ACIL ALLEN CONSULTING

REPORT TO AUSTRALIAN ENERGY MARKET OPERATOR 13 JUNE 2018

PEAK DEMAND AND ENERGY FORECASTS

FOR THE SOUTH WEST INTERCONNECTED SYSTEM-WESTERN AUSTRALIA



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

1.1 Background

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

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

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

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

1.2 Scope of work

1.2.1 Monthly and annual energy forecasts

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

The forecasts cover the outlook period from 2017-18 to 2027-28, and are provided on a financial year (July 1 to June 30) and Capacity Year (October 1 to September 30) basis.

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

1.2.2 Peak demand forecasts

Forecasts of summer and winter electricity peak demand, measured in MW, have been developed for the SWIS covering the time horizon from 2017-18 to 2027-28.

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

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

1.2.3 Rooftop PV and battery storage forecasts

Forecasts of rooftop PV uptake and its associated impact on operational energy and peak demand have been developed by financial year and Capacity Year for the SWIS for the 2017-18 to 2027-28 period, under three separate high, medium and low demand growth scenarios. Forecasts include systems both with and without battery storage. For those systems with battery storage, forecasts of the storage capacity (MWh) have also been included.

Forecasts of battery storage systems and their impact on peak demand have been developed for the period from 2017-18 to 2027-28 under the high, medium and low demand growth cases.

1.2.4 Electric vehicle forecasts

Forecasts of electric vehicle uptake and their associated impact on operational energy have also been developed by financial year and Capacity Year under the three separate demand growth scenarios, high, medium and low.

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
- section 8 describes the methodology by which the rooftop PV and battery storage forecasts were produced
- section 9 describes the methodology by which the electric vehicle forecasts were produced



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







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. In 2016-17, residential consumption was 5,030 GWh, a decline of 2.1% on the previous year.

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. Residential rooftop PV systems generated 796 GWh of energy in 2016-17, having increased from just 190 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 2016-17

SOURCE: ACIL ALLEN

The compound average annual rate of growth in residential energy consumption between 2007-08 and 2016-17 was 0.7%.

2.1.2 Non-residential energy consumption²

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

- commercial
- industrial (including large customers)

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

- street-lighting
- unmetered supply.

Figure 2.3 shows the historical non-residential consumption in the SWIS from 2007-08 to 2016-17.

Annual non-residential consumption increased steadily from 11,405 GWh in 2007-08 to 13,473 GWh in 2015-16, before declining to 13,232 GWh in 2016-17.

This is equivalent to a compound average rate of growth in non-residential energy consumption between 2007-08 and 2016-17 of 1.7%.



FIGURE 2.3 NON-RESIDENTIAL ENERGY CONSUMPTION, 2007-08 TO 2016-17

SOURCE: SYNERGY AND AEMO

Figure 2.4 shows the year on year growth in non-residential energy consumption. Robust growth in 2009-10 and 2010-11 of over 4% was followed by a period of slower growth, particularly in the last three years when growth was 0.6% in 2014-15, -0.1% in 2015-16 and -1.8% in 2016-17. These years reflect slower economic conditions arising from the end of the mining boom and the associated loss of income and employment in the SWIS.

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FIGURE 2.4 ANNUAL GROWTH IN NON-RESIDENTIAL ENERGY CONSUMPTION, 2008-09 TO 2016-17

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 2016-17, total operational energy consumption in the SWIS increased from 16,387 GWh to 18,262 GWh.





SOURCE: SYNERGY AND AEMO

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Over the last nine years, total operational energy consumption increased at a compound average growth rate of 1.2%. 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**). In 2016-17, operational energy declined by 1.9%, the largest decline since 2008-09.



FIGURE 2.6 ANNUAL GROWTH IN TOTAL OPERATIONAL ENERGY CONSUMPTION

The impact of rooftop PV on operational energy consumption in the SWIS is shown in **Figure 2.7** below. The figure shows that in 2016-17, rooftop PV systems generated 912 GWh of energy, compared to 203 GWh in 2011-12.



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

2.2 Residential customer numbers

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

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

As at December 2017, the SWIS had 989,585 residential customers, up from 795,186 in June 2006.

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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 0.7% in 2012-13 up to a 3.4% increase in 2015-16. In 2016-17, growth in residential customer numbers was below average, rising by just 1.6% compared to the eleven average of 2.0% per annum.



FIGURE 2.9 ANNUAL GROWTH IN RESIDENTIAL CUSTOMER NUMBERS

2.3 Peak demand

Figure 2.10 plots the daily peak demand in the SWIS from 21 September 2006 to 31 March 2018.

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 last few years.



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

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 two most recent peaks which occurred in December and March respectively, the remaining peaks all occurred in January and February. The largest peak demand over the last 10 years was 4,013 MW which occurred on February 8 2016.

Another trend that can be observed is the tendency for the peak demand to occur later in the day 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 2017-18 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.

			2001 00 10 201	10		
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	21-12-16	3543	17:00	42.8	20.1	31.5
2017-18	13-03-18	3616	17:30	38.5	23.1	30.8
SOURCE: AEMO						

TABLE 2.1SUMMER PEAK DEMAND, 2007-08 TO 2017-18

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 3,419 in 2017. All winter peaks have taken place in either June or July, with the most recent winter peak occurring in July. The most common time for the winter peak to occur is at 6pm with eight of the last eleven peaks all occurring at this time.

TABLE 2.2	WINTER PEA	K DEMAND, 20	007 10 2017				
Year	Date	MW ³	Time	Daily Max temp	Daily Min temp	Average temp	
2007	22-06-07	2705	17:30	18.2	7.3	12.8	
2008	31-07-08	2774	18:30	13.7	6.5	10.1	
2009	20-07-09	2943	18:00	14.6	8.3	11.5	
2010	28-06-10	3029	18:00	15.5	1.8	8.7	
2011	11-07-11	3095	18:00	12.8	10.1	11.5	
2012	25-07-12	3100	18:30	16.1	-0.7	7.7	
2013	08-07-13	3071	18:00	18.5	2.5	10.5	
2014	23-06-14	3217	18:00	16.0	1.3	8.7	
2015	23-06-15	3135	18:00	16.9	1.8	9.4	
2016	07-06-16	3366	18:00	15.0	10.5	12.8	
2017	31-07-17	3419	18:00	15.8	12.3	14.1	
SOURCE: AEMO							

³ 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.



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 airconditioners 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), for the financial years from 1989-90 to 2016-17.



FIGURE 3.1 WESTERN AUSTRALIAN GROSS STATE PRODUCT, 1989-90 TO 2016-17 \$M (CHAIN VOLUME MEASURE)

SOURCE: ABS, 5220.0 AUSTRALIAN NATIONAL ACCOUNTS: STATE ACCOUNTS

Western Australian economic growth has been positive in all years since 1990-91 except for the most recent year where it declined by 2.7% (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 6.7% in 1993-94, 6.6% in 2001-02, 6.5% in 2006-07 and 9.4% in 2011-12. Economic growth troughs occurred in 1990-91, 2000-01 and 2016-17.

Western Australian GSP growth has slowed significantly in the last three years as a result of declining aggregate demand and household incomes associated with the end of the mining boom. In 2015-16, economic growth was just 1.0% before contracting by 2.7% in 2016-17. This is compared to a long term average of 4.3% per annum from 1990-91 to 2016-17.



FIGURE 3.2 YEAR ON YEAR GSP GROWTH, WESTERN AUSTRALIA 1990-91 TO 2016-17

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.

001			
Year	GSP (expected)	GSP (high)	GSP (low)
2017-18	2.07%	2.14%	2.00%
2018-19	2.56%	2.76%	2.33%
2019-20	2.90%	3.22%	2.54%
2020-21	3.43%	3.77%	3.02%
2021-22	3.56%	3.96%	3.09%
2022-23	3.46%	3.90%	2.93%
2023-24	3.25%	3.73%	2.68%
2024-25	3.56%	4.12%	2.94%
2025-26	3.51%	4.12%	2.83%
2026-27	3.47%	4.15%	2.74%
2027-28	3.43%	4.19%	2.64%
Average	3.20%	3.64%	2.71%
SOURCE: AEMO			

TABLE 3.1FORECAST GSP GROWTH 2017-18 TO 2027-28, EXPECTED, HIGH AND LOW
SCENARIOS



The same forecasts are presented graphically in Figure 3.3 below.



Under the expected economic growth scenario, Western Australian GSP growth is expected to average 3.2% per annum. In 2017-18, economic conditions are expected to improve with growth increasing to 2.1% per annum after a contraction in 2016-17. From 2018-19, GSP growth is forecast to continue increasing before peaking at 3.6% in 2021-22. Under the high economic growth scenario GSP is forecast to average 3.6% over the forecast horizon. Under the low economic growth scenario, GSP is forecast to average 2.7% over the same period.

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





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 2017.

The figure shows a long steady increase in the estimated resident population of Western Australia. In June 2017, the estimated resident population of Western Australia had reached 2.58 million people.





SOURCE: ABS, 3101.0 AUSTRALIAN DEMOGRAPHIC STATISTICS

Growth in the population of Western Australia has followed a cyclical pattern largely in line with the state's economic fortunes (see **Figure 3.6**). Over the long term, Western Australian population growth has averaged 1.9% per annum. Over the last four years, Western Australian population growth has been below average. Population growth in 2014-15, 2015-16 and 2016-17 was 0.8%, 0.6% and 0.8% respectively.





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

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



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

SOURCE: AEMO

2018

2019

2020

2021

2022

■ Expected ■ Low ■ High

2023

2024

2025

2026

2027

2028

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



FIGURE 3.8 FORECAST WESTERN AUSTRALIAN POPULATION, EXPECTED, HIGH AND LOW SCENARIOS

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 developed by ACIL Allen and the methodology used to generate them is described in greater detail section 8.

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 2,273 MW by June 2028. Under the high and low growth scenarios, rooftop PV capacity is forecast to reach 2,419 MW and 2,151 MW respectively.



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

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 25% per annum between 2013-14 and 2016-17.

Future rooftop PV growth is forecast to slow down further, with annual growth expected to average 9.6% per annum under the expected scenario in the 10 year period from 2017-18 to 2027-28. Under the high and low scenarios, rooftop PV capacity is forecast to grow at 10.2% and 9.0% per annum respectively over the same period.



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

3.3.2 Battery storage

To date the deployment of home energy storage systems in Australia has been negligible. However, prices for battery technology are widely expected to reduce in the future and this could have major implications for battery uptake and the level of peak demand that is required to be met using network services. As with the reduction in cost of PV systems over the last decade, a reduction in cost of battery systems could be accelerated by a large scale, subsidy assisted, deployment of this technology as observed in Germany or other countries where there are currently subsidies for the installation of home energy storage systems. No battery subsidies have been assumed in the forecasts.

Forecasts of the uptake of battery storage were developed by ACIL Allen. The methodology used to develop the forecasts is described in more detail in section 8.

Figure 3.11 shows the forecast increase in storage capacity which is expected to reach 436 MWh by 2027-28. Under the high and low growth scenarios, battery storage is forecast to reach 495 MWh and 388 MWh respectively by 2027-28.



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

3.4 Electric vehicles (EV)

Projections of the energy impact arising from the uptake of electric vehicles in Western Australia were developed by ACIL Allen. The underlying methodology is described in more detail in section 9 of this report.

Figure 3.12 shows the forecast annual consumption under separate expected, high and low scenarios to the 2027-28 financial year. Under the expected scenario electric vehicles are forecast to consume 293 GWh by 2027-28. Under the high and low scenarios, annual consumption is forecast to be 571 GWh and 72 GWh respectively. The wide spread between the high and low case reflects the significant uncertainty associated with the underlying factors that are likely to drive demand for EVs in the future. Given current levels of energy consumption in the SWIS, the impact of electric vehicles is expected to be relatively small over the forecast period.

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 times⁴.

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.

⁴ For example, Synergy are currently offering an off peak EV time of use tariff known as the Synergy EV Home Plan offering lower than standard residential tariffs during the EV off peak period from 11pm to 4am. See https://www.synergy.net.au/Your-home/Energyplans/Electric-Vehicle-Home-Plan



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.

