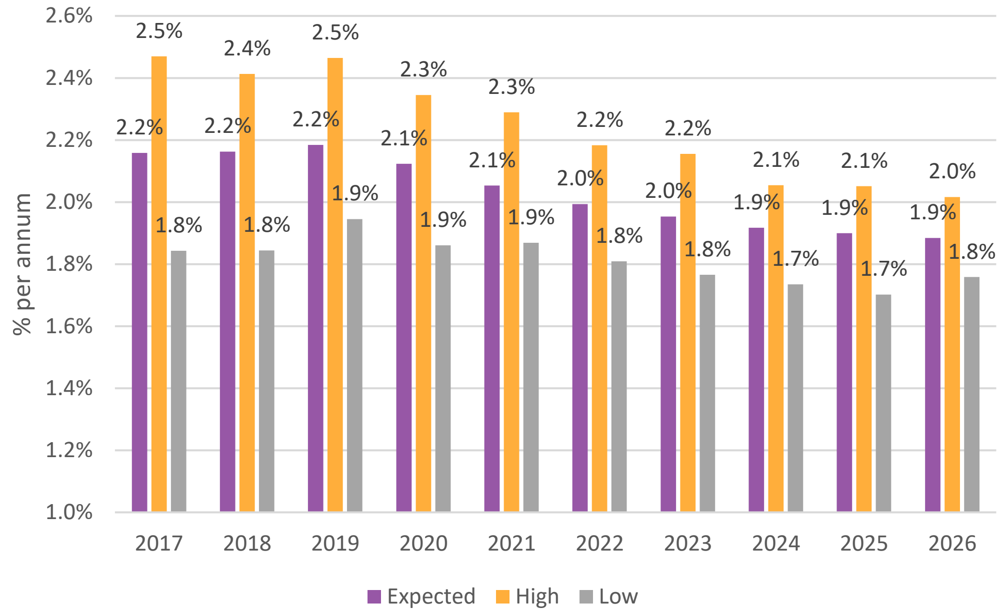
3.2.1 Population growth forecasts

For the purposes of projecting residential customer numbers in the SWIS, population forecasts were sourced from the Western Australian Planning Commission and Department of Planning. The forecasts are released under the publication title '*Western Australia Tomorrow*' and represent an estimate of Western Australia's future population.

The forecasts include a range of bands going from A to E with A representing the lower end and E representing the highest set of forecasts. In our modelling, we used band C for the expected growth scenario, band E for the high growth scenario and band A for the low growth scenario.

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

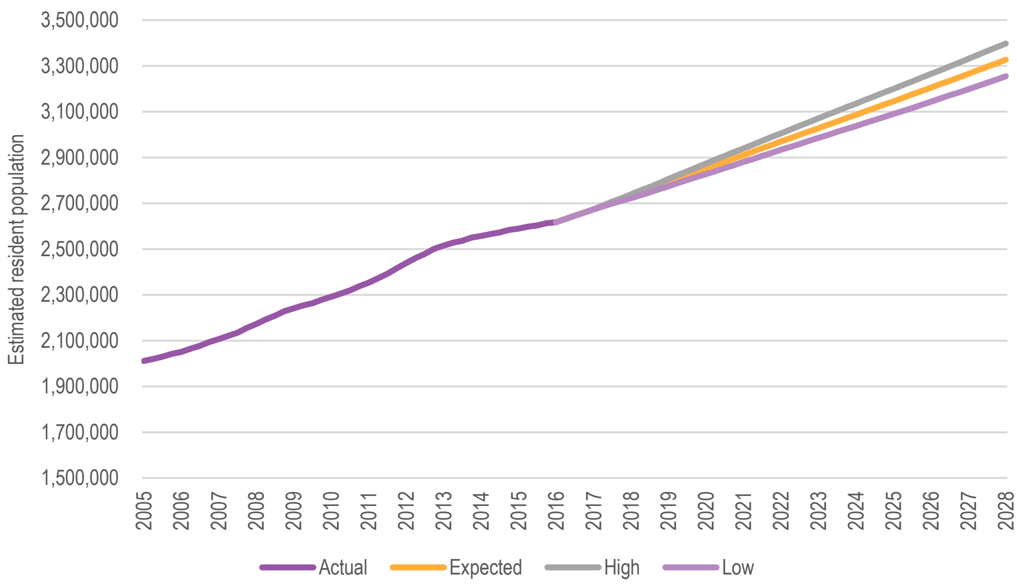
FIGURE 3.7 WESTERN AUSTRALIAN POPULATION GROWTH FORECASTS, EXPECTED, HIGH AND LOW SCENARIOS



SOURCE: WESTERN AUSTRALIA TOMORROW, POPULATION REPORT NO:10

The separate forecast growth rates are then 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



SOURCE: ABS, WA TOMORROW AND ACIL ALLEN CALCULATIONS

3.3 Rooftop PV and battery storage

3.3.1 Rooftop PV uptake

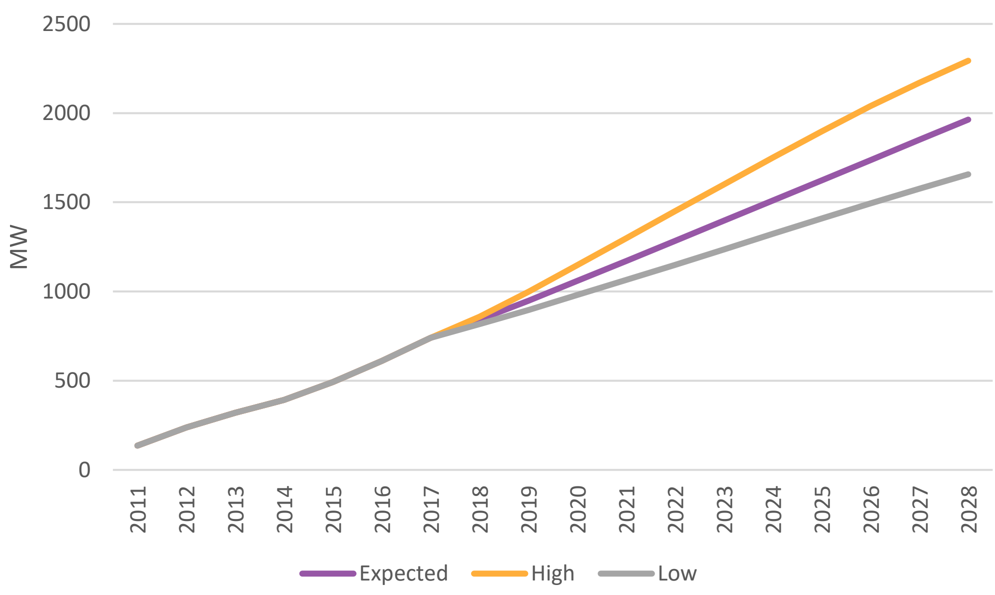
The use of rooftop PV systems has increased dramatically in recent years. To date, this has mainly been in response to government incentives, rising electricity prices and falling system installation costs. Rooftop PV systems have a fairly straightforward impact on energy sales. Simply put, when the 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.

Forecasts of rooftop PV capacity over the forecast period were provided by AEMO and Jacobs. **Figure 3.9** shows the forecast uptake of rooftop PV under the three separate growth scenarios. Under the expected scenario, installed rooftop PV capacity is expected to reach 1,963 MW by June 2028. Under the high and low growth scenarios, rooftop PV capacity is forecast to reach 2,294 MW and 1,657 MW respectively.

FIGURE 3.9 INSTALLED ROOFTOP PV CAPACITY AS AT JUNE 30, HISTORICAL AND FORECAST

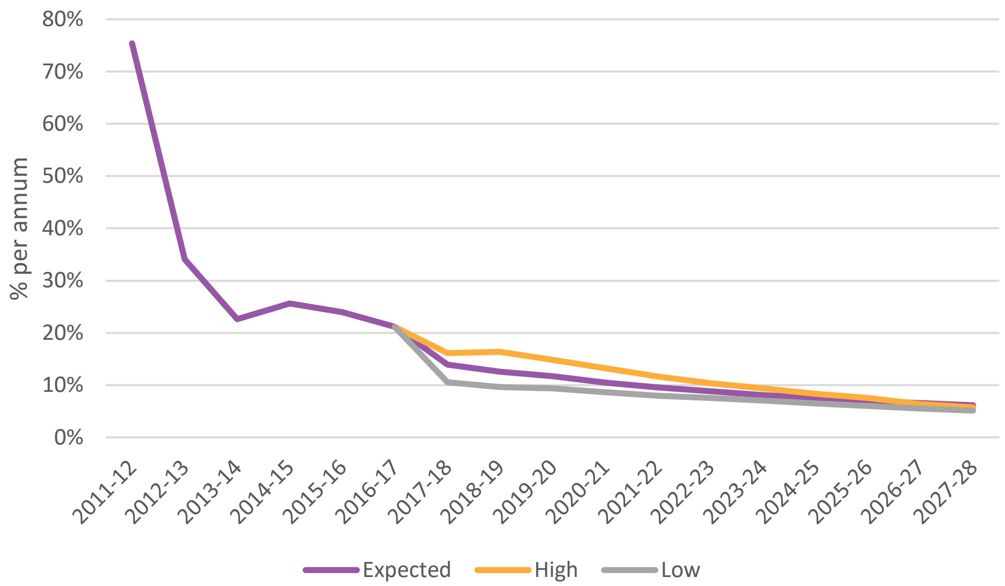


SOURCE: AEMO AND JACOBS

Figure 3.10 shows the historical and forecast annual percentage growth in rooftop PV capacity. Rooftop PV take up has grown very strongly historically, averaging 24% per annum between 2013-14 and 2015-16.

Future rooftop PV growth is forecast to slow down further, with annual growth expected to average 10.2% per annum under the expected scenario. Under the high and low scenarios, rooftop PV capacity is forecast to grow at 11.7% and 8.7% per annum respectively.

FIGURE 3.10 ANNUAL GROWTH IN ROOFTOP PV CAPACITY, HISTORICAL AND FORECAST



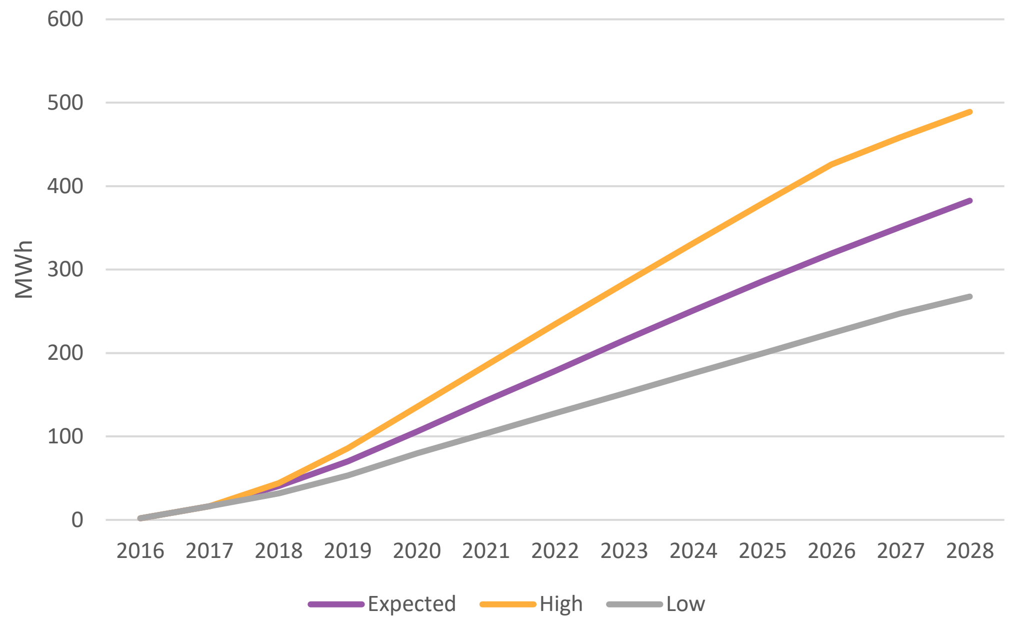
SOURCE: AEMO AND JACOBS

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. Similarly to 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 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 obtained from AEMO and Jacobs. **Figure 3.11** shows the forecast increase in storage capacity which is expected to reach 383 MWh by 2028. Under the high and low growth scenarios, battery storage is forecast to reach 489 MWh and 268 MWh respectively by 2028.