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 are expected to come online in the SWIS during the forecast period.

As the block loads are now expected to proceed, they have been included in the expected and high growth scenario but excluded from the low growth scenario.

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

TABLE 3.2	DETAILS OF PRO	POSED BLOCK LOADS IN THE SWI	15
		Mine expansion project	Minerals processing facility project
Existing load (Co demand)	pincident maximum	8.1 MW	0 MW
Proposed load in	crease (CMD)	13.5 MW	22.5 MW (Stage 1, 11.7 MW and Stage 2 10.8 MW)
Anticipated servi	ce date	Q1 2019	Q1/Q2 2019 for Stage 1, Stage 2 to come online in 2023
SOURCE: AEMO AND V	VESTERN POWER		

TABLE 3.2 DETAILS OF PROPOSED BLOCK LOADS IN THE SWIS

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.

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FIGURE 3.14 PEAK DEMAND (NOVEMBER TO APRIL) VERSUS AVERAGE TEMPERATURE, 2016-17 AND 2017-18



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, 2016 AND 2017







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 2017

SOURCE: BUREAU OF METEOROLOGY AND ACIL ALLEN



FIGURE 3.18 NUMBER OF COOLING DEGREE DAYS (CDD18) BY MONTH, JULY 2005 TO DECEMBER 2017

SOURCE: BUREAU OF METEOROLOGY AND ACIL ALLEN

For the purposes of generating the forecasts, a long run monthly average was applied covering the period from January 1987 to December 2017. 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



4.1 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 R² (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 2017-18 to 2027-28, on both a financial year (July 1 to June 30) and capacity year (October 1 to September 30) basis. Forecasts are generated under expected, high and low economic growth scenarios. In addition, there are separate rooftop PV and electric vehicle scenarios. In the case of electric vehicles, the high uptake case is added to the high economic growth scenario. This in our view, is reasonable as higher uptake of electric vehicles is likely to be associated with higher levels of economic and income growth. In the case of rooftop PV, the expected uptake case is applied to all three economic growth scenarios. The decision to do this was made in consultation with AEMO.

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.



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 from AEMO
- economic growth forecasts under separate expected, high and low growth scenarios from AEMO
- population growth forecasts under separate expected, high and low growth scenarios from AEMO
- historical estimated resident population and WA Gross State Product (GSP) data from the Australian Bureau of Statistics (ABS)
- daily maximum and minimum temperature data for the Perth Airport weather station covering the period from January 1 1987, from the Bureau of Meteorology.

Model calibration

The models were calibrated using monthly time series dating back to July 2005 in the case of the residential data, and October 2006 in the case of the non-residential data. Both the residential and non-residential time series covered the period up to the end of December 2017.

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 where necessary.

4.6 Model specification and estimation

4.6.1 Specification and estimation of the residential consumption models

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

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

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

Residential customers

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

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

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

Coefficient	Std Frr	4 - 4 - 4 - 4 -		
		t statistic	P>t	
0.283	0.00397	71.462	0.000	
46026.199	2029.18335	22.682	0.000	
205376.928	9179.63129	22.373	0.000	
0.9879				
	0.283 46026.199 205376.928 0.9879	0.283 0.00397 46026.199 2029.18335 205376.928 9179.63129 0.9879	0.283 0.00397 71.462 46026.199 2029.18335 22.682 205376.928 9179.63129 22.373 0.9879	0.283 0.00397 71.462 0.000 46026.199 2029.18335 22.682 0.000 205376.928 9179.63129 22.373 0.000 0.9879

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

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 0.283 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

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 coefficient on GSP was found to be statistically insignificant and so was excluded from the final specification. This is the only change in the specification compared to last year's model.

State final demand was also considered as a possible explanatory variable instead of GSP but was also found to be statistically insignificant.

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) Energy per customer_t = $\alpha + \beta_1 \times \text{HDD18}_t + \beta_2 \times \text{CDD18}_t + \varepsilon_t$

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			
Heating degree days (18)	0.0008	0.0001	13.9377	0.0000			
Cooling degree da (18)	ys 0.0006	0.0000	15.1476	0.0000			
Feb	-0.0302	0.0069	-4.3572	0.0000			
Apr	-0.0252	0.0071	-3.5327	0.0006			
Sep	-0.0364	0.0063	-5.7909	0.0000			
Oct	-0.0258	0.0067	-3.8341	0.0002			
Nov	-0.0366	0.0068	-5.4064	0.0000			
Constant	0.4205	0.0073	57.8558	0.0000			
R-squared	0.8062						
SOURCE: ACIL ALLEN							

The coefficients can be interpreted as follows:

- each additional 100 HDDs increases energy consumption per customer by 0.084 MWh per month
- each additional 100 CDDs increases energy consumption per customer by 0.061 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 0.030 MWh below the months excluded from the model
 - This is due to the fact that February contains fewer days than the other months of the year
- in April, average consumption per customer is 0.025 MWh below the months excluded from the model
- in September, average consumption per customer is 0.036 MWh below the months excluded from the model
- in October, average consumption per customer is 0.026 MWh below the months excluded from the model
- in November, average consumption per customer is 0.037 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 80.6%. which means that over 80% of the variation in the historical data was explained by the model.

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



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

SOURCE: ACIL ALLEN

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

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

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

Total non-residential consumption was modelled as a function of 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-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 NC	N-RESIDENTIAL CON	ISUMPTION REGRES	SION RESULTS	
Variable	Coefficient	Std. Err.	t statistic	P>t
GSP	2.291	0.081	28.158	0.000
Heating degree days (18)	606.867	106.651	5.690	0.000
Cooling degree days (18)	1004.666	51.684	19.439	0.000
Feb	-39571.014	9978.627	-3.966	0.000
Мау	47895.508	9883.676	4.846	0.000
Jun	22593.947	11539.969	1.958	0.052
Jul	51094.936	13990.913	3.652	0.000
Aug	37974.368	12269.413	3.095	0.002
Constant	468023.574	18472.17	25.337	0.000
R-squared	0.906			
SOURCE: ACIL ALLEN				

The estimated regression had an R² of 90.6%, 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 229.1 MWh per month
- each additional 100 HDDs increases non-residential energy consumption by 60,687 MWh per month
- each additional 100 CDDs increases non-residential energy consumption by 100,467 MWh per month
- in the case of May, June, July and August monthly non-residential consumption is higher on average compared to the excluded months of December, January, March, April, September, October and November (for which a statistically significant relationship could not be established)
- in February non-residential energy consumption is 39,571 MWh lower on average than the months excluded from the model
 - Just as in the residential consumption per customer model, this is a result of the fact that February contains fewer days than the other months
- in May non-residential energy consumption is 47,896 MWh higher on average than the months excluded from the model
- in June non-residential energy consumption is 22,594 MWh higher on average than the months excluded from the model
- in July non-residential energy consumption is 51,095 MWh higher on average than the months excluded from the model
- in August non-residential energy consumption is 37,974 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

4.7 Model testing and validation

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

The main methods of model validation used are:

- the theoretical basis of the coefficient size and sign
- the goodness of fit of the regression
- the statistical significance of the explanatory variables
- unit root testing and testing for stationarity
- identifying the presence of heterocedasticity and multicollinearity

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

The most commonly used measure of the goodness of fit of the regression model to the observed data is R². In the model validation process, the R² 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 average rooftop PV capacity factors for a subset of customers in the SWIS. The behaviour of these customers was assumed to apply to all the rooftop PV capacity in the SWIS at any point in time.

For the purposes of estimating the contribution of rooftop PV over the forecast horizon, a load trace covering the period from June 1 2011 to March 27 2018 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.

AVERAGE DAILY ROOFTOP PV CAPACITY FACTORS BY MONTH



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 3,074 GWh by 2027-28. Under the high and low growth scenarios, rooftop PV generation is forecast to reach 3,261 GWh and 2,916 GWh respectively.

SOURCE: AEMO AND ACIL ALLEN

FIGURE 4.5



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 developed by ACIL Allen. The methodology used to develop the forecasts is outlined in section 9 of this report. These forecasts are also described briefly in section 3.4 and presented in **Figure 3.12**.



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 2017-18 to 2027-28 in the case of summer and 2018 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.



5.3 Data collection and storage

The data used in the peak demand modelling process were:

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

Model calibration

The models were calibrated using daily time series dating from September 21 2006 to March 31 2018.

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. This threshold was determined by visually inspecting the historical relationship between daily peak demand and average temperature.

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

5.4.3 Choosing an appropriate weather station

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

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

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

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

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

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

- 009225 Perth Metro
- 009201 Perth Airport.

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

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

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

Table 5.1 below shows the estimated correlation coefficients between daily peak demand and average temperature⁵ 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 OUNILLATION DE			
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			

TABLE 5.1 CORRELATION BETWEEN DAILY PEAK DEMAND AND TEMPERATURE

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.

⁵ 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.

There has been a small change in the summer and winter base model specifications this year compared with last year. In last year's models, the maximum and minimum daily temperatures appeared as part of an interaction term with GSP, in addition to the separate main effect for GSP. In this year's specifications we have removed the interaction term and included the daily maximum and daily minimum temperatures separately without any interaction. The interaction terms were originally included to allow for increasing temperature sensitivity over time, however, while the difference between the two specifications was marginal in terms of in-sample fit, the specification with the interaction terms produced significantly stronger growth in peak demand, especially in the second half of the forecast period.

After careful consideration, it was felt that the persistent growth in GSP, particularly in the second half of the forecast period, could result in an overstatement of the sensitivity of peak demand to temperature changes and overinflated growth in peak demand as a result.

Moreover, the presence of the interaction terms presented considerable difficulty in interpreting the model coefficients, particularly as GSP appeared in three separate explanatory variables, leading to multicollinearity issues⁶.

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.⁷ The model expresses daily peak demand as a function of the following factors:

- **GSP**_t: gross state product
- Min_t: minimum daily temperature
- Maxt: maximum daily temperature
- Max_{t-1}: maximum daily temperature on the previous day
- Max_{t-2}: maximum daily temperature on two days prior
- November: dummy variable, equal to '1' if month is November, '0' otherwise
- **December**: dummy variable, equal to '1' if month is December, '0' otherwise
- Januaryt: dummy variable, equal to '1' if month is January, '0' otherwise
- March_t: dummy variable, equal to '1' if month is March, '0' otherwise
- April_t: dummy variable, equal to '1' if month is April, '0' otherwise
- Monday: dummy variable, equal to '1' if day is Monday, '0' otherwise
- Friday: 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 .

(4) $MD_t = 1178.8 + 0.0047 \times GSP_t + 62.975 \times Max_t + 30.791 \times Min_t +$ $10.256 \times Max_{t-1} + 7.702 \times Max_{t-2} + 19.009 \times Monday_t - 26.315 \times$ $Friday_t - 164.52 \times November_t - 91.27 \times December_t - 77.57 \times January_t 74.89 \times March_t - 167.94 \times April_t + \varepsilon_t$

 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	0.0047	0.0001	31.3267	0.0000					
MAXt	62.9747	1.3033	48.3209	0.0000					
					-				

⁶ Multicollinearity refers to a situation where there is a high degree of correlation between two or more independent variables in a regression model. Multicollinearity results in high standard errors and low t statistics on the model coefficients and makes it difficult to disentangle the separate effects of the independent variables in a regression on the dependent variable.

⁷ 'non-mild' days means that weekends, public holidays and days with mild temperatures were omitted.

Variable	Coefficient	Standard error	t-statistic	p-value	
MINt	30.7911	1.8376	16.7563	0.0000	
MAX _{t-1} 10.2561		1.6181	6.3385	0.0000	
MAX _{t-2}	7.7018	1.3031	5.9103	0.0000	
MON	19.0093	11.3531	1.6744	0.0944	
FRI	-26.3149	11.2087	-2.3477	0.0191	
NOV	-164.5240	15.6555	-10.5090	0.0000	
DEC	-91.2738	15.9454	-5.7241	0.0000	
JAN	-77.5656	12.7169	-6.0994	0.0000	
MAR	-74.8855	13.0444	-5.7408	0.0000	
APR	-167.9350	18.7424	-8.9602	0.0000	
Constant	-1178.7762	62.1440	-18.9684	0.0000	
R ² (Adjusted):	0.8938	Standard error of regression:	128.39		
SOURCE: ACIL ALLEN					

The coefficient on GSP is positive, meaning that as the economy grows, the forecast peak demand increases also. For every \$100 million increase in GSP, summer peak demand increases by 0.5 MW.