FIGURE 3.11 FORECAST UPTAKE OF BATTERY STORAGE, EXPECTED, HIGH AND LOW SCENARIOS



SOURCE: AEMO AND JACOBS

3.4 Electric vehicles (EV)

Projections of the energy impact arising from the uptake of electric vehicles in Western Australia were obtained from the publication *'AEMO Insights August 2016, Electric Vehicles'*, jointly produced by AEMO and Energeia.

Figure 3.12 shows the forecast annual consumption under separate expected, high and low scenarios to 2028. Under the expected scenario electric vehicles are forecast to consume 293 GWh by 2028. Under the high and low scenarios, annual consumption is forecast to be 628 GWh and 88 GWh respectively. Given current levels of energy consumption in the SWIS, the impact of electric vehicles is expected to be relatively small.

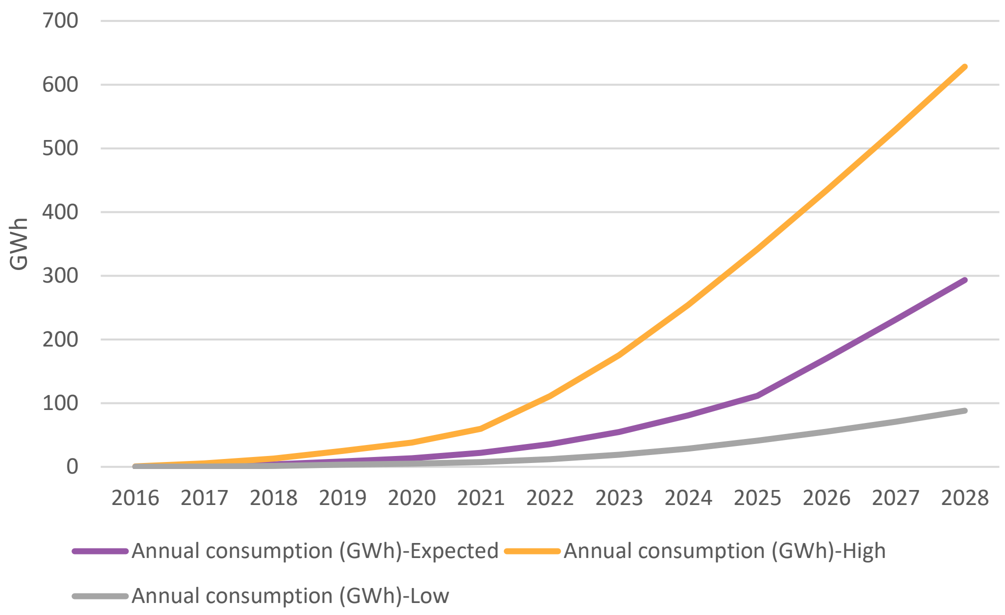
Electric vehicles are not expected to have any significant impact on peak demand. It is anticipated that sufficient tariff incentives will be put in place to ensure that electric vehicles are mostly charged during off peak times.

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 vehicle prices continue to decline and the range that the vehicles can travel before recharging increases, we can expect sales of electric vehicles to increase.

FIGURE 3.12 FORECAST ELECTRIC VEHICLE ENERGY CONSUMPTION, EXPECTED, HIGH AND LOW SCENARIOS



SOURCE: 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 block loads that may come online in the SWIS during the forecast period.

However, as there has been no formal connection application submitted to Western Power, these block loads cannot be considered final and connection dates cannot be confirmed. For this reason, we have opted to include these block loads into the high growth scenario only, and exclude them from the expected and low growth scenarios.

Details of the block loads were provided by Western Power and are shown below in **Table 3.2**.

TABLE 3.2 DETAILS OF PROPOSED BLOCK LOADS IN THE SWIS

	Mine expansion project	Minerals processing facility project
Existing load (Coincident maximum demand)	8.1 MW	0 MW
Proposed load increase (CMD)	13.5 MW	22.5 MW (Stage 1, 11.7 MW and Stage 2 10.8 MW)
Anticipated service date	Quarter 4 2017/Q1 2018	Q2/Q3 2018 for Stage 1, Stage 2 to take place 2 years after Stage 1

SOURCE: AEMO AND WESTERN POWER

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.

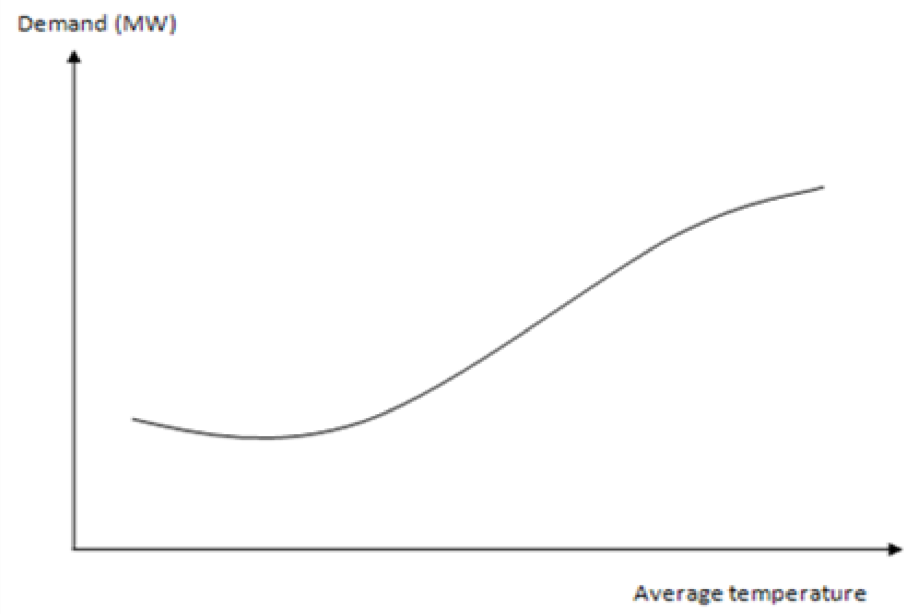
In winter, demand that varies with weather conditions is driven primarily by the 'heating requirement'. Generally, cooler seasons would be associated with a greater heating requirement, and therefore a greater peak demand. In summer this pattern is reversed, with cooling becoming the driver of weather-related 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 3.13**).

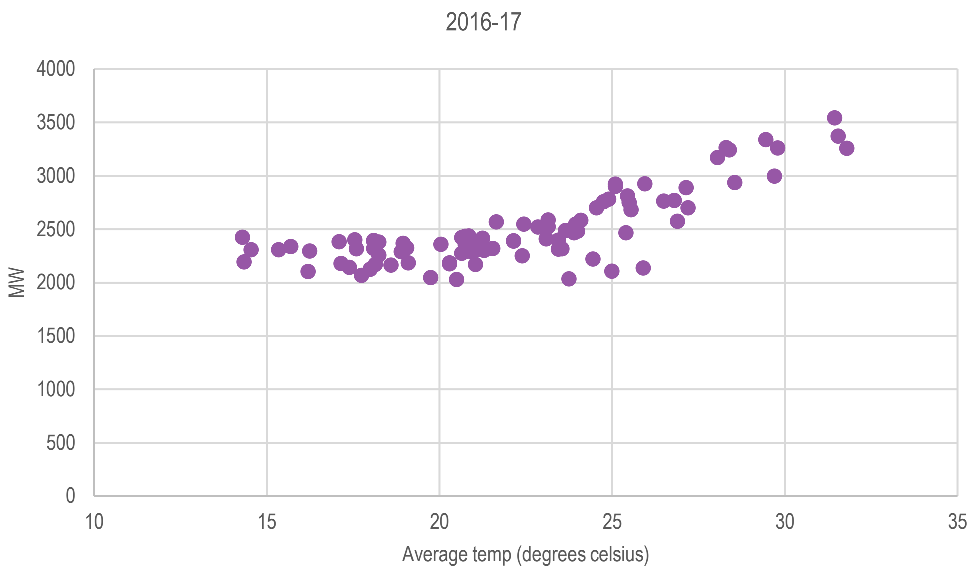
FIGURE 3.13 STYLISED RELATIONSHIP BETWEEN SUMMER DAILY PEAK DEMAND AND AVERAGE DAILY TEMPERATURE

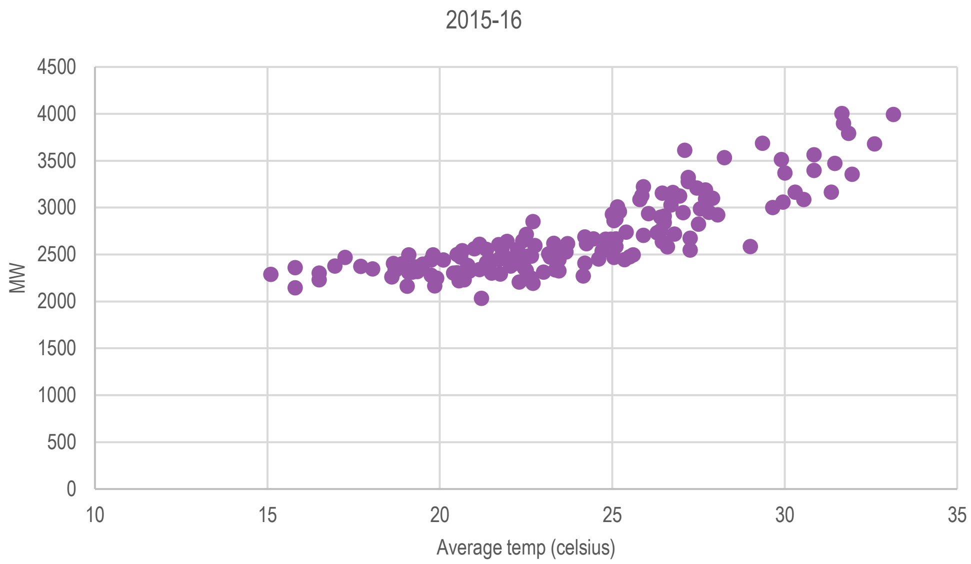


There is also a point on the extreme right of the curve where demand becomes saturated at extremely hot temperatures. At this point, demand becomes unresponsive once again to changes in temperature. This saturation point is rarely observed in practice and corresponds to levels of demand that are well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

Figure 3.14 below shows the actual relationship between daily summer peak demand and average temperature for the last two summer seasons. The stylised pattern described above is evident.

FIGURE 3.14 PEAK DEMAND (NOVEMBER TO APRIL) VERSUS AVERAGE TEMPERATURE, 2015-16 AND 2016-17





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 3.15**).

FIGURE 3.15 STYLISED RELATIONSHIP BETWEEN WINTER DAILY PEAK DEMAND AND AVERAGE DAILY TEMPERATURE

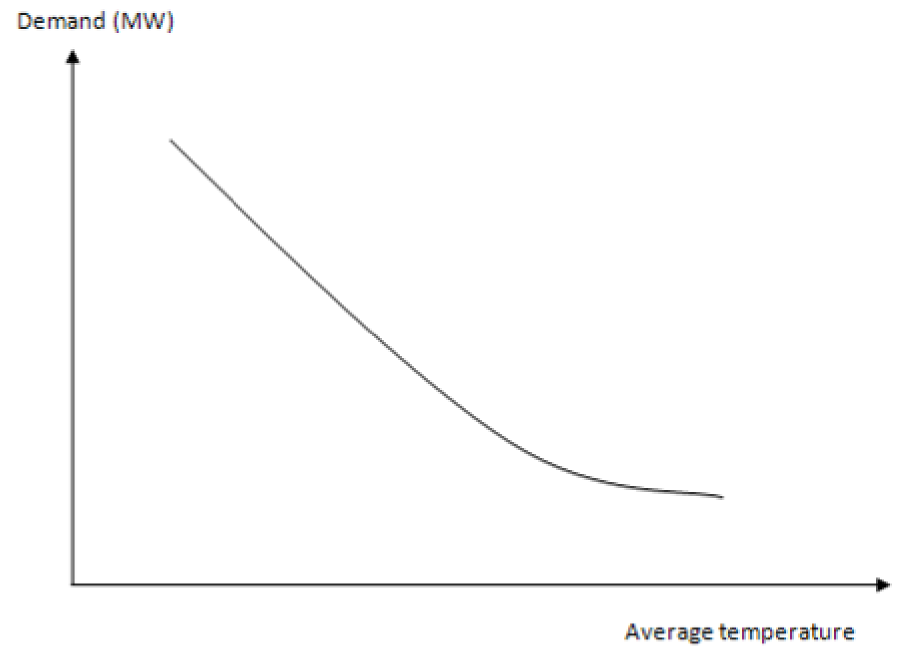
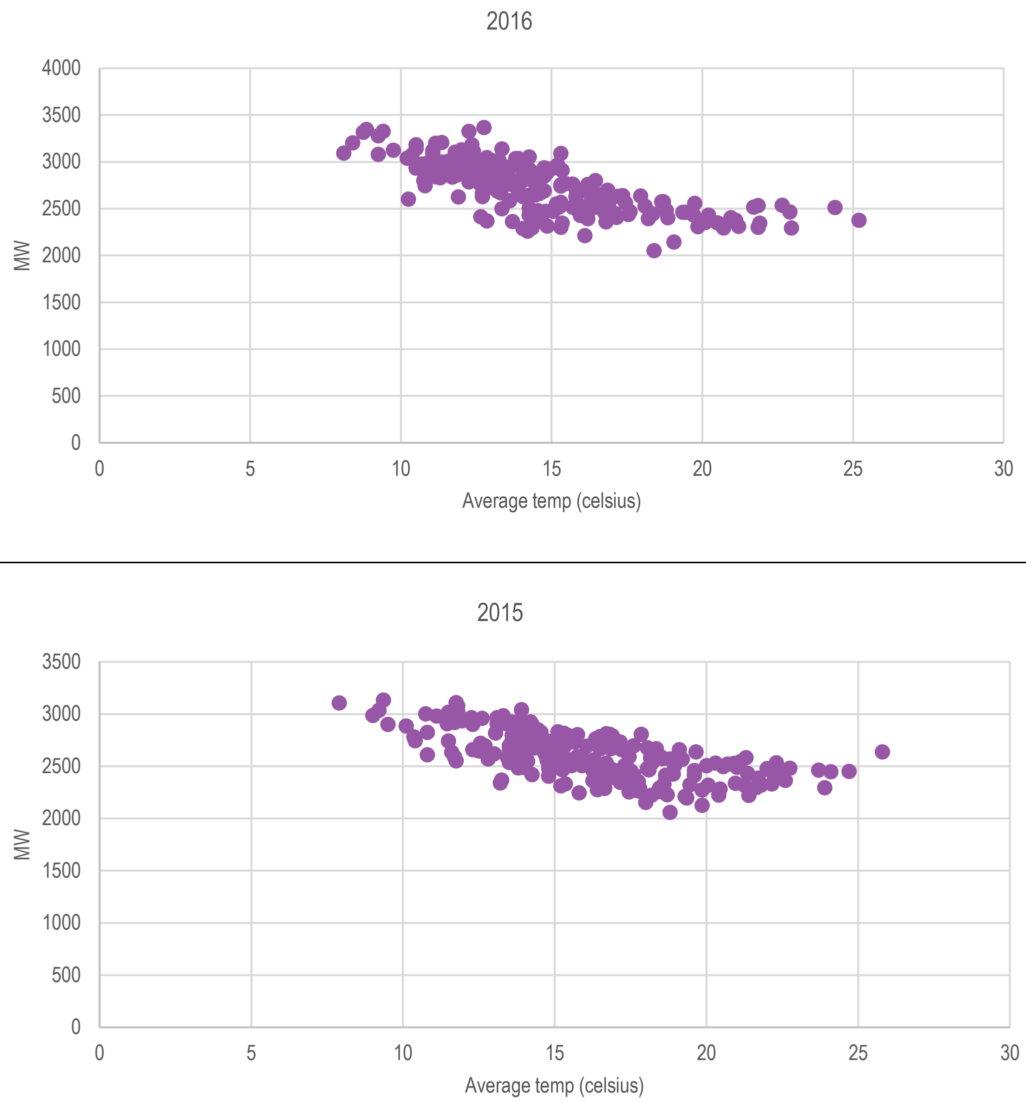


Figure 3.16 below shows the actual relationship between daily winter peak demand and average temperature for the last two seasons.

FIGURE 3.16 PEAK WIINTER DEMAND VERSUS AVERAGE TEMPERATURE, 2015 AND 2016



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. 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 (CDD18) for each year.

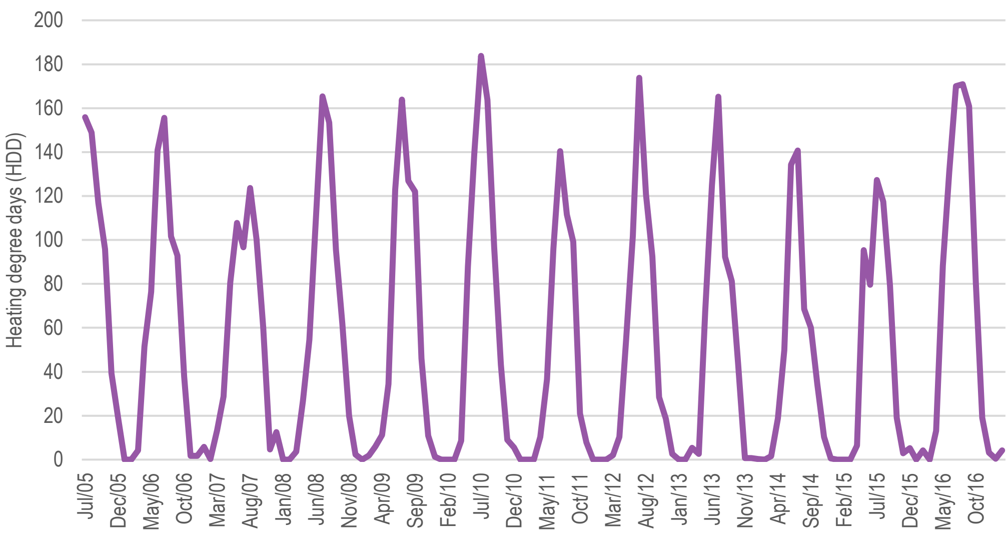
The number of HDD18 in a given year is simply the sum of the difference between some measure of average ambient room temperature which we define as 18 degrees Celsius and the average daily temperature on each day. Any given day makes a contribution to the total number of heating degree days only if the average temperature 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 CDD18 the concept is the same, but the formula takes the sum of degrees that exceed some benchmark (in our case 18 degrees Celsius) for each day. It is therefore an indication of how hot a given year is, with a higher number of CDD18 reflecting a hotter season.

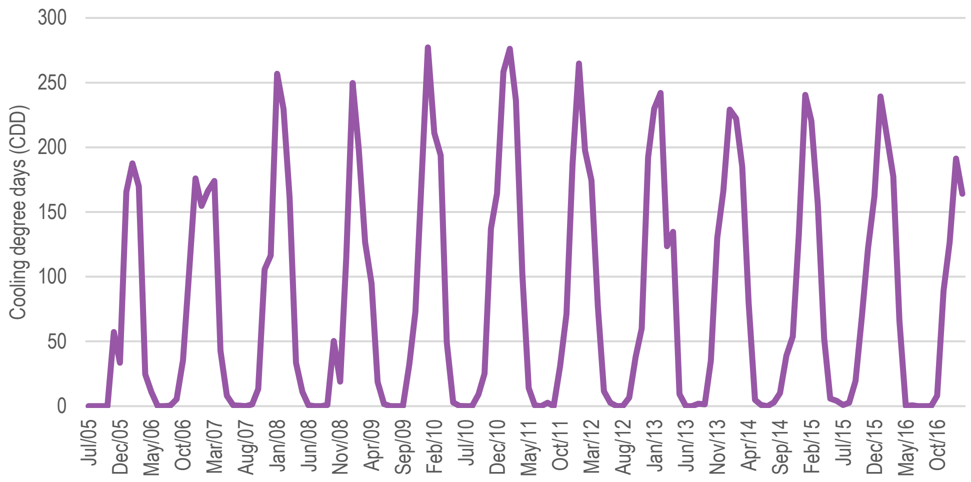
The historical heating degree days (HDD18) and cooling degree days (CDD18) series used in the energy regression models to control for weather variation are shown in **Figure 3.17** and **Figure 3.18** below. The figures show that heating degree days (HDD18) tend to peak in the coldest month of July, while cooling degree days (CDD18) tend to peak in January, reflecting the hotter weather conditions.

FIGURE 3.17 NUMBER OF HEATING DEGREE DAYS (HDD18) BY MONTH, JULY 2005 TO DECEMBER 2016



SOURCE: BUREAU OF METEOROLOGY AND ACIL ALLEN

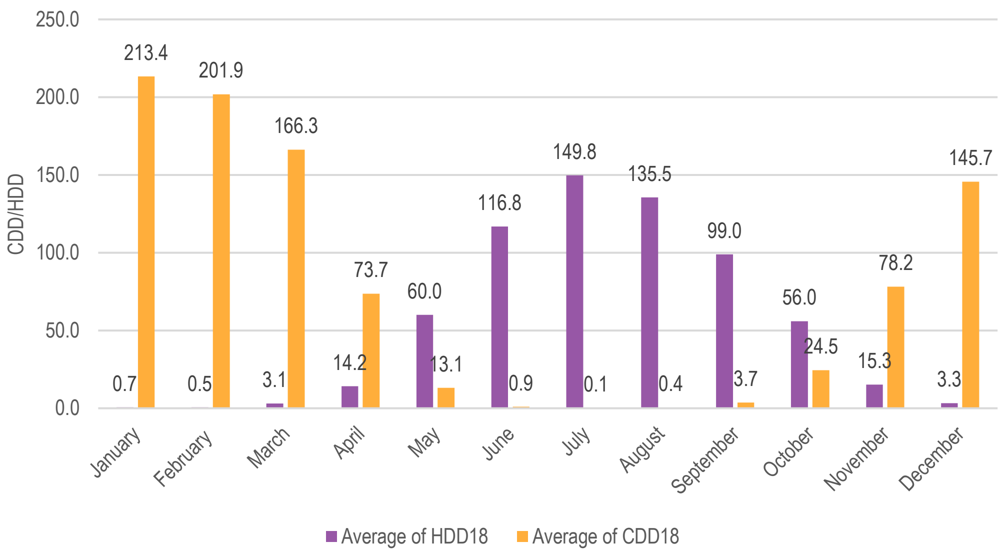
FIGURE 3.18 NUMBER OF COOLING DEGREE DAYS (CDD18) BY MONTH, JULY 2005 TO DECEMBER 2016



SOURCE: BUREAU OF METEOROLOGY AND ACIL ALLEN

For the purposes of generating the forecasts, a long run monthly average was applied covering a 30 year period from January 1987 to December 2016. The average heating degree days and cooling degree days by month are shown in **Figure 3.19**.

FIGURE 3.19 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 is more likely to be driven by overall economic 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 2016-17 to 2026-27, 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 expected, high and low rooftop PV and electric vehicle scenarios. Higher uptake of rooftop PV and electric vehicles is associated with higher economic growth, while the low uptake scenarios correspond to the low economic growth scenario.

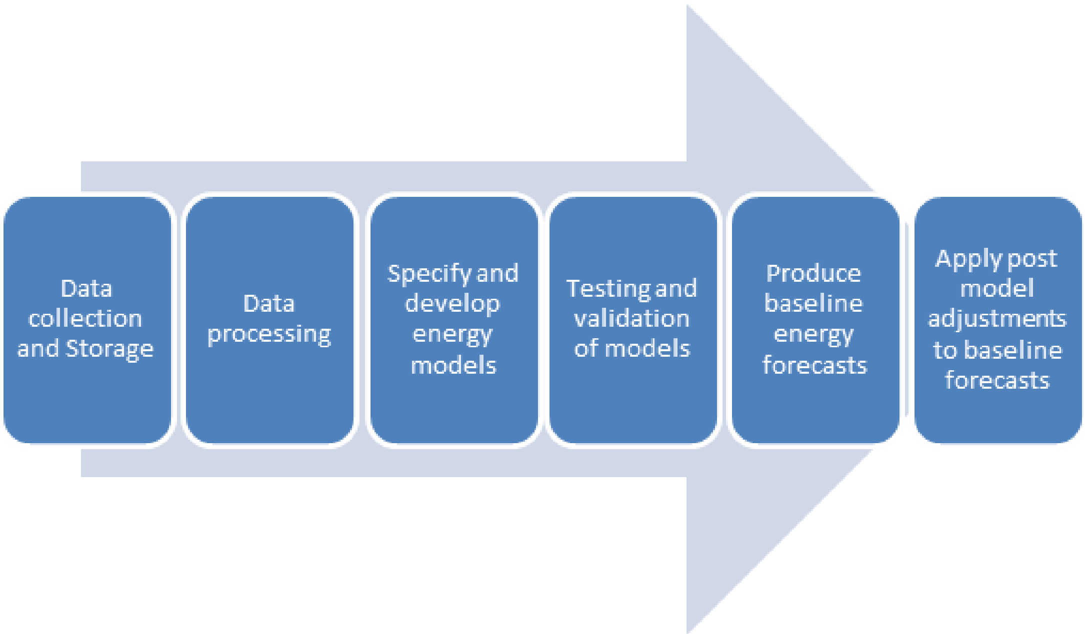
4.3 Model development and forecasting process

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 load trace and rooftop PV capacity forecasts under expected, high and low growth scenarios from AEMO/Jacobs

— forecasts of the take up of electric vehicles under separate expected, high and low growth scenarios from AEMO
— economic 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 a thirty year 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 2016.