There is also a positive relationship between daily maximum and minimum temperature and peak demand. For every 1 degree Celsius increase in the daily maximum temperature, peak demand increases by 63 MW, while a degree increase in the overnight minimum temperature increases peak demand by 31 MW.

The coefficients on lagged temperature are positive, meaning that as temperature increases over several days, peak demand is forecast to increase also. Moreover, peak demand is 19 MW higher on average on Mondays compared to the other days of the week and 26 MW lower on average on Fridays.

5.5.2 System level maximum demand - winter

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

- GSP_t: gross state product
- Max_t: maximum daily temperature
- Mint: minimum daily temperature
- Max_{t-1}: maximum daily temperature on the previous day
- Monday,: dummy variable, equal to '1' if day is Monday, '0' otherwise
- Fridayt: 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 .

(5) $MD_t = 2636.69 + 0.0044 \times GSP_t - 31.27 \times Max_t - 9.47 \times Min_t - 4.76 \times Max_{t-1} + 21.19 \times Monday_t - 86.76 \times Friday_t - 110.45 \times May_t - 74.37 \times August_t - 174.31 \times September_t - 290.01 \times October_t + \varepsilon_t$

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	0.0044	0.0001	49.3478	0.0000		
MAXt	-31.2731	1.2138	-25.7641	0.0000		
MINt	-9.4689	0.8561	-11.0609	0.0000		
MAX _{t-1}	-4.7649	1.1991	-3.9738	0.0001		
MON	21.1939	6.9015	3.0709	0.0022		
FRI	-86.7610	6.7717	-12.8122	0.0000		
MAY	-110.4531	8.6781	-12.7278	0.0000		
AUG	-74.3668	7.8156	-9.5152	0.0000		
SEP	-174.3097	8.1319	-21.4353	0.0000		
OCT	-290.0130	9.3413	-31.0463	0.0000		
Constant	2636.6883	29.0714	90.6970	0.0000		
R ² (Adjusted):	0.853	Standard error of regression:	98.811			
SOURCE: ACIL ALLEN						

The positive coefficient on GSP suggests that peak demand increases with higher levels of economic activity. For every \$100 million increase in GSP, winter peak demand increases by 0.44 MW.

The negative coefficients on the daily maximum and minimum temperature variables indicate that as temperature drops in the colder months, peak demand increases due to rising heating loads. For every 1 degree decline in the daily maximum temperature, winter peak demand increases by 31 MW, while a 1 degree decline in the daily overnight minimum raises winter peak demand by 9MW.

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
- unit root testing and testing for stationarity
- identifying the presence of heterocedasticity and multicollinearity

5.7 Weather normalisation and stochastic analysis

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

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

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

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

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

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

5.8 Apply post model adjustments

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

5.8.1 Rooftop PV

The contribution of rooftop PV to the summer peak demand was calculated by applying a PV capacity factor to forecast rooftop PV capacity. The capacity factors were calculated by averaging a rooftop PV load trace from 2011 to early 2018 by month. The capacity factor that was applied during the forecast period is the average for February between 5pm and 6pm, or the average for the two intervals from 5:00 pm to 5:30pm and from 5:30pm to 6:00 pm.

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 0.450 to correspond to the 5th percentile of solar irradiance. The low case PV capacity factor was scaled up by 1.216 to correspond to the 95th percentile of solar irradiance. These scaling factors were calculated internally by AEMO⁸ and then provided to ACIL Allen.

Year	PV impact (expected)	PV imapct (high)	PV impact (low)	PV capacity factor (expected)	PV capacity factor (high)	PV capacity factor (low)
2018-19	120.6	54.3	146.6	0.1194	0.054	0.145
2019-20	139.7	62.9	169.9	0.1194	0.054	0.145
2020-21	158.6	71.4	192.9	0.1194	0.054	0.145
2021-22	176.5	79.4	214.7	0.1194	0.054	0.145
2022-23	193.4	87.0	235.1	0.1194	0.054	0.145

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

⁸ Please refer to the 2017 Wholesale Electricity Market (WEM) Electricity Statement of Opportunities (ESOO).

Year	PV impact (expected)	PV imapct (high)	PV impact (low)	PV capacity factor (expected)	PV capacity factor (high)	PV capacity factor (low)
2023-24	209.3	94.2	254.5	0.1194	0.054	0.145
2024-25	224.5	101.0	273.0	0.1194	0.054	0.145
2025-26	239.1	107.6	290.7	0.1194	0.054	0.145
2026-27	253.1	113.9	307.8	0.1194	0.054	0.145
2027-28	266.5	119.9	324.0	0.1194	0.054	0.145
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 266.5 MW in 2027-28.



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 calculating 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.
- 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 occur between 5:00pm and 6:00pm 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 54 MW in 2027-28. This is forecast to increase to 62 MW under the high scenario and decline to 49 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 and expected growth case and excluded from the low case.

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



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 2017-18 to 2027-28. The figure shows that residential energy consumption is expected to continue along a gentle downward trend before stabilising towards the end of the forecast period.



Under the expected scenario, residential energy consumption is forecast to grow at -0.9% per annum from 2017-18 to 2027-28. This increases to 0.0 per annum in the high scenario and falls to -1.8% per annum in the low scenario.

Residential consumption is forecast to reach 4,532 GWh by 2027-28, compared to 5,007 GWh in the high scenario and 4,114 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 2017-18 to 2027-28.



Under the expected growth scenario, non-residential energy consumption is forecast to increase from 13,232 GWh in 2016-17 to 15,338 GWh in 2027-28. This is equivalent to an average annual compound rate of growth of 1.4% per annum.

Under the high growth scenario, non-residential consumption is forecast to reach 15,764 GWh in 2027-28, equivalent to an average annual rate of growth of 1.6%. Under the low economic growth scenario, non-residential energy consumption is forecast to grow at just 1.1% per annum, rising to 14,888 GWh by 2027-28.

50

6.3 Total operational energy consumption in the SWIS

Figure 6.3 shows historical and forecast total operational energy consumption in the SWIS from 2017-18 to 2027-28.



FIGURE 6.3 ACTUAL AND FORECAST TOTAL OPERATIONAL ENERGY CONSUMPTION, UNDER

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.

	LOW		·	
Financial year	Actual	Forecast (Expected)	Forecast (High)	Forecast (Low)
2008-09	16,639			
2009-10	17,346			
2010-11	17,952			
2011-12	17,841			
2012-13	18,009			
2013-14	18,479			
2014-15	18,358			
2015-16	18,612			
2016-17	18,262			
2017-18		18,332	18,336	18,328
2018-19		18,296	18,320	18,271

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

Financial year	Actual	Forecast (Expected)	Forecast (High)	Forecast (Low)
2019-20		18,307	18,368	18,243
2020-21		18,382	18,488	18,268
2021-22		18,506	18,668	18,333
2022-23		18,660	18,890	18,417
2023-24		18,820	19,136	18,495
2024-25		19,032	19,456	18,609
2025-26		19,279	19,839	18,735
2026-27		19,561	20,281	18,868
2027-28		19,871	20,772	19,002
Average annual growth rate (p.a.) ⁹		0.8%	1.2%	0.4%
SOURCE: ACIL ALLEN				

Under the expected growth scenario, total operational energy consumption in the SWIS is forecast to increase from 18,262 GWh in 2016-17 to 19,871 GWh in 2027-28. This is equivalent to an average compound rate of growth of 0.8% per annum. Although reasonable, this rate of growth is considerably slower than that observed historically, where total operational energy consumption grew at 1.2% per annum in the nine years from 2007-08 to 2016-17. This is due to lower forecast economic growth compared to that observed historically as well as higher rooftop PV uptake.

Under the high growth scenario, operational energy consumption is forecast to reach 20,772 GWh by 2027-28, equivalent to an average compound rate of growth of 1.2% per annum from 2016-17. On the other hand, if the low growth scenario prevails, total operational energy consumption in the SWIS is forecast to grow at just 0.4% per annum.

⁹ The average annual growth rate is calculated as the compound annual growth rate over the 11 year period from 2016-17 to 2027-28.



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.

	HIGH ANI	D LOW SC	ENARIOS	<u>,</u>					
	Expe	cted scen	ario	Hi	gh scenari	0	Lo	ow scena	rio
	90 POE	50 POE	10 POE	90 POE	50 POE	10 POE	90 POE	50 POE	10 POE
2017-18	3653	3883	4119	3710	3930	4180	3630	3857	4094
2018-19	3689	3909	4146	3751	3978	4213	3627	3858	4090
2019-20	3696	3914	4152	3777	4002	4240	3635	3856	4099
2020-21	3699	3928	4174	3802	4023	4255	3640	3862	4105
2021-22	3719	3951	4193	3833	4054	4295	3651	3866	4110
2022-23	3760	3983	4219	3885	4105	4343	3664	3881	4123
2023-24	3782	3999	4242	3920	4140	4385	3673	3890	4134
2024-25	3806	4024	4270	3955	4182	4421	3685	3903	4148
2025-26	3836	4056	4293	4004	4228	4468	3700	3919	4164
2026-27	3861	4082	4323	4054	4264	4511	3711	3932	4182
2027-28	3892	4113	4365	4098	4326	4570	3736	3954	4197
5 year average growth ¹⁰	0.58%	0.51%	0.48%	0.92%	0.88%	0.77%	0.19%	0.12%	0.14%
10 year average growth ¹¹	0.63%	0.58%	0.58%	1.00%	0.96%	0.89%	0.29%	0.25%	0.25%

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

¹⁰ The 5 year average growth rate covers the 5 year period from 2017-18 to 2022-23.

¹¹ The 10 year average growth rate covers the period from 2017-18 to 2027-28.

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

Figure 7.1, **Figure 7.2**, and **Figure 7.3** show the summer peak demand forecasts under each of the expected, high and low growth scenarios respectively. Under the expected scenario, both the 10POE and 50 POE forecast summer peak demand is expected to grow at 0.6% per annum over the period from 2017-18 to 2027-28. Under this scenario, the 10 POE summer peak demand is forecast to reach 4,365 MW in 2027-28, while the 50 POE summer demand will reach 4,113 over the same period.

This growth in peak demand is driven by increasing economic growth over the forecast horizon, from a low of 2.1% in 2017-18, before increasing to a high of 3.6% in 2021-22, and from then on averaging 3.4% 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 0.9% and 1.0% per annum respectively, driven by average GSP growth over the forecast period of 3.8% per annum. In the low growth scenario, summer peak demand is forecast to grow more slowly, increasing by just 0.25% per annum in the case of the 50 POE peak demand.





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

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.

TADLE 1.2	HIGH AND LOW SCENARIOS									
	Expe	cted scena	rio	Hiç	h scenario	D	Lc	w scenari	o	
	90 POE	50 POE	10 POE	90 POE	50 POE	10 POE	90 POE	50 POE	10 POE	
2017	3173	3245	3337	3185	3257	3351	3164	3238	3330	
2018	3168	3240	3332	3179	3253	3341	3159	3231	3322	
2019	3217	3290	3382	3228	3301	3392	3178	3255	3343	
2020	3246	3319	3408	3262	3332	3426	3205	3280	3368	
2021	3278	3352	3444	3301	3372	3463	3235	3308	3400	
2022	3318	3391	3485	3339	3413	3504	3269	3343	3436	
2023	3369	3443	3537	3402	3470	3560	3306	3378	3468	
2024	3412	3484	3575	3445	3519	3609	3339	3412	3502	
2025	3452	3526	3618	3496	3568	3658	3371	3444	3532	
2026	3499	3573	3660	3548	3621	3712	3409	3482	3574	
2027	3548	3622	3709	3608	3680	3772	3445	3517	3610	
2028	3593	3666	3760	3666	3739	3829	3479	3551	3649	
5 year average growth ¹²	0.90%	0.88%	0.87%	0.95%	0.94%	0.90%	0.66%	0.65%	0.63%	

¹² The 5 year average growth rate covers the 5 year period from 2017 to 2022.

	Expected scenario			High scenario			Low scenario		
10 year average growth ¹³	1.12%	1.10%	1.06%	1.25%	1.23%	1.19%	0.86%	0.83%	0.81%

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 1.1% per annum over the period from 2017 to 2027. Under this scenario the 10 POE winter demand is forecast to reach 3,760 MW in 2028, while the 50 POE is forecast to reach 3,666 MW over the same period.





SOURCE: ACIL ALLEN

Under the high growth scenario, both the 10 POE and 50 POE winter peak demand is forecast to grow by 1.2% over the next 10 years, with the 10 POE and 50 POE reaching 3,829 MW and 3,739 MW by 2028 respectively.

¹³ The 10 year average growth rate covers the 10 year period from 2017 to 2027.



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

SOURCE: ACIL ALLEN



In this section we outline our methodology and assumptions underlying the rooftop PV and battery storage forecasts.

8.1 Historical trends in rooftop PV uptake

The historical capacity of small scale rooftop PV in the SWIS reached 826 MW¹⁴ as at the end of December 2017 (see **Figure 8.1**). Of this, 705 MW of capacity consisted of systems smaller than 10kW (classified as residential in the forecasts) and 121 MW consisted of larger systems (classified as commercial in the forecasts).



FIGURE 8.1 HISTORICAL SMALL SCALE ROOFTOP PV CAPACITY IN THE SWIS, DECEMBER 2010 TO DECEMBER 2017

¹⁴ According to data obtained from the Clean Energy Regulator (CER).

Figure 8.2 and Figure 8.3 show the installed capacity of rooftop PV in the SWIS on an annual basis.

Figure 8.2 shows that the 2017 calendar was a record year for installation of rooftop PV in the SWIS, with a total of 180 MW installed, compared to 126 MW installed in the previous year. This is a pattern that has been consistent across the country and reflects the reality of persistently rising electricity prices over time as well as continued falls in the price of installation of new PV systems. New installations have also been encouraged by the presence of a feed in tariff and the subsidy provided by the creation of STCs under the SRES and through the Solar Credit multiplier.



FIGURE 8.2 TOTAL SMALL SCALE ROOFTOP PV ANNUAL INSTALLED CAPACITY IN THE SWIS

Figure 8.3 splits the annual installations into both residential and commercial installations. In 2017, 143 MW of residential and 37 MW of commercial rooftop PV capacity was installed in the SWIS respectively.

Figure 8.4 presents the historical annual growth rate in rooftop PV uptake in the SWIS for residential, commercial and total installations. Annual growth over the last 5 years has averaged just over 25% for total installations in the SWIS. The annual growth of commercial systems has averaged more than 50% over the same period, although off a considerably lower base than for residential installations. Average annual growth in residential systems over the last 5 years was approximately 23%.

This has been driven predominantly by declining PV system installation costs, rising retail electricity prices, and generous subsidies. Future growth rates are not expected to be as strong due to more moderate declines in PV system costs, lower rates of growth in future electricity prices and the phasing out of subsidies, such as the annual reduction in the deeming period associated with the creation of STCs upon installation. Furthermore, future growth in rooftop PV systems will occur from a significantly higher base than the growth rates experienced up until very recently, meaning that historical rates of growth in rooftop PV uptake are unlikely to be repeated.





SOURCE: AEMO





8.1.1 Large scale systems larger than 100 kW

ACIL Allen has not developed separate forecasts for behind the meter PV systems that exceed 100 kW in size. At the end of 2017, there was only 6.9 MW of installed capacity, up from 3.9 MW in the previous year. This is still a tiny proportion of the total PV capacity installed in the SWIS. ACIL Allen considers that it is likely there will be a requirement to consider systems of this nature in future forecasting exercises as the uptake of these larger systems begins to accelerate. However, at present, forecasting these larger systems is complicated by the following issues:

- There is insufficient historical data which can be used to form the basis of a statistical model
- The businesses that install these systems are very heterogeneous, making it difficult to measure the financial payoff of installation across a very diverse set of businesses. The diversity arises from the fact that large businesses can have very different load profiles and operate under different tariff structures and commercial arrangements.

8.2 Overview of approach to modelling the uptake of rooftop PV and battery storage

ACIL Allen's forecast of the uptake of rooftop PV systems and battery storage is based on regression analysis of historic financial returns to rooftop PV systems and associated rates of uptake in the SWIS distribution area.

The historic relationship between financial returns and uptake is established this way and is used as the basis of forecasting of future rooftop PV uptake, given expectations about changes in rooftop PV system costs and electricity prices (among other things). Future financial returns of rooftop PV systems with and without battery storage are also calculated to estimate uptake of storage.

8.2.1 Historic financial returns to rooftop PV

Assumptions for the model relate principally to either historic uptake of rooftop PV (the regression model's 'dependent variable') or to the real net financial return to rooftop PV installations (the regression model's key 'explanatory variable'). These are discussed separately below. Further, as real financial returns are driven by several distinct factors, these are discussed separately. These factors are:

- PV system installation costs (see section 8.3)
- Rebates and subsidies (see section 8.4)
- Retail electricity prices and the structure of these charges to consumers (see section 8.5)
- Payments for exported electricity, generally known as 'feed-in tariffs' or 'buyback rates' (see section 8.6)
- System output and export assumptions (see section 8.7).

8.2.2 Regression analysis

The model for the uptake of rooftop PV systems uses a quarterly resolution and separately estimates the uptake of rooftop solar for the SWIS, as the percentage of eligible dwellings/buildings where a PV system is installed. Uptake is estimated based on a regression of historical uptake rates against a measure of payback (NPV) to households from installing a certain amount of solar capacity. Separate regression models are estimated for both small scale residential and commercial systems.

Projections of future financial returns from rooftop PV and battery storage as measured by NPV are then used to estimate the future uptake of rooftop PV capacity.

The regression models are calibrated on observations for 32 quarters, from the start of 2010 to the quarter ending December 31 2017.

The vast majority of historical PV installations have been in the residential sector but in recent years commercial installations have also experienced significant growth.

It should be noted that a range of other factors may affect household and business decisions to install rooftop PV systems. Many of these factors are not easily quantifiable, such as environmental attitudes, marketing and anecdotal responses to the experiences of friends and family. Nevertheless, it is still reasonable to project future installation rates for this technology as being related to the financial attractiveness of the systems, even if the decision-making process of the households and businesses making the decision is not directly or exclusively financial.

8.3 Rooftop PV system costs

The capital cost of a rooftop PV system is made up of the module cost and the balance of system cost (BOS).

The rooftop PV module cost is the cost of the PV cells themselves. These are generally driven by factors such as raw material costs, predominantly silicon prices as well as the cost of processing, manufacturing and assembly. The balance of system costs include the cost of the structural and electrical system required for the rooftop PV cells to operate. These costs include site preparation, racks, inverters, transformers, wiring and electrical installation costs.

The cost of installing a PV system has decreased over time. ACIL Allen's estimates of historic system cost are derived by taking a WA average system cost which is scaled to account for differences in cost due to system size and to account for differences in system costs between different states and territories. No allowance is made for the cost of inverter replacement or for ongoing system maintenance costs.

For the period from October 2012, the average cost of installing a PV system in Perth is based on SolarChoice's *PV Price Check* publication (renamed more recently to the residential and commercial solar PV price index).¹⁵ That publication sets out offered prices for systems of different sizes in each capital city. ACIL Allen modifies these price points for GST and rebate values available at the time to estimate an underlying total system cost. The city level estimates were used to derive a national average system cost by weighting in proportion to the size of the market in each state or territory.

Prior to December 2012 this data was unavailable, so different data sources were used in order to recreate a complete historical time series for regression purposes.

The system cost projections anticipate a continuation of recent cost trends in rooftop PV, with system prices flattening on a per kW basis. The main factors at play in the solar PV market include changes in the AUD/USD exchange rate, increasing competition in the domestic market and continued improvements in technical efficiency leading to further reductions in system prices.

Under the expected growth scenario, ACIL Allen projects a 1.5% decline in the real price of rooftop PV systems over the forecast period. This is considerably slower than the rate of price decline observed historically, however, this reflects the fact that the technology has now matured. Under the high growth scenario, the real price of rooftop PV systems is projected to decline by 3.5% per annum, while in the low case, the real price is projected to remain unchanged over the forecast period.

Figure 8.5 shows the projected system cost of a small scale rooftop PV system under the assumed 1.5% per annum real price decline. The starting value is the Solar Choice's February 2018 Solar PV index. For a 5 kW system, the per kW system cost is projected to decline from \$974/kW in 2018 to \$837 in 2028.

¹⁵ See <u>www.solarchoice.net.au</u>. These are also published from time to time in sources such as Climate Spectator.



FIGURE 8.5 PROJECTED SYSTEM COST OF SMALL SCALE ROOFTOP PV SYSTEMS, PERTH \$2018

8.4 Rebates and subsidies

Two sources of upfront rebates and subsidies for PV installations are taken into account:

- the former Solar Homes and Communities Program (SHCP), which provided an upfront cash rebate
- the indirect subsidy provided by the creation of STCs under the SRES, including the creation of additional STCs through the 'Solar Credits multiplier'.

Under SHCP, customers who installed rooftop PV systems received an upfront rebate of \$8,000. SHCP was in place at the beginning of 2009, and was closed during June 2009. However, as systems installed in the second half of that year received assistance based on prior applications for the rebate, it is analysed as having an effect on some installations in the second half of 2009.

In addition to the upfront payment through SHCP, PV systems were eligible to create certificates for the renewable electricity they generate during the historic period. The value of these certificates (initially RECs created under the Renewable Energy Target and then STCs created under the SRES) provides an upfront subsidy to installation of PV systems.

The value of this subsidy depends on the system size and certificate price. From June 2009 until 31 December 2012, it also depended on the 'solar credit multiplier', which was established under the Solar Credits scheme and allowed eligible customers who installed PV systems were deemed to create additional RECs/STCs, thereby increasing the amount of the subsidy. The multiplier was originally 5, meaning that a PV system would create 5 solar credits for every MWh of electricity it was deemed to generate, for the first 1.5 kW of capacity installed. The multiplier then declined over time.

The SHCP was phased out in favour of Solar Credits during 2009. Customers could benefit from either the SHCP or the Solar Credits multiplier, but not both. To address the overlap between these two policies, 50% of PV installations in quarter 3 2009, and 20% in quarter 4 2009 were assumed to receive the SHCP rebate. The remainder were assumed to use the Solar Credits multiplier to generate extra certificates.

The solar multiplier and certificate values factored into the analysis are shown in **Table 8.1**. In effect, a PV system installed in 2009 was assumed to receive part of the SHCP grant and part of its entitlement through Solar Credits.

SOLAR GREDH S WULTIPLIER AND SHOP REBATE							
Until July 2009	Q3 2009	Q4 2009	Q1 2010 – Q2 2011	Q3 2011 – Q2 2012	Q3 & Q4 2012	From January 2013	
1	3.0	4.2	5	3	2	1	
\$8,000	\$4,000	\$1,600	\$0	\$0	\$0	\$0	
	Until July 2009 1 \$8,000	Until July 2009 Q3 2009 1 3.0 \$8,000 \$4,000	Until July 2009 Q3 2009 Q4 2009 1 3.0 4.2 \$8,000 \$4,000 \$1,600	Until July 2009 Q3 2009 Q4 2009 Q1 2010 – Q2 2011 1 3.0 4.2 5 \$8,000 \$4,000 \$1,600 \$0	Until July 2009 Q3 2009 Q4 2009 Q1 2010 - Q2 2011 Q3 2011 - Q2 2012 1 3.0 4.2 5 3 \$8,000 \$4,000 \$1,600 \$0 \$0	Until July 2009 Q3 2009 Q4 2009 Q1 2010 - Q2 2011 Q3 2011 - Q2 2012 Q3 & Q4 2012 1 3.0 4.2 5 3 2 \$8,000 \$4,000 \$1,600 \$0 \$0 \$0	

Unlike the SHCP payment, the value of RECs/STCs, and therefore the total rebate derived from these certificates, varied over time according the market price at the time. Recent historical values to be used within the financial analysis are shown in Figure 8.6. Up until May 2017, the STC price was very close to the Clearing house price of \$40/STC. From June onwards, the STC price declined as a result of an oversupply in certificates, before recovering in recent months.