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 before the calibration of the baseline energy models. The rooftop PV is forecast separately and then added back as a post model adjustment
— transformation of the daily air temperature data into the heating degree day (HDD18) and cooling degree day (CDD18) variables
— checking and imputing for missing data.

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:

(1) $Customers_t = \alpha + \beta_1 \times Population_t + \varepsilon_t$

Where α is a constant, β_1 represents the responsiveness of customers to changes in the population and ε is the error term.

We stress that we are using the entire Western Australian population as a proxy for the SWIS. This is not a significant problem as the vast majority of Western Australians live within the SWIS and that changes in the state's 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

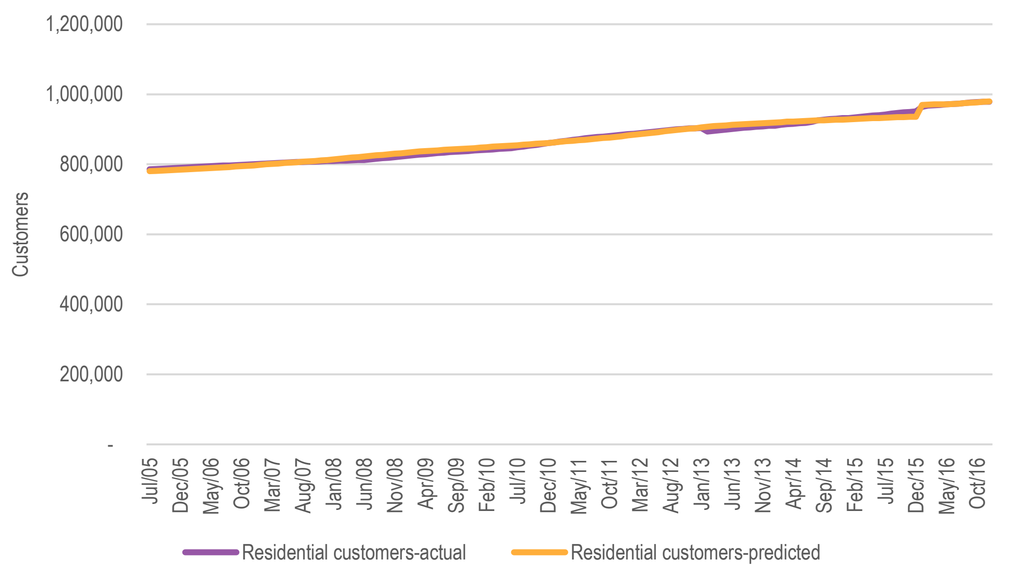
Variable	Coefficient	Std. Err.	t statistic	P>t
Population	0.2638266	0.0030047	87.81	0
Discontinuity dummy	32659.05	2134.053	15.3	0
Constant	248905.4	6976.99	35.68	0
R-squared	0.9879			

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 0.264 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 key 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 potential impact of weather is measured by the CDD18 and HDD18 variables. Moreover, seasonal variation in residential energy consumption per customer is captured through the inclusion of monthly seasonal dummy variables. The consumption per residential household in this model is actually latent consumption (i.e. metered consumption plus PV output).

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

(2) $\text{Energy per customer}_t = \alpha + \beta_1 \times \text{GSP}_t + \beta_2 \times \text{HDD18}_t + \beta_3 \times \text{CDD18}_t + \varepsilon_t$

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
GSP	1.60E-07	4.87e-08	3.28	0.001
Heating degree days (18)	0.0007893	.0000597	13.21	0
Cooling degree days (18)	0.0005797	.0000399	14.54	0
Feb	-0.0293765	.006989	-4.20	0
Apr	-0.0269118	.0071312	-3.77	0
Sep	-0.0400392	.0062924	-6.36	0
Oct	-0.0311523	.0067409	-4.62	0
Nov	-0.0411932	.0068127	-6.05	0
Constant	0.4008252	.012168	32.94	0
R-squared	0.8532			

SOURCE: ACIL ALLEN

The coefficients can be interpreted as follows:

— for every $100 million increase in GSP average residential consumption per customer increases by 0.000016 MWh per month

— each additional 100 HDDs increases energy consumption per customer by 0.079 MWh per month

— each additional 100 CDDs increases energy consumption per customer by 0.058 MWh per month

— in the case of February, April, September, October and November, 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 0.029 MWh below the months excluded from the model

— in April, average consumption per customer is 0.027 MWh below the months excluded from the model

— in September, average consumption per customer is 0.040 MWh below the months excluded from the model

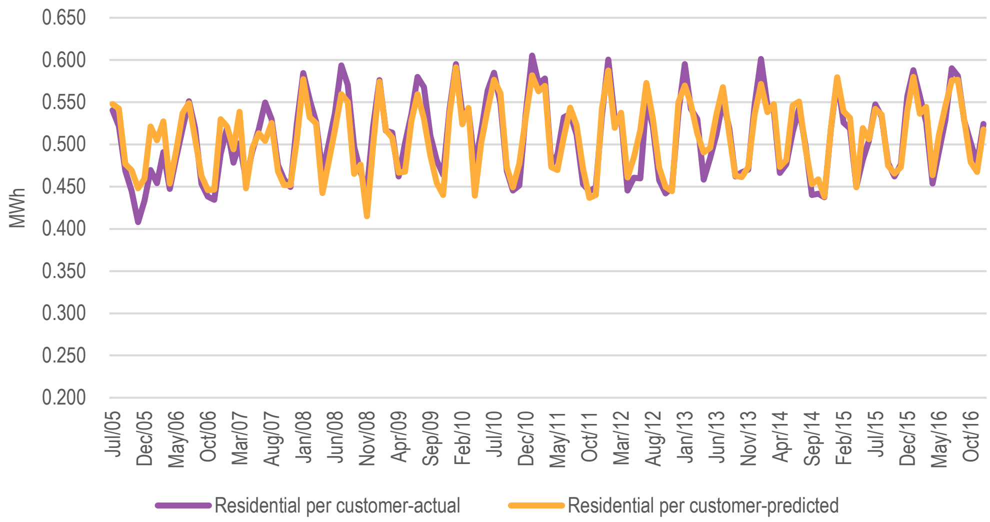
— in October, average consumption per customer is 0.031 MWh below the months excluded from the model

— in November, average consumption per customer is 0.041 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 85.3%, which means that over 85% 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 impact of increasing GSP on residential consumption per customer, although statistically significant, is modest. This means that residential consumption per customer has been relatively flat over the estimation period.

State final demand was also considered as a possible explanatory variable instead of GSP but was found to oscillate too much to provide reasonable results. The in-sample fit of GSP was superior to State Final Demand and also resulted in forecasts that were more reasonable.

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 GSP and heating degree and cooling degree days as well as a number of seasonal dummy variables to capture seasonal variation in non-residential energy consumption.

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

(3) $$Non\text{-}residential\ consumption_t = \alpha + \beta_1 \times GSP_t + \beta_2 \times HDD18_t + \beta_3 \times CDD18_t + \varepsilon_t$$

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
GSP	2.165302	.0729721	29.67	0
Heating degree days (18)	329.4323	137.7794	2.39	0.019
Cooling degree days (18)	1139.736	57.96684	19.66	0
Feb	-30100.95	9776.937	-3.08	0.003
Mar	26746.71	9191.118	2.91	0.004
Jun	95127.78	13819.03	6.88	0
Jul	84472.19	18097.68	4.67	0
Aug	120948.1	22137.26	5.46	0
Sep	98472.27	19116.37	5.15	0
Oct	63761.64	16513.91	3.86	0
Nov	58592.63	11734.58	4.99	0
Constant	29995.43	9657.007	3.11	0.002
R-squared	0.9273			

SOURCE: ACIL ALLEN

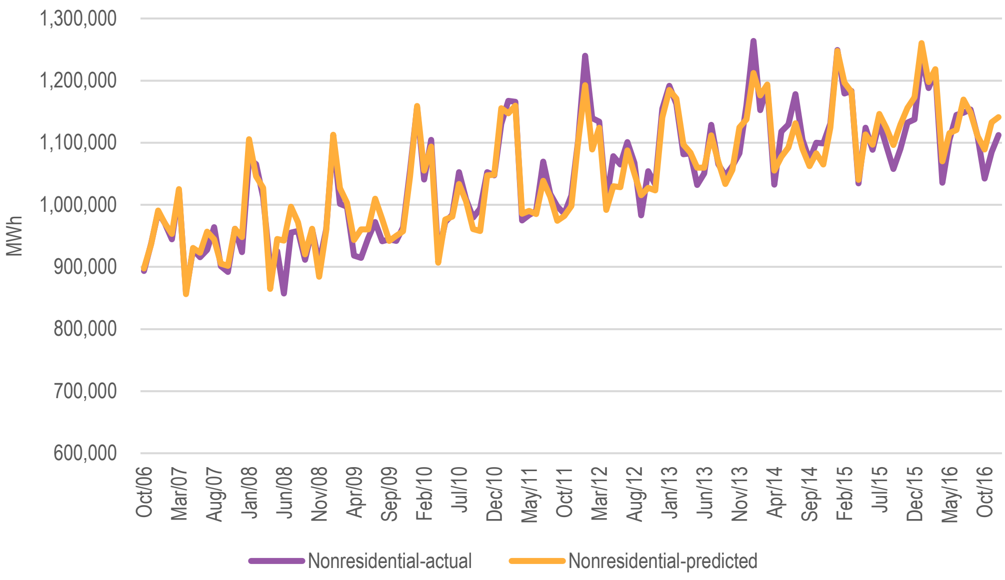
The estimated regression had an R^2 of 92.7%, indicating that over 90% of the historical variation in the data could be accounted for by the estimated model.

The coefficients can be interpreted as follows:

— for every $100 million increase in GSP total non-residential energy consumption increases by 216.5 MWh per month
— each additional 100 HDDs increases non-residential energy consumption by 32,943 MWh per month
— each additional 100 CDDs increases non-residential energy consumption by 113,973 MWh per month
— in the case of March, June, July, August, September, October, and November monthly non-residential consumption is higher on average compared to the excluded months of December, January, April and May (for which a statistically significant relationship could not be established)
— in February non-residential energy consumption is 30,101 MWh lower on average than the months excluded from the model
— in March non-residential energy consumption is 26,747 MWh higher on average than the months excluded from the model
— in June non-residential energy consumption is 95,128 MWh higher on average than the months excluded from the model
— in July non-residential energy consumption is 84,472 MWh higher on average than the months excluded from the model
— in August non-residential energy consumption is 120,948 MWh higher on average than the months excluded from the model
— in September non-residential energy consumption is 98,472 MWh higher on average than the months excluded from the model
— in October non-residential energy consumption is 63,762 MWh higher on average than the months excluded from the model
— in November non-residential energy consumption is 58,593 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.

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 two main post model adjustments applied to the energy consumption forecasts were for rising uptake of rooftop PV and the increasing energy consumption over time due to the uptake of electric vehicles.

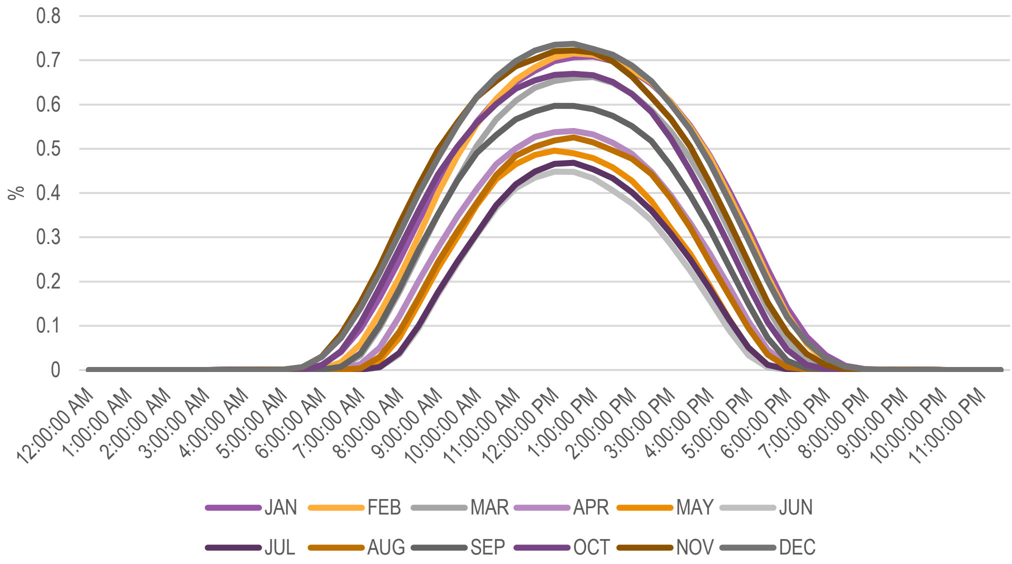
4.8.1 Rooftop PV adjustment

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 an average rooftop PV load trace for a subset of customers in the SWIS. The behaviour of this average load trace 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 March 16 2017 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 LOAD TRACE BY MONTH

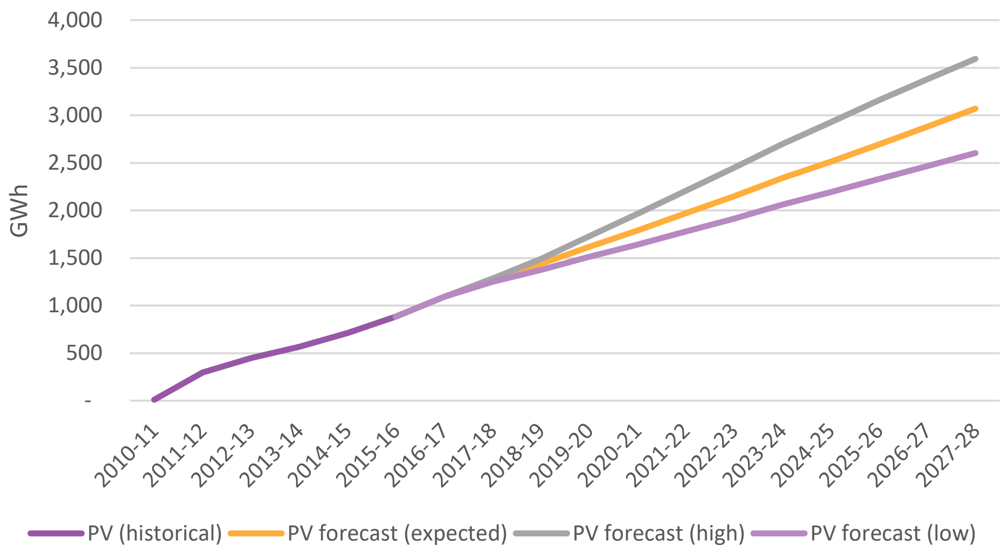


SOURCE: AEMO AND ACIL ALLEN

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 3,070 GWh by 2027-28. Under the high and low growth scenarios, rooftop PV generation is forecast to reach 3,593 GWh and 2,603 GWh respectively.

FIGURE 4.6 FORECAST GENERATION OF ROOFTOP PV SYSTEMS, EXPECTED, HIGH AND LOW 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 obtained independently from a separate report published by AEMO. These forecasts were described previously in section 3.4 and presented in **Figure 3.12**.

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 2016-17 to 2026-27 in the case of summer and 2017 to 2027 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

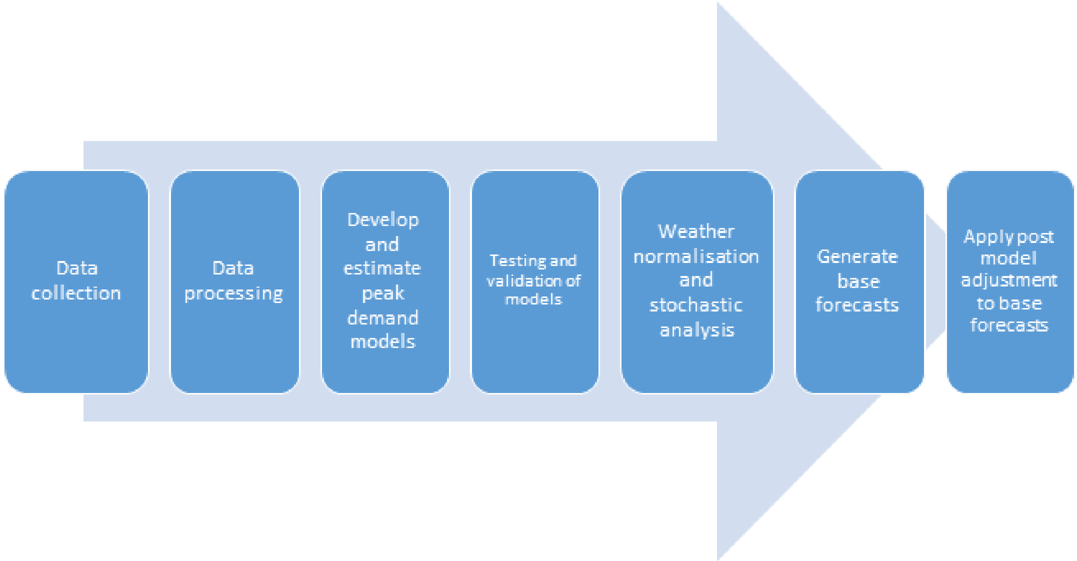
The steps required in peak demand forecasting process are shown in **Figure 5.1** below.

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 rooftop PV capacity forecasts under expected, high and low growth scenarios
— forecasts of battery storage capacity under separate expected, high and low growth scenarios
— details of any block loads expected over the forecast horizon
— details of the expected impact of the Individual Reserve Capacity Requirement (IRCR)
— 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 a thirty year period from January 1 1987.

Model calibration

The models were calibrated using daily time series dating from September 21 2006 to March 31 2017.

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 alternative daily peak demand series with the impact of 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.

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 only exceeded only once every 10 years, 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.

Table 5.1 below shows the estimated correlation coefficients between daily peak demand and average temperature[3] for both summer and winter. As you would expect, there is a positive relationship between demand and temperature in the summer months and a negative relationship during the winter. The table shows that both weather stations display a high degree of correlation between the weather that is recorded and the peak demand on any given day.

During the summer period, the correlation coefficient between the daily average temperature and peak demand is 0.81 for Perth Airport and 0.83 for Perth Metro. In the case of winter, Perth airport displayed a stronger negative correlation of -0.48 between peak demand and average temperature compared to -0.44 for Perth Metro. Based on these measures it not obvious which weather station should be used, with Perth Metro marginally outperforming during the summer, while Perth Airport performs better during the winter period.

TABLE 5.1 CORRELATION BETWEEN DAILY PEAK DEMAND AND TEMPERATURE

Variable	Perth Airport	Perth Metro
Summer maximum temp	0.768	0.779
Summer minimum temp	0.660	0.668
Summer average temp	0.808	0.826
Winter maximum temp	-0.539	-0.517
Winter minimum temp	-0.293	-0.221
Winter average temp	-0.482	-0.435

SOURCE: ACIL ALLEN

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.

[3] Average temperature is the average of the daily maximum and overnight minimum temperatures.

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.

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.[4] The model expresses daily peak demand as a function of the following factors:

— **GSP_t:** gross state product
— **Min_t*GSP_t:** minimum daily temperature, multiplied by gross state product
— **Max_t*GSP_t:** maximum daily temperature, multiplied by gross state product
— **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
— **$Monday_t$:** dummy variable, equal to '1' if day is Monday, '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.

$$MD_t = 1160.2 - 0.0062 \times GSP_t + 0.0003 \times Max_t \times GSP_t + 0.0001 \times Min_t \times GSP_t + 10.434 \times Max_{t-1} + 7.5238 \times Max_{t-2} + 19.467 \times Monday_t - 27.711 \times Friday_t - 178.72 \times November_t - 115.73 \times December_t - 81.06 \times January_t - 75.94 \times March_t - 199.06 \times April_t + \varepsilon_t \quad (4)$$

Table 5.2 summarises the coefficients estimated using this specification.

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

Variable	Coefficient	Standard error	t-statistic	p-value
GSP	-0.0062	2.88E-04	-21.38	0
MAX*GSP	0.0003	6.15E-06	47.04	0
MIN*GSP	0.0001	8.87E-06	16.62	0
MAX_{t-1}	10.4340	1.648966	6.33	0
MAX_{t-2}	7.5238	1.31773	5.71	0
MON	19.4665	11.56155	1.68	0.093
FRI	-27.7109	11.29195	-2.45	0.014
NOV	-178.7188	16.20261	-11.03	0
DEC	-115.7247	16.29264	-7.1	0
JAN	-81.0583	12.80486	-6.33	0
MAR	-75.3944	13.24031	-5.69	0
APR	-199.0619	18.83181	-10.57	0
Constant	1160.2040	59.05761	19.65	0
R^2 (Adjusted):	0.9134	Standard error of regression:	123.74	

SOURCE: ACIL ALLEN

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

The coefficients on lagged temperature are positive, meaning that as temperature increases over several days, peak demand is forecast to increase also.

The GSP coefficient must be interpreted in conjunction with the minimum and maximum temperature interactions. While the coefficient on GSP itself is negative which is counterintuitive, the interaction terms with temperature more than compensate. Because GSP appears in the regression in three separate variables, both by itself and as part of interactive terms with maximum and minimum temperature, the overall relationship between daily peak demand and GSP is determined by the interaction of all three variables rather than by the coefficient on the GSP variable by itself. While the coefficient on GSP is negative, suggesting a negative relationship between peak demand and GSP, after considering the effect of all three variables combined the underlying relationship is in fact positive.

The positive coefficients on interactions between temperature and GSP also suggest that sensitivity to temperature increases as the size of the economy (and electricity market) increases. This is true for both daytime (the maximum temperature interaction) and night-time (minimum temperature interaction).

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*GSP_t:** maximum daily temperature, multiplied by gross state product
- **Min_t*GSP_t:** minimum daily temperature, multiplied by gross state product
- **Max_{t-1}:** maximum daily temperature on the previous day
- **$Monday_t$:** dummy variable, equal to '1' if day is Monday, '0' otherwise
- **$Friday_t$:** 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.

$$MD_t = 1886.98 + 7.51 \times 10^{-3} \times GSP_t - 1.45 \times 10^{-4} \times Max_t \times GSP_t - 0.000043 \times Min_t \times GSP_t - 3.171 \times Max_{t-1} + 20.056 \times Monday_t - 87.012 \times Friday_t - 119.23 \times May_t - 85.25 \times August_t - 175.05 \times September_t - 298.99 \times October_t + \varepsilon_t \quad (5)$$

Table 5.3 summarises the coefficients estimated using this specification.

TABLE 5.3 SYSTEM PEAK DEMAND MODEL (WINTER), ESTIMATED COEFFICIENTS

Variable	Coefficient	Standard error	t-statistic	p-value
GSP	7.51E-03	0.0001453	51.67	0
MAX*GSP	-1.45E-04	5.64E-06	-25.74	0
MIN*GSP	-0.0000426	3.93E-06	-10.84	0
MAX_{t-1}	-3.17052	1.16939	-2.71	0.007
MON	20.05564	6.777951	2.96	0.003
FRI	-87.01151	6.614958	-13.15	0
MAY	-119.2279	8.519286	-14	0
AUG	-85.2511	7.686506	-11.09	0
SEP	-175.046	7.970285	-21.96	0
OCT	-298.992	9.2959	-32.16	0

Variable	Coefficient	Standard error	t-statistic	p-value
Constant	1886.98	29.91545	63.08	0
R^2 (Adjusted):	0.8681	Standard error of regression:	92.356	

SOURCE: ACIL ALLEN

The positive coefficient on GSP suggests that demand increases with higher levels of economic activity. The negative coefficients on the interactions between GSP and temperature indicate that the impact of higher GSP is lessened on warmer winter days. This is consistent with the reasoning that as the size of the economy increases the use of electric heating increases also.