Beyond 2017, the STC is assumed to remain constant (in nominal terms), returning to its longer term average at \$40 per certificate, which is the Clearing house price.

Until 1 January 2017, all systems are assumed to create 15 years of 'deemed' RECs/STCs at the time on installation, and then cease to be eligible for further certificates after 15 years. Between 2017 and 2030 the deeming period is assumed to decline by one year in each year so that systems installed in 2030 are deemed to create certificates for one year only.





8.5 Retail electricity prices

Retail electricity prices are important to the financial return on rooftop PV and battery storage as every kWh of solar output that is consumed by the owner of the system avoids the variable component of the retail electricity price. The significant rise in retail electricity prices in recent history has provided has been a major spur to households and businesses to install rooftop PV capacity.

Residential customers in the SWIS are assumed to be on the Synergy home plan (A1) tariff. The electricity charge in 2018 is 26.474 cents per kWh for residential customers. Commercial customers are assumed to be on the Synergy Business Plan L1 tariff. In 2018, this was 33.3546 cents per kWh for the first 1,650 units.
ACIL Allen has used electricity price forecasts for WA from the AEMCs report, '2017 Residential Electricity Price Trends'¹⁶. The AEMC expects the nominal residential electricity price for the representative consumer to increase by:

- 7.0% in 2018-19
- 5.6% in 2019-20.

ACIL Allen has adopted these price increases and thereafter assumed that the price of electricity remains fixed in real terms. We assume an inflation rate of 2.5%, half way between the RBA inflation target of between 2% and 3%.

8.6 Feed-in tariffs and buy back rates

When rooftop PV systems produce more power than is required at the premises at which they are installed, the electricity is exported to the grid and on-sold to other customers. The value of this exported electricity is another important component of the financial return to PV installation.

In general, exported PV output always displaces electricity that would otherwise be purchased from the wholesale market, and therefore provides some value to the retailer that on-sells this electricity. Accordingly, retailers that supply power to owners of rooftop PV systems are generally willing to pay some amount for exported PV output that is separate from, and additional to, any premium feed-in tariff that might be imposed by legislation. The term 'buyback rate' refers to these payments by retailers that reflect the value of exported PV output to the retailer, and which, whilst sometimes regulated, are not intended to offer a premium rate or purposefully subsidise PV systems.

For the purposes of the modelling we apply a buyback rate of 7.135 cents per kWh for all uptake scenarios, which is in line with the buyback rate currently offered by Synergy's Renewable Energy Buyback Scheme. The buyback rate is only available for systems under 5kW, and so is not applicable to commercial systems.

8.7 System output and export rates

System output is estimated based on four solar zones, created by the CER for the purpose of calculating REC and STC creation by rooftop PV, which have different assumed rates of solar output per kW of installed capacity. Each postcode is assigned a zone, whereas multiple solar zones may exist in a given state, territory or network area. These zones as the solar output values are as follows:¹⁷

- Zone 1: 1.622 MWh per kW of capacity
- Zone 2: 1.536 MWh per kW of capacity
- Zone 3: 1.382 MWh per kW of capacity
- Zone 4: 1.185 MWh per kW of capacity.

Table 8.2 sets out the share of households located in each zone, and implied average output per kW of installed capacity for each state and territory.

TABLE 8.2	SHARE OF FRE	SHARE OF FREE STANDING DWELLINGS BY SOLAR ZONE					
Jurisdiction	Solar zone 1	Solar zone 2	Solar zone 3	Solar zone 4	Assumed Output (MWh/kW/a)		
WA	3%	5%	87%	5%	1.39		
SOURCE: ACIL ALLEN ANALYSIS OF CER DATA							

We assume that residential solar systems exports of energy produced by roof-top solar systems broadly aligns with sampled data from Sunwiz provided in **Figure 8.7**.¹⁸ For commercial systems we

¹⁶ See https://www.aemc.gov.au/sites/default/files/content/bf56a5d5-e2b2-4c21-90ed-79dda97eb8a4/2017-Residential-Electricity-Price-Trends.pdf

¹⁷ Clean Energy Regulations 2001, Schedule 5

¹⁸ These export rates are around 10 percentage points higher than we have used previously.



have assumed a lower export rate of on average 10% due to the better match between commercial load profiles and solar electricity generation.

8.8 System size trends

Data on rooftop PV uptake clearly illustrates a substantial increase in average system size over time, in particular as the incentives created by the Solar Credits formula to install smaller systems has dissipated and been overwhelmed by the attraction of lower system costs. Reductions in buyback rates and feed-in tariff payments have however limited the attractiveness of larger systems which tend to export a larger share of produced electricity to the grid. Further, space available for the installation of rooftop PV systems on a roof-top is limited and the size of systems installed on residential roof-tops cannot be expected to grow indefinitely. We also note that system size will be limited to some degree by Synergy's Renewable Energy Buyback Scheme which limits eligibility to receive the buyback rate to systems that are smaller than 5 kW.

Between March 2010 and December 2017 the average size of new residential installations in the WA has grown from around 1.5kW to about 5kW as shown in **Figure 8.8**. In the case of commercial systems, the average installation size at the end of December 2017 was approximately 30kW. Just like residential systems, the average installation size has grown considerably over time (see **Figure 8.9**).



FIGURE 8.8 AVERAGE SIZE OF NEW RESIDENTIAL PV INSTALLATIONS OVER TIME

Note: For systems smaller than 10kW

SOURCE: ACIL ALLEN BASED ON CER DATA



FIGURE 8.9 AVERAGE SIZE OF NEW COMMERCIAL PV INSTALLATIONS OVER TIME

Note: For systems greater than 10 kW and less than 100 kW SOURCE: ACIL ALLEN BASED ON CER DATA

8.9 Available residential building stock

ACIL Allen has related the uptake of PV systems in the residential sector to the number of freestanding dwellings. For each quarter uptake was measured as the percentage of freestanding dwellings where a PV system had been installed. Each installation was assumed to reduce the pool of freestanding dwellings where a PV system could be installed.

Measuring rooftop PV uptake in this way provides a proxy for the saturation of the residential roof-top solar market. The number of freestanding dwellings in WA was obtained from the 2016 ABS Census of Population and Housing and includes freestanding houses as well as semi-detached terrace houses. The number of free-standing and semi-detached dwellings from the 2016 Census was 808,386. This was used as the starting point and was projected forward using the demographic forecasts of WA population under the expected, high and low population growth scenarios.

The projected number of free-standing dwellings in WA under the three scenarios is shown in **Figure 8.10** below. Under the expected scenario, the number of free-standing dwellings is projected to reach 966,936 in 2028. Under the high growth scenario, the number of free-standing dwellings is projected to increase to 1,013,358 in 2028, while under the low scenario the number of free-standing dwellings 921,912.

FIGURE 8.10 PROJECTED NUMBER OF FREE STANDING DWELLINGS, WA, EXPECTED, HIGH AND LOW SCENARIOS



8.10 Forecasting rooftop PV system returns

Forecasting net financial returns to PV systems requires forecasting the core components of the financial return metric, specifically:

- PV installation costs
- Rebates, subsidies and feed-in tariffs (FiTs)
- Exports rates (that is, the percentage of a PV system's output that is exported rather than consumed by the owner)
- Electricity prices.

PV installation costs were assumed to decline at 1.5% in real terms annually under the expected case, while they are assumed to decline by 3.5% and 0% under the high and low case respectively.

Policy changes to rebates, subsidies and FiTs are relatively easy to predict as most policy advantages to rooftop PV systems have been discontinued. The Solar Credits multiplier was assumed to remain at 1 for the remainder of the period, whilst the STC price was assumed to remain at \$40 in nominal terms for the length of the analysis.

Further, as STC creation is typically based on 'deeming' over a 15 year period, the level of STC subsidy to a rooftop PV system was adjusted to reflect the recent policy change such that STCs would only be credited for the period to 2030 (the end of the SRES). This means that systems installed in 2017 have only 14 years of deeming, those in 2018 have 13 years of deeming, and so on. The 7.135 c/kWh buyback rate is assumed to continue for the entire forecasting horizon.

Export rates were assumed to be constant for systems of a given size, irrespective of date of installation.

8.10.1 Summary of main rooftop PV model assumptions

Table 8.3 below presents a summary of the key assumptions employed in producing the rooftop PV forecasts under the three scenarios. As can be seen, the two key variables driving the differences across the three scenarios are the annual population growth and the real percentage decline in the real purchase price of a rooftop PV system. All the other factors are kept constant across the three scenarios.

PV assumptions	Low	Medium	High
Population growth	1.10%	1.60%	2.00%
System real price decline	0%	1.50%	3.50%
Buyback rate	7.135 c/kWh	7.135 c/kWh	7.135 c/kWh
STC certificate price	\$40	\$40	\$40
Real electricity price (residential)	26.474 c/kWh in 2017-18, rising by 4.5% in real terms in 2018-19 and 3.1% in real terms in 2019-20, Constant after 2020-21	26.474 c/kWh in 2017-18, rising by 4.5% in real terms in 2018-19 and 3.1% in real terms in 2019-20, Constant after 2020-21	26.474 c/kWh in 2017-18, rising by 4.5% in real terms in 2018-19 and 3.1% in real terms in 2019-20, Constant after 2020-21
Real electricity price (commercial)	33.3546 c/kWh in 2017- 18, rising by 4.5% in real terms in 2018-19 and 3.1% in real terms in 2019-20, Constant after 2020-21	33.3546 c/kWh in 2017- 18, rising by 4.5% in real terms in 2018-19 and 3.1% in real terms in 2019-20, Constant after 2020-21	33.3546 c/kWh in 2017- 18, rising by 4.5% in real terms in 2018-19 and 3.1% in real terms in 2019-20, Constant after 2020-21
Export rates	see table 8.4	see table 8.4	see table 8.4
Discount rate (%) (real)	7%	7%	7%
Inflation rate (%)	2.50%	2.50%	2.50%
SOURCE: ACIL ALLEN			

 TABLE 8.3
 MAIN ASSUMPTIONS APPLIED IN THE ROOFTOP PV PROJECTIONS

Table 8.4 shows the assumed export rates for rooftop PV systems in the SWIS across a range of system sizes.

System size (kW)	Low	Medium	High
1.5	35%	35%	35%
2	45%	45%	45%
3	60%	60%	60%
4	65%	65%	65%
5	70%	70%	70%
6	70%	70%	70%
8	70%	70%	70%
10	70%	70%	70%
10 < and <100 (Commercial)	10%	10%	10%
SOURCE: ACIL ALLEN			

 TABLE 8.4
 ASSUMED ROOFTOP PV EXPORT RATES

8.11 Uptake of battery storage systems

At the household level, battery storage systems are currently economically unviable for most consumers in Australia. This is due to high installation costs, technical limitations relating to depth of discharge and the number of charge/discharge cycles that can be achieved. The number of cycles that can be achieved with a system plays a crucial role in determining its profitability. At a given rate of use, the number of cycles amounts to the system's useful life.

The benefits to end user customers from using an energy storage system are that they can:

- store solar generation that would otherwise be exported to the grid, thus enhancing the financial value of that electricity to the customer
- avoiding network charges especially charges related to peak network demand i.e. kVa charges noting that most households are not charged for peak demand at present, though this is likely to change in the medium term
- using lower priced off-peak electricity to meet day time energy demand¹⁹.

By storing excess solar generation in an energy storage system, customers forego any payments they would otherwise receive for electricity exported to the network i.e. renewable energy buyback rates or feed-in tariffs. Net benefits to households from storing excess solar generation therefore arise from the difference in the renewable energy buyback rate and the variable electricity tariff incurred by the household.

ACIL Allen models the impact of battery storage systems on peak demand by projecting the uptake of such systems under three separate scenarios. Our model relates installation rates of battery storage systems to the Net Present Value (NPV) achieved by installing such a system.

Storage has not been adopted in any meaningful volume by households in Australia, and so storage (battery) costs are not relevant to ACIL Allen's analysis of historic financial returns to rooftop PV systems. However, this analysis did examine the potential for widespread uptake of battery storage by households and businesses in the future based on expected financial returns to storage.