The negative coefficients on the interactive terms between GSP and temperature have the effect of tempering the impact of the GSP variable itself, though the relationship between peak demand and GSP in winter remains positive.

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 higher on Mondays and 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.

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 from 2011 to early 2017 by month. The capacity factor that was applied during the forecast period is the average for February at 5:30pm.

Table 5.4 shows the contribution of rooftop PV to each summer peak under the expected, high and low scenarios.

An additional adjustment made under the high and low scenarios was to assume that the high case occurs on a day of low solar irradiance (high cloud cover) while the low case was assumed to occur on a day of high solar irradiance (low cloud cover). Based on the distribution of solar irradiance, the high case PV capacity factor was scaled down by 0.523 to correspond to the 5th percentile of solar irradiance. The low case PV capacity factor was scaled up by 1.134 to correspond to the 95th percentile of solar irradiance. These scaling factors were calculated internally by AEMO[5] and then provided to ACIL Allen.

TABLE 5.4 FORECAST ROOFTOP PV IMPACT (MW) ON SUMMER PEAK DEMAND AND PV CAPACITY FACTOR UNDER EXPECTED, HIGH AND LOW SCEANRIOS

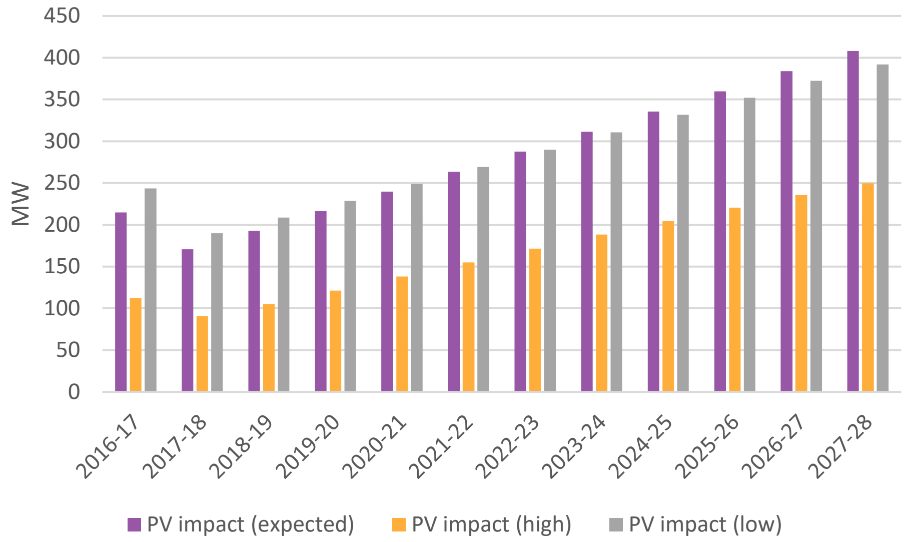
Year	PV impact (expected)	PV imapct (high)	PV impact (low)	PV capacity factor (expected)	PV capacity factor (high)	PV capacity factor (low)
2017-18	171	90	190	0.2124	0.1111	0.2408
2018-19	193	105	209	0.2124	0.1111	0.2408
2019-20	216	121	229	0.2124	0.1111	0.2408
2020-21	240	138	249	0.2124	0.1111	0.2408
2021-22	264	155	269	0.2124	0.1111	0.2408
2022-23	288	172	290	0.2124	0.1111	0.2408
2023-24	312	188	311	0.2124	0.1111	0.2408
2024-25	336	205	332	0.2124	0.1111	0.2408
2025-26	360	221	352	0.2124	0.1111	0.2408
2026-27	384	236	372	0.2124	0.1111	0.2408
2027-28	408	250	392	0.2124	0.1111	0.2408

SOURCE: AEMO AND ACIL ALLEN

The rooftop PV impact on summer demand is presented graphically in **Figure 5.3**. Under the expected scenario, rooftop PV is forecast to reduce the baseline summer demand by 408 MW in 2027-28.

[5] Please refer to the 2017 Wholesale Electricity Market (WEM) Electricity Statement of Opportunities (ESOO).

FIGURE 5.2 FORECAST IMPACT OF ROOFTOP PV ON SUMMER PEAK DEMAND, EXPECTED, HIGH AND LOW SCENARIOS



SOURCE: ACIL ALLEN

5.8.2 Battery storage

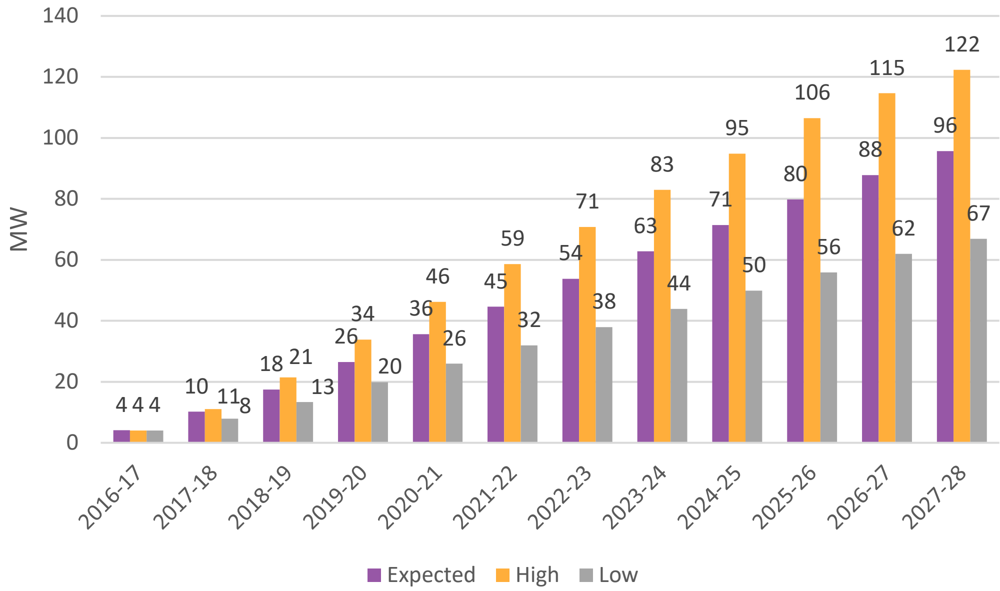
Battery storage is expected to reduce the summer peak demand over time as the installed capacity of systems increases.

In order to calculate the impact of new battery storage systems on summer peak demand the following assumptions were made:

— batteries are charged at a constant rate in the morning and early afternoon hours until fully charged
— battery systems are charged only from the households attached rooftop PV panels and not from the grid
— batteries are then discharged evenly over a four hour period in the late afternoon / early evening which includes the time of summer system peak, assumed to be 5:30pm over the forecast period.
— batteries are used only to shift consumption of rooftop PV generation over the course of the day and for no other purpose
— the batteries charge and discharge rates do not contravene the technical constraints of the technology.

The forecast impact of battery storage on summer peak demand is shown in **Figure 5.3**. Under the expected scenario, battery storage systems are forecast to reduce peak demand by 96 MW in 2027-28. This is forecast to increase to 122 MW under the high scenario and decline to 67 MW under the low scenario. Even with the very 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

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 in the high growth case only and excluded from the expected and low case.

The details of the block loads themselves are presented in **Table 3.2**.

5.8.4 Individual Reserve Capacity Requirement

An additional post model adjustment was made to the summer peak demand forecasts to account for the impact of the Individual Reserve Capacity Requirement (IRCR) which provides financial incentives to customers to reduce consumption during periods of very high demand.

We applied an annual reduction in the baseline summer peak demand forecast of 77MW in each year of the forecast horizon.

6 OPERATIONAL ENERGY FORECASTS

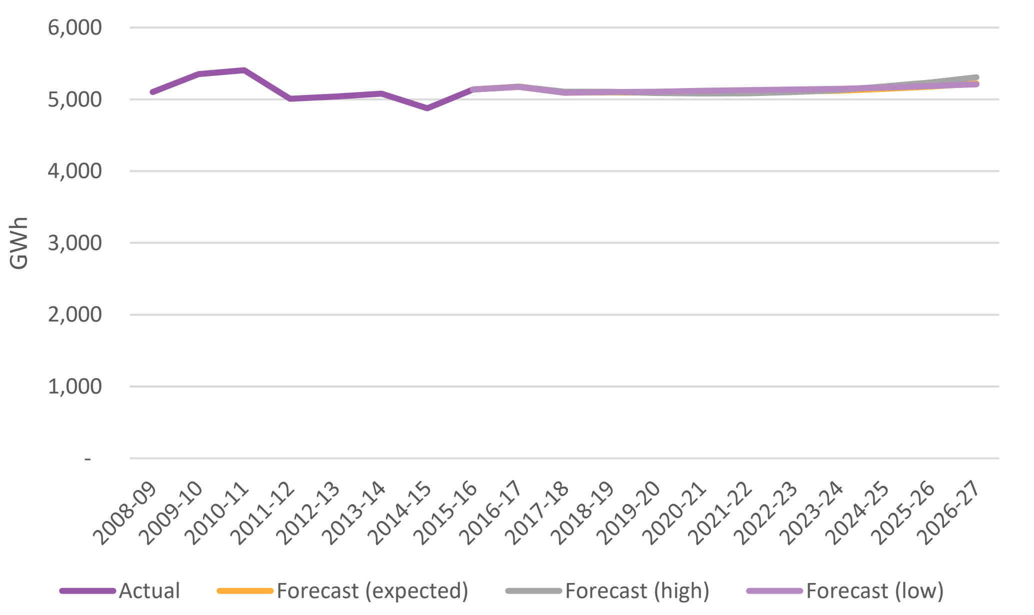
In this section we present the final energy consumption forecasts generated after applying the methodology described in the previous sections of this report.

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 2016-17 to 2026-27. The figure shows that residential energy consumption is expected to remain relatively flat over the forecast period.

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



SOURCE: ACIL ALLEN

Under the expected scenario, residential energy consumption is forecast to grow at 0.3% per annum from 2017-18 to 2026-27. This increases to 0.4% per annum in the high scenario and falls back to 0.3% per annum in the low scenario.

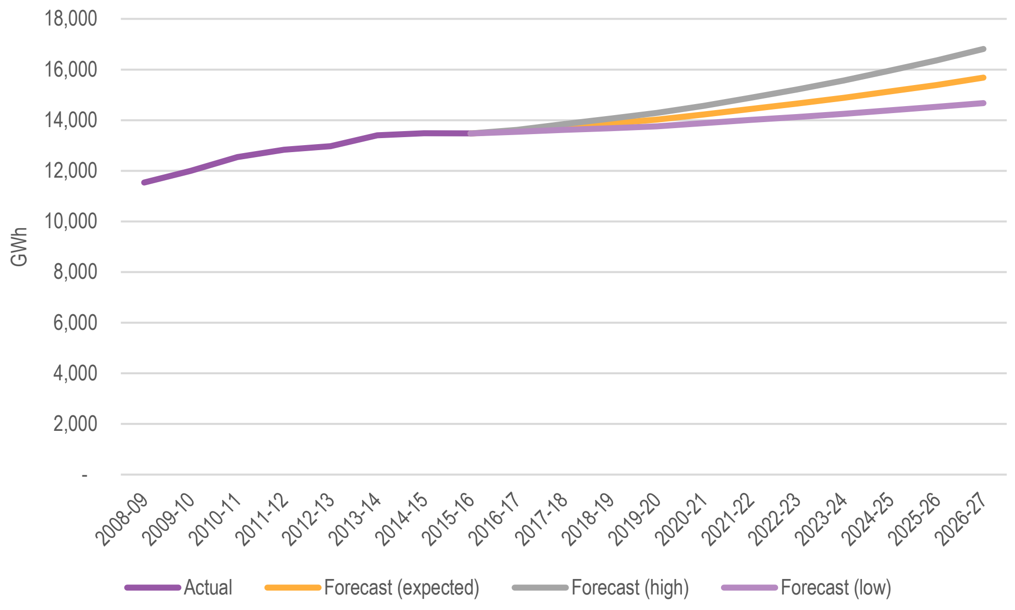
Residential consumption is forecast to reach 5,221 GWh by 2026-27, compared to 5,308 GWh in the high scenario and 5,209 GWh in the low scenario. The main cause of the slow growth in residential consumption is the continued rapid uptake of rooftop PV systems which are expected to maintain a strong rate of growth over the whole forecast horizon.

6.2 Non-residential energy consumption

Non-residential energy consumption is forecast to grow more strongly than residential. This very much in line with the historical performance of this sector, as well as the forecast recovery in economic growth in Western Australia over the next few years, which is expected to flow through into higher non-residential energy consumption.

Figure 6.2 shows historical and forecast non-residential energy consumption from 2016-17 to 2026-27.

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



SOURCE: ACIL ALLEN

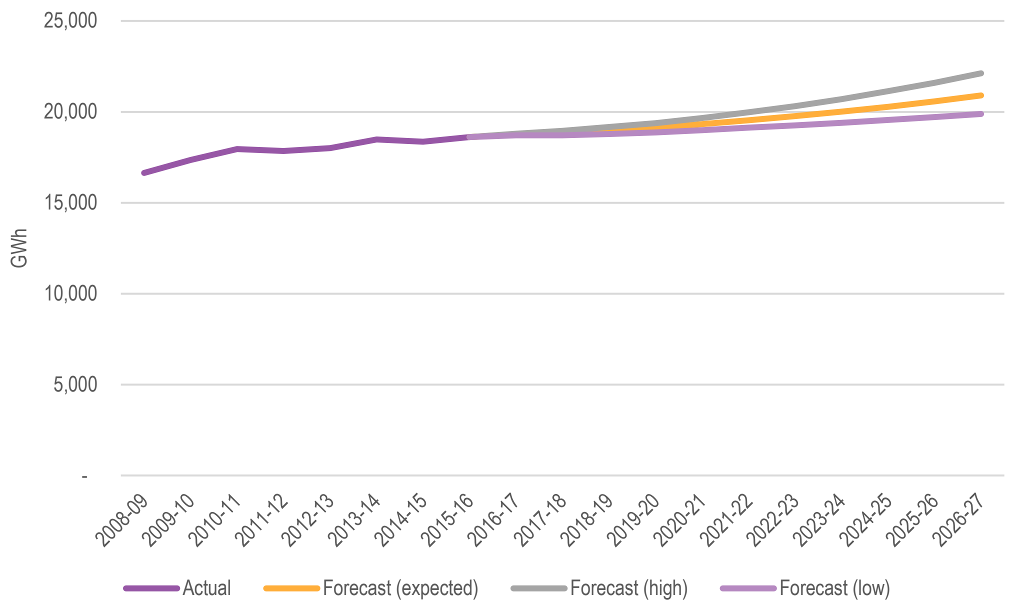
Under the expected growth scenario, non-residential energy consumption is forecast to increase from 13,725 GWh in 2017-18 to 15,679 GWh in 2026-27. This is equivalent to an average annual compound rate of growth of 1.5% per annum.

Under the high growth scenario, non-residential consumption is forecast to reach 16,811 GWh in 2026-27, equivalent to an average annual rate of growth of 2.2%. Under the low economic growth scenario, non-residential energy consumption is forecast to grow at just 0.8% per annum, rising to 14,673 GWh by 2026-27.

6.3 Total operational energy consumption in the SWIS

Figure 6.3 shows historical and forecast total operational energy consumption in the SWIS from 2016-17 to 2026-27.

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		18,753	18,798	18,710
2017-18		18,819	18,947	18,705
2018-19		18,962	19,160	18,786
2019-20		19,110	19,372	18,866
2020-21		19,316	19,650	18,994
2021-22		19,538	19,967	19,129
2022-23		19,766	20,318	19,262
2023-24		20,004	20,698	19,393

Financial year	Actual	Forecast (Expected)	Forecast (High)	Forecast (Low)
2024-25		20,274	21,133	19,546
2025-26		20,570	21,600	19,706
2026-27		20,901	22,119	19,882
Average annual growth rate (p.a.)		**1.2%**	**1.7%**	**0.7%**

SOURCE: ACIL ALLEN

Under the expected growth scenario, total operational energy consumption in the SWIS is forecast to increase from 18,819 GWh in 2017-18 to 20,901 GWh in 2026-27. This is equivalent to an average compound rate of growth of 1.2% per annum. Although reasonable, this rate of growth is considerably slower than that observed historically, where total operational energy consumption grew at 1.6% per annum in the eight years from 2007-08 to 2015-16. This is most likely due to lower forecast economic growth compared to that observed historically as well as high rooftop PV uptake.

Under the high growth scenario, operational energy consumption is forecast to reach 22,119 GWh by 2026-27, equivalent to an average compound rate of growth of 1.7% per annum from 2017-18. On the other hand, if the low growth scenario prevails, total operational energy consumption in the SWIS is forecast to grow at just 0.7% per annum.

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
2016-17	3628	3845	4073	3740	3948	4182	3587	3804	4039
2017-18	3709	3927	4169	3844	4053	4294	3658	3868	4104
2018-19	3739	3968	4213	3911	4138	4392	3669	3887	4126
2019-20	3782	4009	4253	3986	4219	4490	3689	3903	4153
2020-21	3835	4076	4326	4088	4328	4597	3717	3931	4192
2021-22	3893	4133	4401	4187	4437	4716	3744	3971	4227
2022-23	3951	4201	4466	4283	4547	4830	3772	4006	4257
2023-24	4005	4267	4541	4383	4665	4959	3796	4048	4307
2024-25	4073	4338	4626	4502	4791	5099	3836	4075	4345
2025-26	4139	4414	4707	4616	4922	5248	3866	4119	4388
2026-27	4217	4505	4799	4767	5080	5407	3901	4161	4447
5 year average growth	**1.3%**	**1.4%**	**1.4%**	**2.2%**	**2.3%**	**2.4%**	**0.6%**	**0.7%**	**0.7%**
10 year average growth	**1.4%**	**1.5%**	**1.6%**	**2.4%**	**2.5%**	**2.6%**	**0.7%**	**0.8%**	**0.9%**

SOURCE: ACIL ALLEN

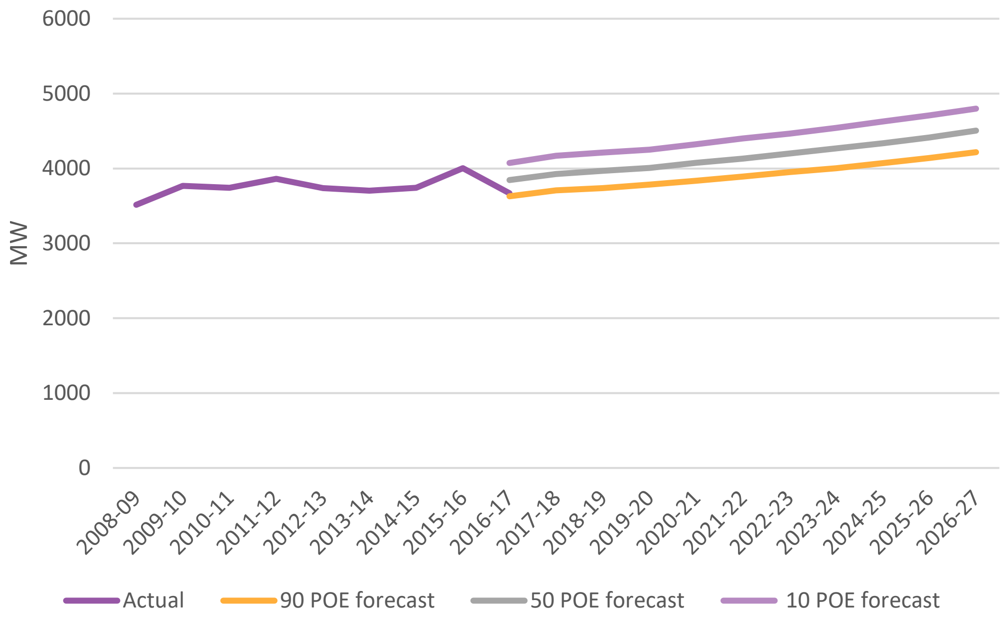
The results in the table are also presented graphically in the next four figures.

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, the 10POE and 50 POE forecast summer peak demand is expected to grow at 1.6% and 1.5% per annum respectively, over the period from 2017-18 to 2026-27. Under this scenario, the 10 POE summer peak demand is forecast to reach 4,799 MW in 2026-27, while the 50 POE summer demand will reach 4,505 over the same period.

This growth in peak demand is driven by increasing economic growth over the forecast horizon, from a low of 1.4% in 2016-17, before increasing to a high of 3.9% in 2020-21, and remaining at or above 3.5% for the remainder of the forecast horizon.

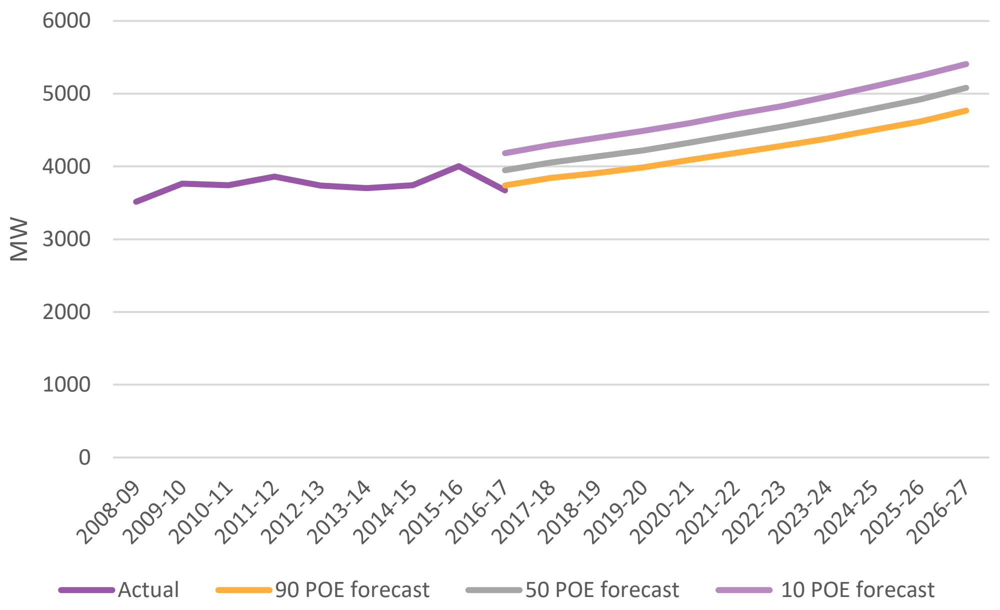
Under the high scenario, the 10 POE and 50 POE summer peak demand is forecast to grow at a faster rate of 2.6% and 2.5% per annum respectively, driven by average GSP growth over the forecast period of 4.5% per annum. In the low growth scenario, summer peak demand is forecast to grow more slowly, increasing by just 0.8% per annum in the case of the 50 POE peak demand.