This analysis was based on two main elements:

- The financial cost of storage, being upfront battery installation costs and expected battery replacement costs
- The financial benefit of storage, being the change in export rates multiplied by the difference between the retail price of electricity (the benefit of own consumed electricity) and the buy-back rate for exported electricity (the benefit of exporting electricity).

¹⁹ The same electricity tariffs have been assumed to apply in projecting battery storage as in the case of rooftop PV systems. In the case of residential it's the Synergy home plan (A1) tariff and for commercial customers it's the Synergy Business Plan L1 tariff.

We assume that the relationship between the NPV and installation rates of battery storage systems will be similar to the relationship between the NPV and installation rates of rooftop PV systems, which can be observed historically. All existing and future residential and commercial solar installations are assumed to be candidates for the installation of battery storage.

The economics of battery installations are also affected by the technical characteristics of battery technology. The depth of battery discharge negatively affects battery life - the higher the depth of discharge the shorter the life of the battery. We assume daily cycling of the battery with a depth of discharge of 80% and a lifetime of 10 years (equivalent to 3,650 cycles in its lifetime). The main assumptions deployed under the three separate scenarios are shown in Table 8.5 below.

Battery storage assumptions	Expected scenario	High scenario	Low scenario
Population growth (% p.a.)	1.10%	1.60%	2.00%
Battery pack life (years)	10.00	10.00	10.00
Real battery cost decline rate (% p.a.)	5.0%	8.0%	3%
Efficiency	90.0%	90.0%	90.0%
Cycle depth	80%	80%	80%
SOURCE: ACIL ALLEN			

MAIN ASSUMPTIONS APPLIED IN STORAGE PRO JECTIONS

FIGURE 8.11

Figure 8.11 shows the projected real cost of a battery plus inverter under the expected scenario cost decline assumption²⁰. The cost of a battery plus inverter across all system sizes is projected to decline from \$1340 per kWh in 2018 to \$802 per kWh in 2028.



SOURCE: SOLAR CHOICE, BATTERY STORAGE INDEX21- FEBRUARY 2018 AND ACIL ALLEN CALCULATIONS

²⁰ Please see https://www.solarchoice.net.au/blog/home-solar-battery-storage-prices-february-2018

²¹ https://www.solarchoice.net.au/blog/home-solar-battery-storage-prices-february-2018

8.12 Rooftop PV and battery storage forecasts

Total rooftop PV installed in the SWIS is projected to increase from 731 MW at June 30 2017 to 2273 MW in June 2028 (see Figure 8.12).



FIGURE 8.12 INSTALLED ROOFTOP PV CAPACITY AS AT JUNE 30, HISTORICAL AND FORECAST

This is equivalent to an annualised growth rate of 10.9% per annum over the full period. Figure 8.13 shows the year on year growth rate during the forecast period. The figure shows a steady downward trend in the annual growth of rooftop PV systems. There are several reasons for this:

- Real electricity prices which have grown considerably over the historical period are assumed to stop rising after 2019 and remain stable thereafter
- The number of STCs created under the SRES for each new system declines in every year of the forecast period as the deeming period is assumed to decline by 1 year in each year after 2017. A system installed in 2028 will be deemed to create certificates for 3 years, while a system installed prior to 2017, was deemed to create certificates for 15 years.
- As the installed capacity continues to rise strongly, the number of available premises (households and businesses) in which rooftop PV can be installed declines.



FIGURE 8.13 ANNUAL GROWTH IN ROOFTOP PV CAPACITY, HISTORICAL AND FORECAST

Figure 8.14 shows the historical and projected residential rooftop PV capacity for the SWIS. Residential rooftop PV is expected to increase from 631 MW in June 2017 to 1776 MW in June 2028. This is equivalent to an annual growth rate of 9.9% per annum over the next 11 years.



FIGURE 8.14 RESIDENTIAL INSTALLED ROOFTOP PV CAPACITY AS AT JUNE 30, HISTORICAL AND FORECAST, EXPECTED

SOURCE: ACIL ALLEN



Figure 8.15 presents the historical and projected commercial rooftop PV installed in the SWIS over the forecast period.

Commercial PV capacity in the SWIS is projected to increase from 101 MW as at June 30 2017 to 498 MW in 2028. This is equivalent to an annualised rate of growth of 15.6%.

The projected uptake of total battery storage systems in the SWIS under the three separate scenarios is presented in **Figure 8.16** below. Under the expected scenario, the capacity of installed battery systems in the SWIS is projected to increase from an estimated 19 MWh in 2018 to 436 MWh in 2028. This is equivalent to an average annual rate of increase of 36.8%. This strong rate of growth is very much a function of a sustained and strong reduction in the projected cost of installation as battery costs continue to decline and economies of scale lead to further cost reductions.

Under the high growth scenario, battery storage capacity is projected to reach 495 MWh in 2028, which translates into an average annual growth rate of 38.1%. Under the low growth scenario, battery capacity in the SWIS is projected to increase to 388 MWh in 2028.



FIGURE 8.16 FORECAST UPTAKE OF BATTERY STORAGE, EXPECTED, HIGH AND LOW SCENARIOS



This section examines the possible take-up of electric vehicles covering the period from 2018-2028. The approach taken involves projecting the number of passenger and light commercial vehicles in WA and then using a logistic model specification to calculate the share of new vehicle sales that are captured by plug-in electric vehicles. The market share of electric vehicles will depend on the financial and other attributes of plug-in electric vehicles relative to conventional internal combustion engine (ICE) vehicles. The most important factors to be accounted for are the relative upfront capital costs of purchasing the vehicle, vehicle running costs, including relative fuel prices and fuel consumption over time, and the relative ranges that the vehicles can travel.

Forecasts of both the number, market share and energy impact of electric vehicles are produced under three separate scenarios, high, expected and low.

9.1.1 Definition of Vehicles

There are four specific vehicle types. These are:

- ICE (internal combustion engine)
- HEV (hybrid electric vehicle)
- PHEV (plug-in hybrid electric vehicle)
- EV (electric vehicle)

While HEVs are classified as electric vehicles, we do not consider these as part of the projections and instead focus on plug-in electric vehicles.

The two categories of vehicles which are relevant to this study are PHEVs and EVs. Both are charged by connecting to the electricity grid. While PHEVs also run on conventional fossil fuels, EVs are completely powered by electricity.

Separate projections are produced for passenger and light commercial vehicles.

9.2 Market for Electric Vehicles

The potential size of the market for electric vehicles is limited only by the size of the market for passenger and light commercial vehicles.

9.2.1 Historical Vehicle Registrations

The number of light passenger vehicles and light commercial vehicles in WA has grown steadily over time (see **Figure 9.1**).

The number of light passenger vehicles in WA has grown from 1.0 million vehicles in 2001 to 1.6 million in 2017. This is equivalent to an average annual growth rate of 2.7% over the period.



Similarly, the number of light commercial vehicles has increased from 216.2 thousand to 383.8 thousand over the same period. This is equivalent to an average annual growth rate of 3.7%.

Over the more recent seven-year period, growth in passenger vehicles has been a little slower compared to the long term average, with average annual growth measuring 2.2% over the period from 2010 to 2017. In the case of light commercial vehicles, growth has also been weaker over the last seven years, with average annual growth measuring 3.2% compared to 3.7% over the last sixteen years.

9.2.2 Vehicle Ownership Rates

The car remains the preferred form of transport for the majority of Australians. **Figure 9.2** shows that the rate of light passenger and light commercial vehicle ownership in WA continues to rise over time. Between 2001 and 2017, the number of registered passenger vehicles has increased from 0.545 per person to 0.617 per person. This is equivalent to an average annual growth rate of 0.8%. Over the most recent seven years, growth has moderated to a degree, with average annual growth in the ownership rate of passenger vehicles measuring 0.5%.





In the case of light commercial vehicles, average annual growth in the number of vehicles per person, has measured 1.7% over the period from 2001 to 2017. This rate of growth has decelerated over the last seven years, declining to 1.4% per annum.

9.2.3 Projected Vehicle Ownership Rates

To project the potential size of the market for electric vehicles in WA, it is necessary to project vehicle ownership rates going forward. At some point, it can be expected that the rate of vehicle ownership will reach saturation and will plateau. The difficulty lies in determining when this point is likely to be reached.

In projecting the rate of motor vehicle ownership in WA, ACIL Allen has decided to fit and extrapolate a linear trend based on the last 12 years of data. The rate of increase over this period is lower than that observed over longer periods, and perhaps reflects the early stages of saturation. **Figure 9.3** shows the historical and projected passenger vehicles per person in WA.

The number of passenger vehicles per person in WA is forecast to increase from 0.617 vehicles per person in 2017 to 0.645 vehicles per person in 2028. The number of light commercial vehicles per person in WA is forecast to increase from 0.149 vehicles per person in 2017 to 0.162 vehicles per person in 2028.



FIGURE 9.3 HISTORICAL AND PROJECTED PASSENGER VEHICLES AND LIGHT COMMERCIAL VEHICLES PER PERSON, WA 2001 TO 2028

SOURCE: ABS AND ACIL ALLEN

9.2.4 Projected Passenger and Light Commercial Vehicle Numbers

The projected total number of passenger and light commercial vehicles have been calculated by multiplying the forecast vehicle ownership rate with the projected WA population in each year. Three sets of motor vehicle projections are prepared, one for each of the separate high, expected and low population growth scenarios.

Under the expected case, the number of passenger vehicles is projected to increase from 1.59 million vehicles in 2017 to 1.98 million passenger vehicles in 2028 (see Figure 9.4). This is equivalent to an average annual rate of growth of 2.0%. Under the low scenario, the number of passenger vehicles is projected to reach 1.88 million vehicles by 2028, reflecting a lower rate of population growth for WA relative to the expected scenario. Under the low scenario, the number of passenger vehicles is expected to grow at an average annual rate of 1.5% to 2028. Under the high growth scenario, the number of passenger vehicles in WA is projected to reach 2.07 million vehicles in 2028, equivalent to an annual average growth rate of 2.4%.



FIGURE 9.4 HISTORICAL AND PROJECTED PASSENGER VEHICLES IN WA, 2001 TO 2028, EXPECTED, HIGH AND LOW CASE

The number of light commercial vehicles under the expected growth scenario are projected to increase from 383.8 thousand vehicles in 2017 to 495.0 thousand in 2028 (see **Figure 9.5**). This is equivalent to an average annual growth rate of 2.3%. Under the high growth scenario, the number of light commercial vehicles in WA is projected to reach 518.7 thousand vehicles in 2028. This is equivalent to an average annual growth rate of 2.8%. Under the low growth scenario, the number of light commercial vehicles is projected to reach 471.9 thousand vehicles in 2028, equivalent to an average annual growth rate of 1.9%.



FIGURE 9.5 HISTORICAL AND PROJECTED LIGHT COMMERCIAL VEHICLES IN WA, 2001 TO 2028, EXPECTED, HIGH AND LOW CASE

9.3 Current Take-Up of Electric Vehicles

According to a report released by ClimateWorks Australia and the Electric Vehicle Council in June 2017, entitled "The State of Electric Vehicles in Australia"²², global sales of electric vehicles were in excess of 750,000 in 2016, a 40% increase from 2015.

In contrast, Australian plug-in electric vehicle sales remain miniscule, representing only 0.1% of the market. In 2016, Australians bought 701 plug-in hybrid electric vehicles and 668 fully electric vehicles.

Figure 9.6 shows the number of plug-in electric vehicle sales from 2011 to 2016. Interestingly, there appeared to be a loss of momentum in 2016, with sales declining by 23% to 1,369 compared to 1,771 in 2015.

²² Please see https://climateworksaustralia.org/sites/default/files/documents/publications/state_of_evs_final.pdf



FIGURE 9.6 ELECTRIC VEHICLE SALES IN AUSTRALIA, 2011 TO 2016

According to the same publication, there were 298 purchases of electric vehicles in WA between 2011 and 2016. We have chosen to adopt this number as the starting value for our forecasts. While this number is now a little dated, we do not have a more up to date estimate of the number of electric vehicles in WA. Moreover, any additional EV purchases since 2016 are small in number and have had a negligible impact on operational energy consumption.