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



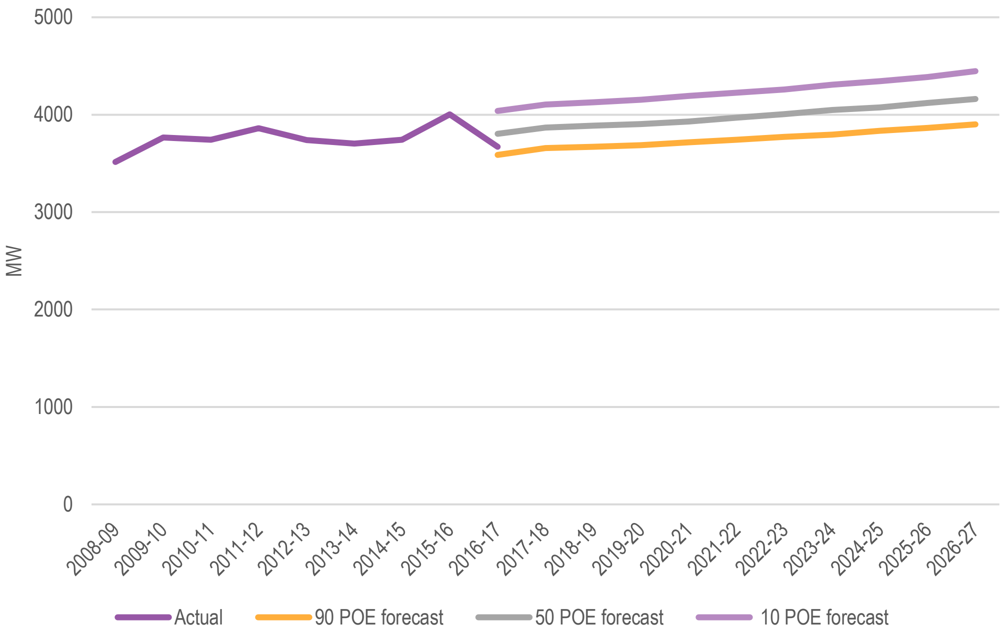
SOURCE: ACIL ALLEN

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



SOURCE: ACIL ALLEN

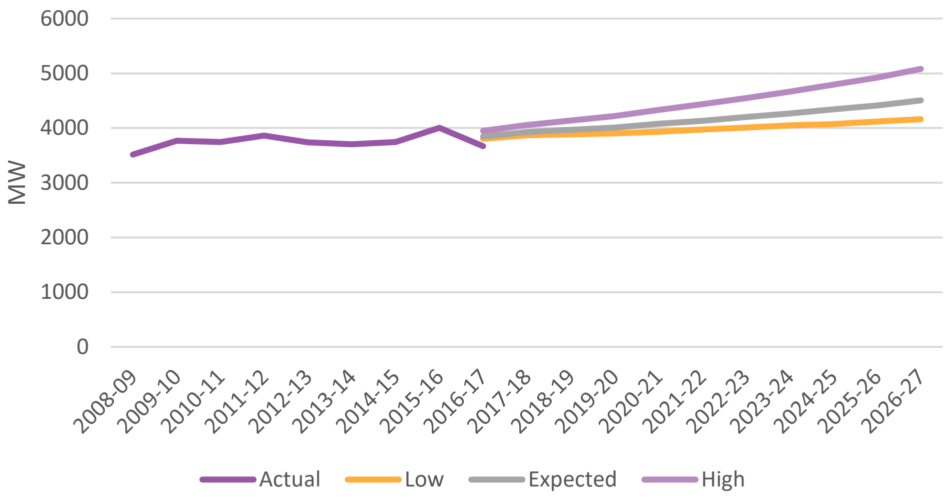
FIGURE 7.3 SUMMER PEAK DEMAND FORECAST, MW, 10POE, 50POE AND 90POE, LOW SCENARIO



SOURCE: ACIL ALLEN

Figure 7.4 presents the 50POE summer peak demand forecasts under each of the expected, high and low scenarios.

FIGURE 7.4 50 POE SUMMER PEAK DEMAND FORECAST, MW, EXPECTED, HIGH AND LOW SCENARIOS



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

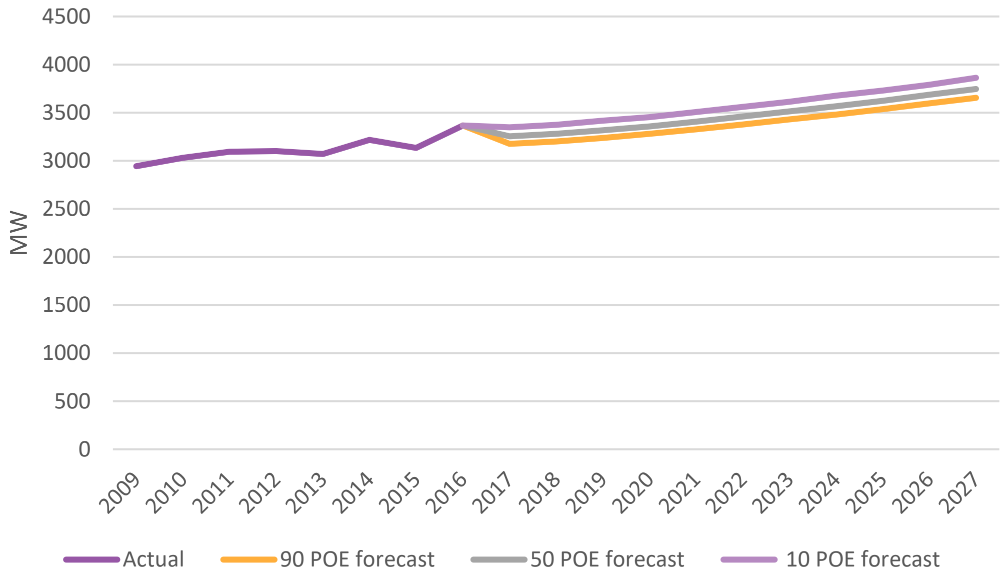
	Expected scenario			High scenario			Low scenario		
	90 POE	50 POE	10 POE	90 POE	50 POE	10 POE	90 POE	50 POE	10 POE
2017	3176	3254	3348	3184	3258	3356	3172	3246	3340
2018	3201	3279	3375	3236	3313	3411	3183	3257	3352
2019	3238	3316	3415	3302	3378	3478	3206	3282	3373
2020	3281	3358	3455	3355	3436	3539	3224	3303	3402
2021	3326	3407	3507	3431	3517	3617	3257	3334	3432
2022	3376	3460	3560	3505	3592	3698	3287	3368	3470
2023	3430	3513	3612	3579	3667	3780	3320	3400	3501
2024	3482	3568	3676	3657	3749	3861	3354	3437	3537
2025	3535	3625	3731	3738	3831	3945	3387	3471	3573
2026	3596	3686	3791	3829	3920	4038	3417	3507	3608
2027	3654	3746	3863	3916	4015	4136	3458	3545	3650
5 year average growth	**1.2%**	**1.2%**	**1.2%**	**1.9%**	**2.0%**	**2.0%**	**0.7%**	**0.7%**	**0.8%**
10 year average growth	**1.4%**	**1.4%**	**1.4%**	**2.1%**	**2.1%**	**2.1%**	**0.9%**	**0.9%**	**0.9%**

SOURCE: ACIL ALLEN

Figure 7.5, **Figure 7.6** and **Figure 7.7** 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 1.4% per annum over the period from 2017 to 2027. Under this scenario the 10 POE winter demand is forecast to reach 3,863 MW in 2027, while the 50 POE is forecast to reach 3,746 MW over the same period.

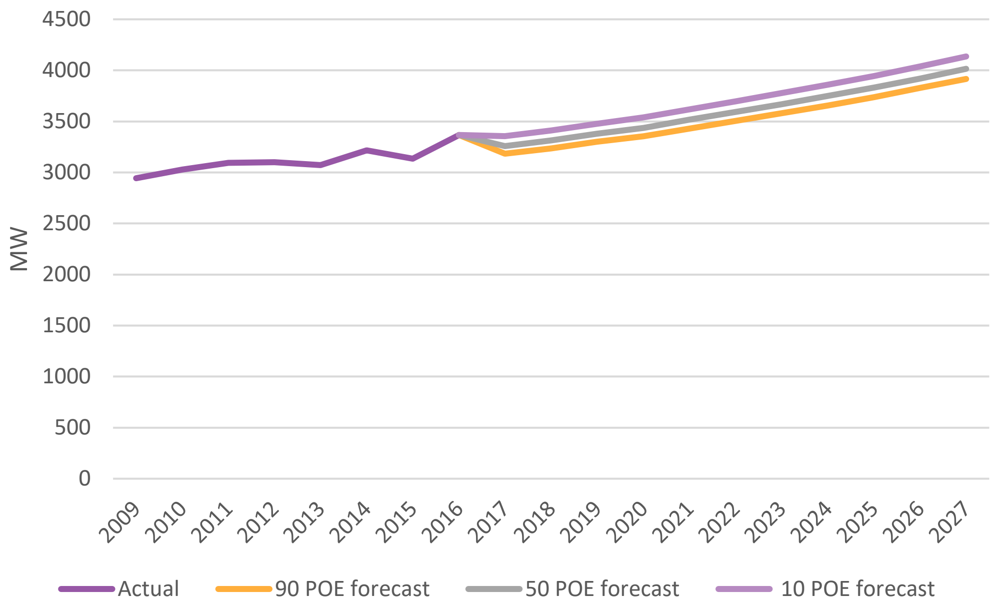
FIGURE 7.5 WINTER PEAK DEMAND FORECAST, MW, 10POE, 50POE AND 90POE, EXPECTED SCENARIO



SOURCE: ACIL ALLEN

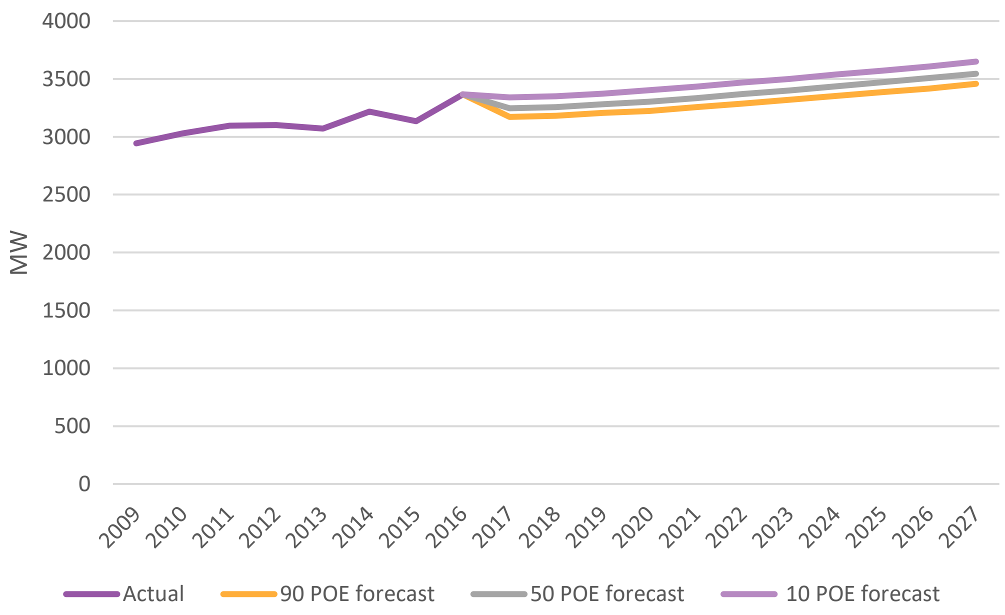
Under the high growth scenario, 10 POE and 50 POE winter peak demand is forecast to grow by 2.1% per annum over the next 10 years, with the 10 POE and 50 POE reaching 4,136 MW and 4,015 MW by 2027 respectively.

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



SOURCE: ACIL ALLEN

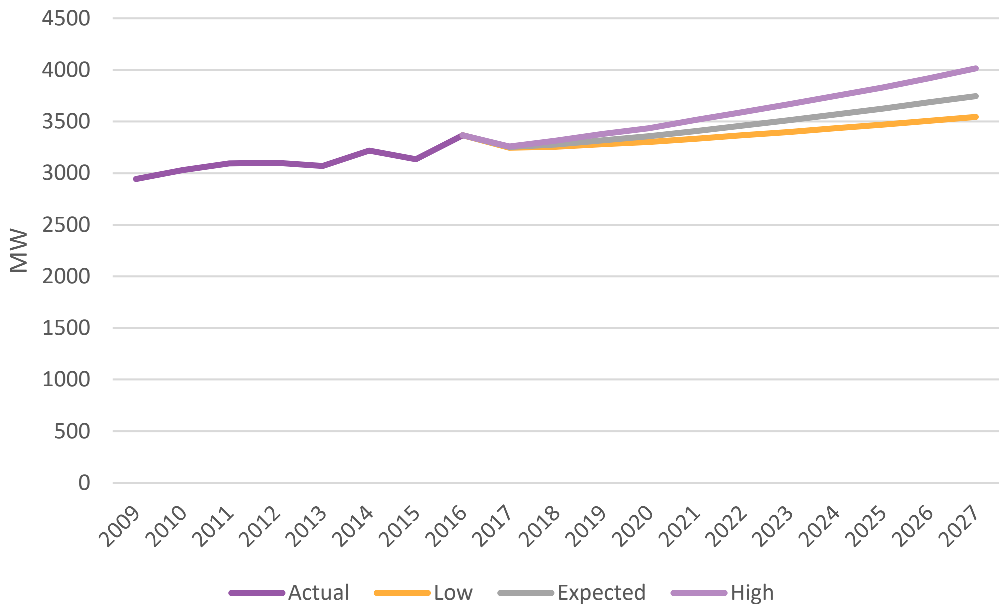
FIGURE 7.7 WINTER PEAK DEMAND FORECAST, MW, 10POE, 50POE AND 90POE, LOW SCENARIO



SOURCE: ACIL ALLEN

Figure 7.8 presents the 50POE winter peak demand forecasts under each of the expected, high and low scenarios.

FIGURE 7.8 50 POE WINTER PEAK DEMAND FORECAST, MW, EXPECTED, HIGH AND LOW SCENARIOS



SOURCE: ACIL ALLEN