9.4 Economics of Electric Vehicles

This section considers the key economic factors that are likely to play a significant role in the potential take up of electric vehicles in the next decade or more.

These key factors are:

- vehicle prices
 - fuel costs (including fuel prices and fuel consumption)
- range
- charging convenience.

9.4.1 Vehicle Prices

The largest and most significant cost associated with plug-in electric vehicles at present is the relatively large upfront cost. This cost is largely attributed to the relatively high cost of the battery required to power the vehicle. Future reductions in the price of the vehicles will come from the development of cheaper battery technology over time.

Figure 9.7 shows that as at 2018, the price differential between ICE and PHEV/EV vehicles is very large, making PHEV/EVs very unattractive against conventional ICE vehicles based on vehicle cost. Vehicle price comparisons are made across small, medium and large passenger vehicles.

The distinction across the three size classes is made on the basis engine size. A small passenger car is the equivalent of a passenger vehicle with 1-3 cylinders, a medium sized vehicle is the equivalent of a 4 cylinder engine and a large passenger vehicle is equivalent to a 6 cylinder engine.



As part of the modelling exercise, ACIL Allen assume that the real price of electric vehicles will decline by 7.5% per annum over time, under the expected growth scenario, relative to the price of ICE vehicles. This is equivalent to a rate of growth that will see the price of electric vehicles approach that of ICEs by the second half of the 2020s.

It is important to note that it is the relative price that matters in projecting the market share of electric vehicles, rather than the absolute prices of the vehicles. For this reason, the real prices of ICE vehicles have been fixed at their 2018 levels for the entire forecasting horizon, while allowing the price of EVs to decline by 7.5% every year.

Under these assumptions, the real prices of plug-in electric vehicles approach those of ICE vehicles by the late 2020s.

Under the low growth scenario, the real price of electric vehicles relative to the price of ICE vehicles is expected to decline by 4% every year, almost half the rate of that assumed under the expected case. Under this slower rate of convergence in real prices, EV prices remain well above the price of ICE vehicles in 2028 (see **Figure 9.8**).



Under the high growth scenario, the real price of electric vehicles relative to the price of ICE vehicles is expected to decline by 9.5% every year, two percentage points above the rate of that assumed under the expected case. Under this faster rate of convergence in real prices, EV prices finally reach parity with the price of ICE vehicles in 2028 (see **Figure 9.9**).



9.4.2 Fuel Costs

Petrol Prices

Petrol prices in Australia are largely determined by the following factors:

- the international benchmark retail petrol price known as Singapore Mogas (Mogas 95) (about 45% of the pump price)²³
- customs and excise duty and GST (about 40% of the pump price)
- other costs and margins (about 15% of the retail price), covering retail and wholesale operating costs and margins

Changes in the international benchmark price of petrol are the main driver of movements in the Australian petrol price over time. Movements in international oil prices and the US\$/\$A exchange rate play a key role in the underlying retail cost of the product sold in Australia. As oil is a fundamental input into the refining process, increases in the price of oil will translate into higher petrol prices in Australia, all other things being equal. Oil is priced in US dollars. Consequently, any movements in the exchange rate will change the Australian dollar price of petrol as well. If the exchange rate appreciates over time, this reduces the Australian dollar price of the international benchmark, and leads to a reduction in Australian retail petrol prices. If the exchange rate depreciates, this results in an increase in the international benchmark price which flows through to higher retail petrol prices in Australia.

²³ How are petrol prices determined in Australia?, Australian Institute of Petroleum. See https://www.aip.com.au/resources/glance-how-are-petrol-prices-determined-australia

Figure 9.10 shows the monthly unleaded petrol (ULP) price against the Australian dollar oil price for the period from April 2006 to June 2017. The figure shows that there is a very strong degree of correlation between the retail petrol price and movements in the Australian dollar oil price.



FIGURE 9.10 MONTHLY NOMINAL ULP PETROL PRICES VERSUS THE AUSTRALIAN DOLLAR OIL PRICE

9.4.3 Historical Petrol Prices

Figure 9.11 shows the average annual retail price of petrol in WA from 2002 to 2017. The figure shows that there has been quite a bit of variation in petrol prices over time in WA, although for most of the period there has been an upward trend. In 2017, WA petrol prices averaged 129.6 cents per litre, having declined from a high of 149.6 cents per litre in 2014.



FIGURE 9.11 AVERAGE WA UNLEADED PETROL PRICES, 2001 TO 2017, NOMINAL

9.4.4 Petrol price forecasts

An econometric approach was adopted to forecast petrol prices in WA out to 2028. The approach involved fitting a log-linear regression to monthly ULP petrol prices in WA. The main explanatory variables used in the regression were:

- an intercept term
- the US\$ oil price (WTI)
- The US\$/\$A exchange rate
- a trend term.

The model was estimated on data covering the period from April 2006 to June 2017. While the oil price and exchange rate were used to capture movements in the international benchmark over time, the trend term was included to capture the impact of changes in wholesale and retail costs and margins over time.

The estimated coefficients are shown in Table 9.1 below. Because the model was estimated in logarithmic form, the estimated coefficients can be interpreted as elasticities. A 1% increase in the US\$ oil price results in a 0.34% rise in the WA ULP petrol price. A 1% appreciation in the \$A exchange rate results in a 0.16% decline in the WA ULP petrol price. Moreover, the positive coefficient on the trend term indicates that the contribution of margins and other costs have been slowly increasing over time.

TABLE 9.1	ESTIMATED COEFFICIENTS FROM THE MODEL				
Variables	Coefficients	Standard error	T statistic		
Intercept	3.318	0.109	30.320		
Oil WTI \$USD	0.340	0.023	14.770		
\$USD/\$AUD	-0.158	0.053	-2.963		
Time trend	0.002	0.000	15.275		
SOURCE: ACIL ALLEN					

PEAK DEMAND AND ENERGY FORECASTS FOR THE SOUTH WEST INTERCONNECTED SYSTEM-WESTERN AUSTRALIA

The estimated model achieved an adjusted R² of 82.8, meaning that 82.8% of the variation in the WA retail price of petrol could be explained by variation in the explanatory variables. **Figure 9.12** shows the actual historical values of retail petrol prices against the predicted values from the estimated regression model. The figure confirms that the oil price and exchange rate perform reasonably well in explaining movements in the historical price of petrol.



FIGURE 9.12 ACTUAL AND PREDICTED WA ULP PETROL PRICES

The estimated coefficients are then combined with forecasts of the explanatory variables to generate forecasts of the WA retail petrol price.

The latest set of real oil price forecasts were obtained from the US Energy Information Administration (EIA) and are shown in **Figure 9.13**. According to the EIAs medium case, real oil prices are expected to increase steadily out to 2028, starting from about US\$63 per barrel in 2018, and increasing to US\$91 per barrel in 2028. This is equivalent to an average annual rate of growth of 3.7%.



FIGURE 9.13 FORECAST OIL PRICES, US\$ REAL (\$2016)

ACIL Allen's forecast of the \$US/\$A exchange rate is shown in **Figure 9.14** below. The exchange rate is forecast to fall slightly to 76.5 cents in 2020 before advancing slowly to 78.2 cents in 2028.



Forecasts of WA ULP petrol prices are shown in **Figure 9.15**. The real price of ULP in WA is projected to increase from 148.9 cents per litre in 2018 to 170.2 cents in 2028.



FIGURE 9.15 FORECAST WA ULP PETROL PRICES, 2018 TO 2060, \$2017

9.4.5 Retail Electricity Prices

A key input into the costs of running an electric vehicle is the retail price of electricity. ACIL Allen has used electricity price forecasts for WA from the AEMCs report, '2017 Residential Electricity Price Trends'²⁴. The AEMC expects the nominal residential electricity price for the representative consumer to increase by:

- 7.0% in 2018-19
- 5.6% in 2019-20.

ACIL Allen has adopted these price increases and thereafter assumed that the price of electricity remains fixed in real terms. We assume an inflation rate of 2.5%, half way between the RBA inflation target of between 2% and 3%.

The tariff that is used as the starting point for the projections is Synergy's Electric Vehicle Home Plan which offers a special off-peak electricity charge of 18.474 cents per kWh for people to charge their electric vehicles.

The projections are presented in Figure 9.16 below.

²⁴ https://www.aemc.gov.au/sites/default/files/content/bf56a5d5-e2b2-4c21-90ed-79dda97eb8a4/2017-Residential-Electricity-Price-Trends.pdf





9.4.6 Fuel Consumption

The average rate of fuel consumption of motor vehicles is driven by a large number of factors. These include vehicle and fuel technology, driving behaviour, weather factors, and the roadway and roadside environment. The large array of factors is summarised by a diagram presented in the BITRE report, *Fuel Economy of Australian Passenger Vehicles-A Regional Perspective*²⁵. This report was based on the ABS Survey of motor vehicle use covering the 12-month period ending on 31 October 2016. The diagram has been reproduced in **Figure 9.17** below.

²⁵ Please see https://bitre.gov.au/publications/2017/files/is_091.pdf





The BITRE report notes that fuel consumption depends on many factors which have very little to do with the vehicle itself. These include weather conditions, driver behaviour such as hard braking and speed changes, road conditions such as the type of road surface. These and the other factors shown in the diagram can increase the rate of fuel consumption to levels that are well above the official fuel consumption that is published in the Green Vehicle Guide (GVG)²⁶.

The weight of vehicle and the engine size are important factors in driving fuel economy. BITRE cites a study by Knittel (2009)²⁷ which found that a 10% decrease in a vehicle's weight is associated with a 4% improvement in fuel economy. Moreover, a 10% reduction in engine size was associated with a 2.6% improvement in fuel economy.

Speed plays a role in fuel efficiency. According to *Fuel Economy.Gov*, an online resource maintained by the US Department of Energy, vehicle fuel economy decreases as the speed increases beyond a threshold which was estimated to be around 89 km per hour.

Figure 9.18 below shows the average rate of fuel consumption of Australian passenger and light commercial vehicles over time. From 1998 to 2016, average fuel consumption has declined slowly, probably reflecting improvements in vehicle and fuel technology, although it is not possible to completely rule out changes in behavioural patterns or the road environment.

In 1998, the average passenger vehicle on the road consumed 11.4 litres of petrol per 100 km travelled. By 2016, this had declined to 10.6 litres per 100 km, a decline of 7% over the entire historical period. In contrast, fuel consumption of light commercial vehicles remained steady over the period, hovering around 13 litres per 100 km. It is important to note that these estimates are based on an ABS survey and are therefore subject to some degree of statistical error.

²⁶ Please see https://www.greenvehicleguide.gov.au/

²⁷ Knittel ,C., "Automobiles on Steroids: Product Attribute Trade-Offs and Technological Progress in the Automobile Sector", NBER Working Paper 15162, 2009.



FIGURE 9.18 AVERAGE FUEL CONSUMPTION OF PASSENGER AND LIGHT COMMERCIAL VEHICLES, 1998 TO 2016

Internal Combustion Engine (ICE) vehicles

For the purposes of forecasting the fuel consumption of ICE vehicles over time, ACIL Allen has applied an annual improvement of 0.4% per annum over the entire forecasting horizon. This value corresponds to the historical average annual reduction in fuel consumption in passenger vehicles from 1998 to 2016.

The projections are shown in **Figure 9.19**. Separate projections are presented by vehicle size and type. The fuel consumption of a medium sized vehicle is projected to decrease from 10.9 litres/100km in 2018 to 9.96 litres/100km in 2028. For small passenger vehicles, fuel consumption is projected to decline from 7.7 litres/100km in 2018 to 7.0 litres/100 km in 2028, while for large vehicles, fuel consumption is projected to decline from 12.2 litres/100 km to 11.2 litres/100km over the same period.



FIGURE 9.19 FORECAST INTERNAL COMBUSTION ENGINE (ICE) VEHICLE FUEL CONSUMPTION, 2018 TO 2028

Electric Vehicles

In the case of electric vehicles, a similar rate of improvement in fuel consumption is assumed to ICE vehicles (see **Figure 9.20**). This is because electric vehicles are a very new technology and there is currently no historical information to enable the reliable estimation of changes to fuel consumption over time. Future improvements in the fuel economy of electric vehicles are subject to a high degree of uncertainty and may vary significantly from the assumptions made in this report.

Starting electricity consumption values were obtained from the published specifications for current electric vehicle models on sale in Australia. For a large passenger vehicle, ACIL Allen used the specified electricity consumption of the Tesla Model S, which uses 20.1kWh of electricity per 100km travelled. This is projected to decline to 19.3 kWh per 100km by 2028.

For the small passenger class, ACIL Allen used the specifications of the BMWi3 and Nissan Leaf as the basis of its starting value in 2018. The small passenger electric vehicle is estimated to use 15.0 kWh per 100km travelled. This is projected to decline gradually to 14.4 kWh per 100km by 2028.

The medium-sized vehicle electricity consumption starting value was obtained by taking a point in the mid-range between the value for small and large passenger vehicles. Electricity consumption of a medium-sized electric vehicle is projected to decline from 17.5 kWh per 100km travelled to 16.8 kWh per 100km in 2028.

FIGURE 9.20 FORECAST ELECTRIC VEHICLE ELECTRICITY CONSUMPTION, 2018 TO 2028



9.4.7 Total fuel costs

Projected fuel prices and fuel consumption can then be combined to calculate the total fuel cost of travelling 100 km. The estimates are shown in **Figure 9.21** for ICE vehicles.

For a small ICE passenger vehicle, the cost of driving 100 km is \$11.47 in 2018. This is projected to increase over time, reaching \$11.97 in real terms in 2028. In the case of a medium-sized passenger vehicle, the cost of travelling 100 km increases from \$16.23 in 2018 to \$16.95 in 2028 under the base case. For large passenger vehicles, the cost of travelling 100 km is projected to increase from \$18.17 to \$18.97 in 2028.

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The total fuel cost of running an electric vehicle for 100 km is shown in Figure 9.22.

The real electricity cost of driving an electric vehicle for 100km is projected to rise over the next few years in line with rising electricity prices. After 2020 it is expected to remain relatively stable. For a medium-sized electric vehicle, the electricity cost is projected to rise from \$3.23 per 100 km in 2018 to \$3.34 per 100km in 2028.



The combination of fuel consumption and fuel prices allows the cost of travelling a given distance to be calculated. This then allows a direct comparison of fuel costs between ICE and PHEV/EV vehicles. **Figure 9.23** shows the cost of travelling 100 km in the various categories of ICE and EV vehicles.



From these figures, it is clear that electric vehicles have a significant cost advantage over ICE vehicles when it comes to running costs for all classes of vehicle.

For example, for a medium sized passenger vehicle, the cost of travelling 100 km is \$16.23 in an ICE in 2018. For a medium PHEV/EV, the cost of travelling an equivalent distance is only \$3.23. Similar cost advantages are also evident in the other size categories.

Moreover, not only is this advantage clear in 2018, it is expected to be maintained over the next decade.

This suggests that take up of PHEV/EVs is expected to accelerate significantly once the problem of the relative high up-front cost is surmounted. As the price of electric vehicles approach that of ICEs, the low running costs of electric vehicles is likely to make them a very attractive alternatives to ICEs.

9.4.8 Range

Another factor that currently limits the potential of electric vehicles concerns their limited range compared to conventional ICEs.

For a large-sized passenger vehicle, an ICE has a range of about 550 km before it requires re-fuelling. A large passenger electric vehicle such as the Tesla Model S has a current range of about 410km.

The range of a small electric vehicle is only about 200 km by comparison (see **Figure 9.24**). This compares unfavourably with the range available from a typical small passenger ICE vehicle which is around 650 km.



The range of the vehicles is assumed to increase over time in line with improvements in fuel economy. Moreover, ACIL Allen has assumed that the range of EVs will increase at an additional rate of 3% per year as technological improvements accrue over time.

ACIL Allen considers that the limited range of electric vehicles is unlikely to pose a major issue for the majority of motor vehicle users. This is because most trips are relatively short, with the average passenger motor vehicle in WA being driven for 36.4 km per day. The 200km range for EVs is likely to be sufficient to cover at least 95% of trips. The vehicles will also be able to be charged every evening when they are garaged, allowing the driver to commence driving each day with a fully charged battery.

9.4.9 Convenience

A potential difficulty with PHEV/EVs is the lack of convenience when it comes to ease of charging.

There are several issues that are relevant here. These are:

- insufficient charging locations
- slow rate of charging.

Charging Locations

A potential constraint to the take up of electric vehicles is the limited number of locations where the car can be charged.

While we expect most vehicles to be charged at night when they are garaged, there will be a need for some vehicles to have access to charging facilities at other locations.

The slow roll-out of charging infrastructure could impose a constraint on the take up of electric vehicles. **Table 9.2** shows that WA has a total of 63 charging stations available to electric vehicle

100

drivers. This is guite a low number, and is equivalent to only 2.4 charging stations per 100,000 people. Adjusted for population size, WA has more charging stations than all other states except for the ACT. Tasmania and SA. Nevertheless, the number of charging locations should continue to increase as the economic attractiveness of EVs continue to improve against conventional ICE vehicles.

Charging locations	ACT	NSW	NT	QLD	SA	TAS	VIC	WA
Total number of charging stations	14	130	2	75	42	16	134	63
Charging stations per 100,000 residents	3.5	1.7	0.8	1.5	2.5	3.1	2.2	2.4
Total AC charging stations	11	119	1	70	41	16	127	51
Total DC charging stations	3	11	1	5	1	0	7	12
Total capital city charging stations	14	60	2	28	17	4	78	34
Total regional charging stations	0	70	0	47	25	12	56	29

TABLE 9.2 PUBLIC CHARGING INFRASTRUCTURE IN AUSTRALIA, 2017

Rate of Charging

There is currently an issue with the slow rate of charging electric vehicles. Charging is slow, with even the most rapid forms of charging expected to take at least 30 minutes. According to the report, "The State of Electric Vehicles in Australia" jointly published by Climateworks and the Electric Vehicle Council, the majority of chargers available in Australia are AC chargers which require the car to be parked for at least an hour. The report states that AC charging power levels range from 2.4 kW to 22 kW, with an average installation of 11 kW. At the average power level, charging the vehicle delivers 50 km of range per hour.

In contrast, DC chargers which are much fewer in number (11 DC chargers in NSW versus 119 AC chargers), offer significantly faster charging rates.

ACIL Allen believes the most common form of charging will take place over a period of 3 to 4 hours when the car is garaged overnight. Slower rates of charging are therefore only an inconvenience when the vehicle is travelling longer distances which necessitate charging the vehicle at a location away from home.

9.4.10 Summary of EV model input assumptions

Table 9.3 below presents a summary of the key assumptions employed in producing the electric vehicle forecasts under the three scenarios. As can be seen, the two key variables driving the differences across the three scenarios are the annual population growth and the real percentage decline in the purchase price of an EV relative to an ICE vehicle. All the other factors are kept constant across the three scenarios.

TABLE 9.3	3LE 9.3 MAIN ASSUMPTIONS APPLIED IN THE ELECTRIC VEHICLE PROJECTIONS				
EV assumptions		Low Medium		High	
Population growt	h (% p.a.)	1.10%	1.60%	2.00%	
Real percentage relative decline in EV price v. ICE price (% per annum)		4%	7.5%	9%	
Vehicle ownership rate increase (%)		0.4% per year for passenger vehicles, 0.75% per year for light commercial	0.4% per year for passenger vehicles, 0.75% per year for light commercial	0.4% per year for passenger vehicles, 0.75% per year for light commercial	

EV assumptions	Low	Medium	High	
Real electricity price	2017-1818.474 c/kWh,2017-1818.474 c/kWh,2018-1919.285 c/kWh,2018-1919.285 c/kWh,2019-2019.868 c/kWh,2019-2019.868 c/kWh,Constant after2020-21Constant after2020-21		2017-18 18.474 c/kWh, 2018-19 19.285 c/kWh, 2019-20 19.868 c/kWh, Constant after 2020-21	
Real petrol price increase	1.3% per year	1.3% per year	1.3% per year	
Average distance travelled per day (km)	36.4	36.4	36.4	
EV Range increase per year	3%	3%	3%	
Annual improvement in ICE fuel efficiency (%)	-0.90%	-0.90%	-0.90%	
Annual improvement in PHEV/EV fuel efficiency (%)	-0.40%	-0.40%	-0.40%	
SOURCE: ACIL ALLEN				

9.5 Modelling the Take-Up of Electric Vehicles

9.5.1 Logistic Framework

A logistic modelling framework is used to convert the underlying economic drivers of electric vehicles into an impact on the market share and take-up of the technology. It involves creating a model that values each attribute that drives the decision to adopt the technology and then applying an elasticity or measure of responsiveness of market share to each factor.

The logistic function is useful in that it can take as its inputs any value from negative to positive infinity (i.e. the key economic drivers described previously) and convert them into an output whose value is confined to lie between 0 and 1. This value can then be interpreted as the market share of the new technology. The function takes the form of an S curve and is shown in below.





The logistic formula takes the form:
$$\pi(x) = 1/(1 + \exp(-y))$$

where $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_n x_n$

The value of y is constructed as a linear function of the driving factors denoted by x_1 to x_n in the equation, and the β 's which represent the relative weights associated with each of the factors.

This formula simply converts the set of driving factors and their weights into some value between zero and one that represents the market share of the new technology over time. This value is represented by $\pi(x)$.

This approach will be used to determine the market share of each technology under consideration. The market shares are then applied to a base number of projected motor vehicles in WA to convert the market share into a projected number of electric vehicles.

9.5.2 Key Economic Drivers

The key drivers used as inputs into the modelling process are:

- vehicle price
- running costs
- range.

9.6 Projections of Electric Vehicles

Figure 9.26 shows the share of the light vehicle fleet that is projected to be made up of electric vehicles under the three separate scenarios. Under the expected case, the electric vehicle share of the stock of light passenger vehicles is projected to reach 11.7% by 2028. In the case of light commercial vehicles, 7.7% of the stock of motor vehicles is projected to be electric vehicles by 2028 under the expected growth case.

The charts demonstrate a rapid increase in the share of electric vehicles commencing from the late 2020's, which corresponds with the relative improvement in the economic attractiveness of EVs relative to ICE vehicles.

FIGURE 9.26 PLUG-IN ELECTRIC VEHICLE SHARE OF TOTAL LIGHT VEHICLES – EXPECTED, HIGH AND LOW GROWTH CASE



Figure 9.27 shows the projected number of electric vehicles under all three scenarios. Under the expected scenario, the stock of electric vehicles is projected to reach 268.3 thousand vehicles by 2028. Under the high growth scenario, the number of EVs is projected to be 502.3 thousand vehicles, while under the low scenario the stock of EVs will reach 69.0 thousand vehicles in 2028. The take up of electric vehicles is projected to remain low well into the 2020s, before undergoing a significant growth phase driven by improvements in the financial attractiveness of the vehicles.



FIGURE 9.27 PROJECTED NUMBER OF ELECTRIC VEHICLES, 2018 TO 2028

9.7 Impact on operational energy consumption

In calculating the energy consumption of the stock of electric vehicles, we apply an assumption for the average distance driven per day for WA. ABS statistics indicate that the weighted average distance travelled per day by passenger and light commercial vehicles is 36.4 km. This is equivalent to 13,300 kilometres per annum²⁸.

The average driving distance is then multiplied by the actual and projected energy consumption of electric vehicles. The energy consumption of the average electric vehicle is determined in this way. The total energy consumption of the entire stock of electric vehicles is then calculated by multiplying this measure by the number of projected electric vehicles. **Figure 9.28** below shows the forecast EV energy consumption for each of the three growth scenarios. Under the expected scenario, EV energy consumption is forecast to be 293 GWh by 2027-28. Under the high and low scenarios, EV energy consumption is forecast to reach 571 and 72 GWh respectively.

²⁸ 92080DO001_1231201610 Survey of Motor Vehicle Use, Australia, 12 months ended 30 June 2016

http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/9208.012%20months%20ended%2030%20June%202016?OpenDocument

